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Three Essays on Water Economics

Fahad Alzahrani

**Dissertation submitted to the
Davis College of Agriculture, Natural Resources, and Design
at West Virginia University
in partial fulfillment of the requirements
for the degree of**

**Doctor of Philosophy in
Natural Resource Economics**

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Morgantown, West Virginia
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Keywords: Water quality, Health care expenditures, Hedonic price models, Residential water charges, Spatial econometrics

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Abstract

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Fahad Alzahrani

The reliable provision of safe drinking water is one of the most important health-related programs in the United States. Since enactment of the Safe Drinking Water Act in 1974, great progress has been made in drinking water quality and regulation in the United States. Despite this progress, drinking water outbreaks continue to occur nationwide and negatively affecting the welfare of the people. In particular, rural residents suffer from drinking water quality and reliability issues due to the aging water infrastructure and the lack of funding to the small water systems serving such areas. This dissertation consists of three essays that explore how changes in water supply quality and/or reliability affect health care expenditures, residential property prices, and residential water charges.

The first essay explores the relationship between episodes of contaminated drinking water and health care expenditures in the United States. The analysis relies on panel data from the 48 contiguous states from 2000 to 2011. Using the population served by public water systems that violate health-based standards of the Safe Drinking Water Act as a proxy for contaminated drinking water, spatial and non-spatial models are estimated with controls for factors that may affect per capita health care expenditures including variables that reflect air quality violations along with ability to pay plus demand for and supply of health care services. The results from a Spatial Durbin Model indicate that a 1% decrease in the percentage of population exposed to drinking water quality violations is associated with reductions in in state and regional effects equal to 0.005% (\$0.32) and 0.035% (\$2.26) of per capita health care expenditures, respectively. Drinking water violations have a larger impact on expenditures than air quality violations (whose effects are not statistically different from zero). However, compared to other factors, such as health status and income, the impact of these violations on health care expenditures is relatively small. Regional health care expenditure impacts from drinking water violations are found to be substantially greater than in-state impacts. Thus, a regional approach is recommended to addressing drinking water quality improvements.

In the second essay, spatial and non-spatial hedonic property price models are used to examine the problem of water supply reliability due to aging infrastructure of public water systems on residential property prices. Water supply unreliability is measured by issuance of boil water notices (BNWs) linked to home sale observations (e.g. number of notices affecting the house prior to the sale). The analysis is based on 1,985 housing transactions and 350 BWNs throughout Marion County, West Virginia between 2012-2017. Important control variables include home size and age, lot size, number of bedrooms, construction quality, physical condition, and presence of house amenities (air conditioning, fireplace, and fence). Mapping and

distance tools in ArcGIS are used to measure neighborhood characteristics such as school quality and distance to the nearest highway interchange. Finally, the models include fixed effects for both time and tax district. Statistically significant, negative impacts are found for BWNs from the previous year before a house sale. Depending upon how water supply unreliability is measured – in either days, BWN episodes, or presence versus absence, BWNs can depreciate housing prices between 0.57% and 18%. A quantile regression approach is used to find that BWNs have a larger impact on low-price compared to high-price houses. Based upon quantile regressions, a reduction in one day under BWN per year will increase housing values at the lower end of the housing price distribution by \$2,100 to \$2,700, whereas houses at the mid-range of the distribution will increase by \$850 to \$1,000. However, houses at the higher end of the housing price distribution (0.7 quantile and above) show no statistically significant impact from this BWNs variable. Overall, water supply unreliability has a substantial impact on the value of residential properties in Marion County where the aggregate marginal willingness to pay for a one-day reduction of BWN is equal to \$4.60 million.

The third essay examines the impact of access to raw water sources on residential water charges by public service districts (PSDs) in West Virginia. This analysis determines the relative value of raw water from each source. Using regression analysis, we compare residential water charges per 4,500 gallons for PSDs that utilize different raw water sources including the surface water, purchased water, or multiple sources. We examine the difference in water charges between those PSDs that use NRCS's flood control impoundments as a water source compared to those who use other sources. Our analysis is based on data for 110 PSDs throughout the state of West Virginia. Our results show that PSDs that use multiple sources have higher residential water charges by about 29% of the average water charges compared to PSDs who utilize only one raw water source. Therefore, policies that encourage public water utilities to utilize multiple sources, such as the Source Water Protection (Senate Bill 373) passed by the West Virginia legislature in 2014, may result in higher rates. No statistically significant difference is found between water charges of PSDs that use NRCS's flood control impoundments and those who use conventional sources. Other factors, such as providing sewer plus water service in the same time result in lower residential water charges. Conversely, larger long-term debt and greater network length result in higher residential water charges.

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CHAPTER 1

Chapter 1: Background and Significance

After Flint, Michigan water crisis in 2014, many Americans have lost the confidence in the safety and reliability of the water supplied by public water systems (Baum et al., 2016). This incident shed light on water quality and reliability issues and drew the attention of the press, policymakers, and researchers nationwide. For example, a recent study by Allaire et al. (2018) found that in 2015, about 21 million people were served by public water systems that incurred violations of health-based quality standards of the Safe Drinking Water Act across the United States. This is not a new problem. In fact, many studies have examined the economic and health consequences of changes in water quality or reliability (e.g. Guilfoos et al., 2018; Grossman & Slutsky, 2017; Heflin et al., 2014). In light of this growing literature, I study three topics that are concerned with the impact of water quality and/or reliability on health care expenditures, residential property values, and residential water charges.

1.1. Purpose of This Study

This research aims to improve our understanding of how changes in water quality and/or reliability impact health care expenditures, residential property values, and residential water charges.

1.1.1. Aim of essay 1: Examine the impact of drinking water contamination on per capita health care expenditures in the United States.

Since 1970s, health economists and health policymakers have been interested in identifying the factors that drive health care expenditures in the United States. Previous studies have examined the impact of multiple factors including income, population age structure, and number of practicing physicians among others. However, published empirical works that examined the impacts of environmental quality on health care expenditures are fewer in number

and have used air quality as a proxy for environmental quality (e.g. Jerrett et al, 2003). The aim of this essay is to improve our understanding on how state-level health care expenditures responses to changes in drinking water contamination episodes across the United States.

1.1.2. Aim of essay 2: Examine the impact of water supply unreliability on residential property values in Marion County, West Virginia.

Many of the pipes and main lines that deliver water across the country are more than 100 years old and subject to variety of stressors (American Society of Civil Engineers [ASCE], 2017). The costs associated with replacing outdated water infrastructure are large, which were estimated to be around \$1 trillion and \$17 billion in the United States and West Virginia, respectively (American Water Works Association [AWWA], 2012; West Virginia Infrastructure and Jobs Development Council [WV IJDC], 2017). Most of the needed improvements in water infrastructure are funded by local governments and public water systems revenues generated by ratepayers. Since it is not optimal for a water system to achieve 100% reliability, decision makers need to make decisions that require a trade-off between cost and risk (Howe et al., 1994). In such cases, the required investment costs are usually known, but the risk preferences of the affected consumers are not. In this essay, the aim is to examine the impact of water supply unreliability on residential property values and estimate the marginal willingness to pay (MWTP) for improving the reliability of public water services in Marion County, West Virginia.

1.1.3. Aim of essay 3: Examine the impact of access to the different raw water supply sources on residential water charges in rural West Virginia.

The raw water supply sources that are utilized by public water systems play an important role in affecting not only the cost of treatment, but also the residential water charges (Erfanian & Collins, 2018). Previous studies, such as Bae (2007), found that public water systems that use groundwater sources have lower residential water charges compared water systems that use

surface water or purchased water. After the Elk River chemical spill in 2014, legislators in West Virginia passed a new law (SB 373) requiring public water systems that use surface water or groundwater influenced by surface water as supply sources to complete or update their source water protection plans. One of the main goals of these plans was to assess the ability of public water systems to construct or establish a secondary or backup source that to be used in cases of emergency or contamination of their primary water source. This push toward public water systems to have more than one water supply source may affect the residential water charges, especially in rural areas. The aim of this essay is to examine the impact of the different water supply sources on residential water charges for public service districts in West Virginia.

1.2. References

- Allaire, M., Wu, H., & Lall, U. (2018). National trends in drinking water quality violations. *Proceedings of the National Academy of Sciences*, 115(9), 2078–2083. <http://doi.org/10.1073/pnas.1719805115>
- American Society of Civil Engineers. (2017). *Infrastructure report card: Drinking water*. Retrieved from <https://www.infrastructurereportcard.org/cat-item/drinking-water/>
- American Water Works Association. (2012). *Buried no longer: Confronting America's water infrastructure challenge*. Retrieved from <http://www.climateneeds.umd.edu/reports/American-Water-Works.pdf>
- Bae, S. (2007). Explaining geographical differences in water prices: Do institutional factors really matter? *The Review of Regional Studies*, 37(2), 207–250.
- Baum, R., Bartram, J., & Hrudey, S. (2016). The Flint water crisis confirms that U.S. drinking water needs improved risk management. *Environmental Science & Technology*, 50, 5436–5437. <http://doi.org/10.1021/acs.est.6b02238>
- Erfanian, E., & Collins, A. R. (2018). Charges for water and access: What explains the differences among West Virginian municipalities? *Water Economics and Policy*, 04(04), 1850017. <http://doi.org/10.1142/s2382624x18500170>
- Grossman, D. S., & Slusky, D. J. G. (2017). *The effect of an increase in lead in the water system on fertility and birth outcomes: The case of Flint, Michigan*. Retrieved from http://busecon.wvu.edu/phd_economics/pdf/17-25.pdf
- Guilfoos, T., Kell, D., Boslett, A., & Hill, E. L. (2018). The economic and health effects of the 2014 chemical spill in the Elk River, West Virginia. *American Journal of Agricultural Economics*, 100(2), 609–624. <http://doi.org/10.1093/ajae/aax089>
- Heflin, C., Jensen, J., & Miller, K. (2014). Understanding the economic impacts of disruptions in water service. *Evaluation and Program Planning*, 46, 80–86. <http://doi.org/10.1016/j.evalprogplan.2014.05.003>
- Howe, C. W., Smith, M. G., Bennett, L., Bredeeke, C. M., Flack, J. E., Hamm, Robert, M., ... Wunderlich, K. (1994). The value of water supply reliability in urban water systems. *Journal of Environmental Economics and Management*, 26(1), 19–30.
- Jerrett, M., Eyles, J., Dufournaud, C., & Birch, S. (2003). Environmental influences on healthcare expenditures: an exploratory analysis from Ontario, Canada. *Journal of Epidemiology and Community Health*, 57(5), 334–338. <http://doi.org/10.1136/jech.57.5.334>

West Virginia Infrastructure and Jobs Development Council. (2017). *Needs assessment*.
Retrieved from
<https://assets.documentcloud.org/documents/5396603/2017NeedsAssessment-IJDC.pdf>

CHAPTER 2

Essay 1: Drinking Water Quality Impacts on Health Care Expenditures in the United States

2.1. Introduction

Health care expenditures in the United States have been rising at a rate faster than any other country in the world (Sawyer and Cox, 2018). In 2015, health care expenditures accounted for 17.8% of the country's GDP (Centers for Medicare and Medicaid Services [CMS], 2018). However, higher health care expenditures do not necessarily lead to better health outcomes. Compared to most Organization for Economic Co-operation and Development (OECD) countries, the United States has a lower life expectancy, a higher obesity rate, a lower percentage of health insurance coverage, and below average numbers of doctors and hospital beds (OECD, 2017). This has led health economists and health care policymakers to explore what factors are causing increases in health care expenditures and to devise cost containment measures.

Since the 1970s, many studies have attempted to identify what factors impact health care expenditures. We categorize those factors into two groups: (1) non-environmental factors, and (2) environmental factors. Most of the literature on the determinants of health care expenditures has focused on non-environmental factors such as income, population age structure, inflation, number of practicing physicians, number of hospital beds, technological progress, and public financing of health care services. among many others. Gerdtham and Jönsson (2000) and Martín et al. (2011) provide reviews of this literature. Published empirical works that have examined the impacts of environmental quality on health care expenditures are fewer in number and have used air quality as a proxy for environmental quality (Jerrett et al., 2003; Narayan and Narayan, 2008; Qureshi et al., 2015; Yahaya et al., 2016; Zou et al.2016).

Environmental quality is an important factor that affects the health of individuals (World Health Organization, 2018). Poor air and/or water quality can have adverse effects on human health (Hunter et al., 2010; Katsouyanni, 2003). For example, in the case of air pollution, it has been found that sulfur dioxide (SO₂) causes changes in airway physiology (Chen et al., 2007); carbon monoxide may cause pulmonary edema (Raub et al., 2000); and particulate matter has been associated with cardiovascular diseases (Pope and Dockery, 2006).

Water pollution can affect human health through exposures from direct consumption or recreational use. The main acute effects of drinking polluted water on health is gastrointestinal infections (Hunter et al., 2010). In addition, chronic or acute exposure to different organic and inorganic chemicals in water can cause more severe health impacts including cancer, developmental or reproductive effects, neurological effects, and organ damage (United States Environmental Protection Agency [U.S. EPA], 2018a).

Over the years, multiple laws have been enacted in the United States to ensure a health-sustaining rather than health-threatening environment. The Clean Air Act (CAA) of 1970, the Federal Water Pollution Control Act of 1948 (re-authorized as the Clean Water Act (CWA) in 1972), and the Safe Drinking Water Act (SDWA) of 1974 are few examples of federal environmental pollution laws passed to improve and protect the quality of air and water. Under these laws, the EPA establishes national environmental quality standards. States then have the option to apply for primacy and if accepted, they will be responsible for implementing and enforcing these laws. In addition, primacy states are authorized to set their own regulations to be stricter than the EPA's minimum requirements. Because of these laws, the United States has witnessed numerous improvements in terms of human health and environmental quality. For

example, Sullivan et al. (2018) found that from 1970 to 1990 the CAA provided an estimated improvement of \$22 trillion in cumulative human health and reduced mortality benefits.

In terms of environmental quality, between 1970 and 2015, aggregate national emissions of six common air pollutants (particles, ozone, lead, carbon monoxide, nitrogen dioxide, and sulfur dioxide) dropped an average of 70% (U.S. EPA, 2018b). Moreover, before the SDWA, about 40% of public water systems failed to meet basic health standards, and now this value decreased to only 10% (U.S. EPA, 2014). In 2015, about 21 million people living in the United States were served by public water systems that incurred violations of health-based quality standards of the SDWA (Allaire et al., 2018). While not all violations cause immediate health problems, it has been estimated that contaminated drinking water is responsible for between 16.4 to 19.5 million cases of acute gastroenteritis every year in the United States (Duggal et al., 2015; Messner et al., 2006).

Despite these efforts towards improving environmental quality as well as the significant progress in water treatment technology, multiple mid- and large-scale drinking water contamination episodes have been observed over the past few years (Duggal et al., 2015; Guilfoos et al., 2018). One example is the Flint, Michigan crisis in 2014 where approximately 100,000 residents were exposed to high levels of lead from drinking water. Compared to other cities in Michigan, fertility rates decreased by 12%, fetal death rates increased by 58%, and overall health at birth decreased in Flint during the time of exposure (Grossman and Slusky, 2017). Another contamination incident occurred in 2014 in Charleston, West Virginia where chemical spills into the Elk River contaminated the drinking water for about 300,000 residents. This incident resulted in immediate and long-term health impacts. For the immediate health impacts, there were about 369 cases of acute gastrointestinal illness and 13 hospitalizations

attributed to this contamination episode (Benedict et al., 2017). For the long-term health impacts, Guilfoos et al. (2018) estimated the causal effects of this incident on infant health outcomes and found a significant decrease in 5-minute Apgar Scores. Finally, another example is the Toledo, Ohio crisis in 2014 when toxic algae were found in the municipal drinking water affecting about 500,000 residents. This incident resulted in about 110 cases of acute gastrointestinal illness (Benedict et al., 2017). Toledo spent an estimated \$200,000 per month to mitigate the effects of this event (Duggal et al., 2015).

The exposure to contaminants in drinking water has been demonstrated to increase the consumption of health care services due to its deleterious impacts on human health and in turn, health care expenditures are bound to increase as well. For example, spending on medical care and water provisions in Flint amounted to about \$60 million in response to the 2014 water crisis (Muennig, 2016). Furthermore, Naumova et al. (2016) estimated the costs of treating infections related to drinking contaminated water from 1991 to 2006 to be about \$600 million per year for Medicare beneficiaries alone. Given the existence of this relationship between drinking contaminated water and health care expenditures, this research seeks to statistically validate and quantify the connection between drinking water quality and health care expenditures at an aggregated state level on an annual basis.

The remainder of this paper is organized as follows. The rest of this section provides a background of the SDWA and in the next section we review of the literature that examined the impact of environmental quality on health care expenditures. Then, the following sections are data, the empirical model, and results describing the analytical framework and empirical results. Finally, the paper concludes with policy implications and research limitations plus future research.

2.1.1. The Safe Drinking Water Act: Background

The SDWA was initially passed in 1974 and then amended in 1986 and 1996. This act authorizes the U.S. EPA to regulate drinking water sources and infrastructure to protect public health by setting national health standards for drinking water against both naturally-occurring and man-made contaminants occurring in drinking water. Currently, the U.S. EPA has drinking water regulations for more than 90 contaminants. These standards apply to every one of the more than 150,000 active public water system in the United States (U.S. EPA, 2013).

The SDWA requires water systems to report their water quality periodically to the state primacy agency to make sure they meet the minimum requirements. The U.S. EPA has set different monitoring and sampling schedules for public water systems based on certain criteria such as population served, water source type, and historical monitoring data. For example, for microbial contaminants regulated under the total coliform rule (TCR), a public water system is required to take monthly samples based on its size as follows: 1 sample/month (very small), 2–3 samples/month (small), 4–10 samples (medium), 15–100 samples/month (large), and 120–480 samples/month (very large) (U.S. EPA, 2010). If a water system is collecting less than 40 samples/month and has more than one total coliform-positive sample, then the water system will be considered in violation to SDWA standards. On the other hand, if it is collecting 40 or more samples/month, and has more than 5% of the samples with total coliform-positive, then the system will be in violation of SDWA standards. Each quarter, the primacy agency then reports any violations of the SDWA to the U.S. EPA.

Violations to the SDWA standards are grouped into two main categories: (1) health-based violations, and (2) monitoring and communication with the public violations. Health-based violations include violations to the Maximum Contaminant Levels (MCLs), Maximum Residual Disinfectant Levels (MRDLs), and Treatment Techniques (TT) standards. MCL and MRDL set

the highest level of a contaminant or a disinfectant residual that is allowed in drinking water without imposing any danger to the human health. If it is technically not possible to monitor a certain contaminant or not economically feasible to do so, a TT is used instead. For example, lead has no known safe levels and since it is impossible to monitor it under the MCL regulations, a TT is used, where any detection of lead may result in replacing some of the service lines to consumers.

Monitoring and communication with the public violations include violations to Monitoring and Reporting (MR) and other standards such as not sending the annual drinking water quality report to the customers. If a water system has a MR violation, this indicates that the system has failed in completing the regular testing requirements or failed to submit test results to the state primacy agency in the required time.

In this paper, we follow Carrie et al. (2013) and Allaire et al. (2018) and focus only on health-based violations since it is unclear whether the monitoring and communication with the public violations pose a health threat. In addition, monitoring and communication with public violations have poor data quality since only a small portion of these violations (9-23%) are reported to the national Safe Drinking Water Information System (SDWIS) database (U.S. EPA, 2004).

2.2. Literature Review

As mentioned in the introduction, previous research has focused on the relationship between health care expenditures and non-environmental factors, such as income and population age structure. Those studies have used different methodologies and models to explore these relationships. Previous research shows variable coefficient estimates with conflicting results. For example, some studies such as Wang (2009) and Thornton and Rice (2008) found that the

number of beds has a positive impact on per capita health care expenditures, whereas others such as Prieto and Lago-Peñas (2012) and Reich et al. (2012) found the opposite impact. However, income has been found to consistently have a positive impact on health care expenditures (Baltagi and Moscone, 2010; Xu et al., 2011). Some researchers argue that the inconsistent findings from non-income factors can be attributed to differences in estimation methods used or the lack of a formal economic theory regarding the determinants of health care expenditures (Gerdtham and Jönsson, 2000; Wilson, 1999).

Some older studies attempted to capture the effect of environmental quality by using urbanization as a proxy, which coincides with industrialization and, in turn, industrial pollution (Gbesemete and Gerdtham, 1992; Gerdtham et al., 1992; Kleiman, 1974). However, urbanization is highly correlated with income and other variables, and these studies found either insignificant coefficients or unexpected signs.

Jerrett et al. (2003) were among the first authors to investigate the direct relationship between health care expenditures and environmental indicators. They represented environmental indicators as total toxic pollution emissions in all environmental media and government environmental protection expenditures. Cross-sectional data from 49 counties in Ontario, Canada were employed in a sequential two-stage regression model to consider the endogenous relationship between health care expenditures and mortality. They found that counties with higher pollution emissions tend to have higher per capita health care expenditures, where a one-ton increase in emissions is associated with \$0.03 higher per capita health expenditures. Moreover, counties that spend more on improving environmental quality have lower per capita health care expenditures. It was estimated that a one dollar increase in defensive expenditures are associated with \$0.31 lower per capita health expenditures.

Narayan and Narayan (2008) examined the relationship between environmental quality and health care expenditures using data for eight OECD countries from 1980 to 1999. As a proxy for environmental quality, they used air emissions of sulfur oxide, nitrogen oxide, and carbon monoxide emissions. Furthermore, they used a panel cointegration approach to estimate both short- and long-run impacts of environmental quality on health care expenditures. They found that in the long-run, sulfur oxide and carbon monoxide emissions had statistically significant, positive impacts on per capita health care expenditures. For example, they estimated that a 1% increase in sulfur oxide emissions increases per capita health care expenditures by 0.04%. In the short-run, carbon monoxide emissions were the only environmental quality indicator that had a statistically significant, positive impact on per capita health care expenditures. However, the magnitude of the impact was smaller than the long-run.

Using a panel cointegration approach similar to Narayan and Narayan (2008), other studies such as Qureshi et al. (2015), Yahaya et al. (2016), and Zou et al. (2016) examined the relationship between environmental quality, proxied by various indicators related to air pollution, and health care expenditures. Generally, the results from these studies indicate that in the long-run, air pollution has a statistically significant and positive impact on health care expenditures, but this estimated impact is smaller in the short-run.

Past studies that explored the relationship between environmental quality and health care expenditures have largely used air quality to proxy environmental quality. Thus, a possible extension to the literature is to use other proxies to environmental quality, such as drinking water quality, which is the research objective of this paper.

2.3. Data

In this section, we provide background information and data sources for the variables used in the analysis. The empirical analysis is based on annual, state-level data for 48 contiguous U.S. states for the period 2000 to 2011.

2.3.1. *Dependent variable – Health care expenditures*

To measure health care expenditures, we use the per capita Personal Health Care (PHC) expenditures component of the National Health Expenditure Accounts (NHEA) estimates provided by the Centers for Medicare and Medicaid Services (CMS). The NHEA comprise the official government estimates of aggregate health care spending in the U.S. These annual estimates are comprehensive since they encompass all the main elements of the health care system in a unified, mutually exclusive and exhaustive structure. These are multidimensional because they include information about expenditures on medical goods and services, and those who paid to finance these expenditures. Consistent methodology and classification systems are used that employ a common set of definitions which allows comparisons between groups over time (Catlin and Cowan, 2015; CMS, 2015).

The NHEA categorizes state health care spending data into two types: spending by state of provider and spending by state of residence. In the former, the estimates include all revenues obtained by health care providers in a state for supplying health care goods and services to both residents and non-residents. These estimates are used to measure the GDP of a state from the health care sector. In the latter, the estimates contain all health care expenditures by residents of a state whether the service is provided in or out of the state. These latter estimates are used to develop the per capita measures to compare between states which are used in this paper.

To estimate health care expenditures by state, the CMS follows a multi-step process: (1) expenditures by state of provider (or the state where health care goods and services are

consumed) are developed for each PHC service using provider-based survey data; (2) estimates of spending by payer (Medicare, Medicaid, and private health insurance) are developed using a combination of administrative claims data and survey data; and (3) the provider-based expenditures for each service and for Medicare are converted to a state of residence basis using information on health care expenditure patterns (or flows) between states. Expenditure estimates for Medicaid and for private health insurance are both assumed to be already on a state of residence basis. The aggregate values then are divided by the total state population to obtain the per capita PHC.

PHC is defined as total spending on health care goods and services minus administration and the net cost of private health insurance, government public health activities, and investment in research, structures, and equipment. Various goods and services are included in the PHC such as hospital care, physician and clinical services, dental services, and home health care. However, two types of health care spending are not included in the PHC due to the availability of the data: (1) health care expenditure estimates for health services provided to recipients outside the country that were paid for by Medicare, and (2) health care services obtained by individuals residing in United States territories who returned to the United States to receive them. According to Cuckler et al. (2011) those limitations do not affect the findings when using the per capita PHC data.

Since the values provided by the CMS are nominal, we use the Personal Health Care index to adjust for inflation, which according to Dunn et al. (2016) is the most preferred index to use when adjusting total medical expenditures for general medical price changes. Finally, it is important to note that health care expenditures do not measure health outcomes. While measurement of direct health outcomes is preferable (such as a measure of improved health

status) to examine the impact of water contamination episodes, these data are not available at the scale of analysis we are considering here.

2.3.2. Independent variables

We group the independent variables into four categories based upon how they affect health care expenditures: drinking water quality, ability to pay, demand for health care services, and supply of health care services.

2.3.2.1. Drinking water quality

In this paper, we are interested in the impact of health-based violations for drinking water, so our focus is limited to the population served by public water systems. The percentage of the population served by public water systems in each state that experience at least one violation of the MCL or TT standards during a year are used as a proxy for drinking water quality since MRDL violations rarely occur. Even if MRDL violations are used, they are too small to result in consistent outcomes (Wallsten and Kosec, 2008). We obtain the population served by those systems that experienced violations in each year from the U.S. EPA's Factoids: Drinking Water and Ground Water Statistics reports. We then divide these U.S. EPA estimates by each state's population to compute the percentage of the state population that has been exposed to health-based violations for drinking water provided by public water systems at any time during the year.

2.3.2.2. Ability to pay for health care services

Income: One of the most important factors that drives health care expenditures is income. Previous studies that explored the determinants of health care expenditures at the international, national, and regional levels have all shown that an increase in income will result in an increase in health care expenditures (Murthy and Ukpolo, 1994; Newhouse, 1977; Wang,

2009). To control for this variable, we use real per capita state GDP as a proxy for income. These data were obtained from the United States Bureau of Economic Analysis (BEA).

Unemployment and uninsured rates: The impacts of unemployment and uninsured rates on health care expenditures are ambiguous. An increase in state's unemployment rate or uninsured rate could limit the ability to pay for health care goods and services, and therefore, health care expenditures would decrease. On the other hand, an increase in states' unemployment rate or uninsured rate could also increase per capita health care expenditures since while less people will be covered by private health insurance, more people will be covered by programs such as Medicaid. These two variables represent access to health care, which is an important determinant of health care expenditures. Data for these two variables were obtained from two different sources. The first is the Bureau of Labor Statistics (BLS), and the second is the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS) survey. To measure uninsured rate, the BRFSS asks the participants the following question: "Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, government plans such as Medicare, or Indian Health Service?" Each of these variables are measured as a percentage of the state population.

2.3.2.3. Consumption of health care services

Health status: The health status of the state's residents will determine how much of health care goods and services will be consumed. To measure population health status, we use the health status variable from the BRFSS survey, where participants are asked, "How is your general health?", and respondents can choose among the provided answers (excellent, very good, good, fair, or poor). This measure is the percentage of population who have excellent health,

therefore, we expect the coefficient to be negative since better health status will lead to less health care expenditures.

Population age structure: Another important determinant of health care expenditures is the state's population age structure. It is well observed that personal health care expenditures are unevenly distributed through a person life, with larger spending during older ages (Reinhardt, 2003). Therefore, we use the proportion of the state population who are enrolled in Medicare as measure of state's elderly population. According to CMS (2017), this measure has an advantage over the proportion of population over 65 years old because it is more closely related to state health spending. The data for this variable came from the CMS's Medicare Enrollment Dashboard. It is expected that an increase in this proportion will result in an increase in health care expenditures.

Environmental expenditures: Following Jerrett et al. (2003), we control for state's environmental expenditures to avoid the risk of omitted variable bias since it is expected that environmental expenditures may be correlated with the number of violations in a state. To measure this variable, we use state's spending on natural resources as a proxy similar to Fredriksson et al. (2011) and List and Sturm (2006). We use per square mile measures to account for size variation between states. It is expected that an increase in state's environmental expenditures will improve the state environmental quality and the overall public health, and therefore decrease health care expenditures. We obtain the data for this variable from the annual survey of state government finances from the Census Bureau.

Air quality: Following other studies that examined the impact of environmental quality on health care expenditures, we control for the impact of air quality by using the percentage of population that live in nonattainment areas (counties) that violate air quality standards. To

compute this variable, we first obtain detailed information about those areas from the U.S. EPA's Green Book, which shows the status of each county in terms of attainment of nonattainment of the National Ambient Air Quality Standards (NAAQS). Then using population estimates from the Census Bureau we calculate the percentage of population affected by air pollution in each state. Since some states have no violations in some years, we transform this variable using $\log(\text{air quality} + 0.001)$.

2.3.2.4. Supply of health care services

The supply of health care services varies across the states. To account for this variation, we use the number of hospital beds per 1,000 population as an indicator for health care capacity in a state. As mentioned previously, the impact of this variable is ambiguous. In a competitive market environment, we would expect that a greater availability of health care services would lead to lower per capita health care expenditures, all other things being equal. However, it has been shown repeatedly in the literature that a greater supply of health care services may result in increased demand for health care services leading to higher health care spending. This positive impact is often explained as the supply-induced demand problem, where increasing competition leads health providers to recommend unnecessary services (Frech, 1996; McGuire, 2000). The data for this variable were obtained from the CDC's Health, United States reports.

2.3.3. Descriptive statistics

Table 2.1 provides summary statistics for the annual variables used in the analysis. The dependent variable is state level, real per capita health care expenditures. This variable ranges from \$4,003 in Utah to a maximum of \$9,417 in Massachusetts. Figure 2.1 illustrates the distribution of the average real per capita health care expenditures across the states between 2000 and 2011. Some of the highest levels of per capita health expenditures are observed in the

Northeast and Mid-Atlantic regions, whereas some of the lowest levels are observed in the Southwest and Southeast regions.

In a similar manner to per capita health care expenditures, Massachusetts was also the state with the highest percentage of population served by public water systems that violated the health-based standards with 78.56% of its population affected in one year (Table 2.1). Figure 2.2 shows the distribution of population served by public water systems that violated health-based standards. To examine how per capita health care expenditures and drinking water quality variables moved together during the analysis period, we divided the U.S. into EPA regions and calculated the average of per capita health care expenditures and the percentage of population affected by health-based violations in each region and report them in Figures 2.3 through 2.12. Per capita health care expenditures show a continuous increase in all regions from 2000 to 2011. On the other hand, except for regions 6 and 10, health-based violations mainly fluctuate over the years in most regions.

The statistical values for the other variables vary widely across the states over the analysis period. Real environmental expenditures per square mile vary from \$910 for Nevada to \$74,070 for New Jersey. Real per capita GDP also covers a large range, from \$29,730 to \$86,200, with Mississippi and Idaho having the lowest values and Delaware and Connecticut having the highest values. The percentage of the population with excellent health ranges from 13.40% to 28.80% across the states, where the lowest value is for West Virginia and the highest is for Connecticut. Finally, variation in the percentage of population affected by air pollution is large between states, where some have almost no pollution and others have all the population in the state affected by air pollution.

2.4. Empirical Models

We estimate two sets of models: non-spatial and spatial. First, we use variations of state level fixed effects (FE) and random effects (RE) models motivated by Reich et al. (2012), Cantarero and Lago-Peñas (2010), and Crivelli et al. (2006). Five models are estimated: (1) pooled OLS, (2) state fixed effects (FE), (3) random effects (RE), (4) state FE with year fixed effects, and (5) RE with year fixed effects. Results from the Hausman (1978) specification test indicate that the FE model is more appropriate than the random effects model. However, since most of the variables do not vary much over time within the sample period, FE methods can lead to imprecise estimates (Wooldridge, 2002).¹ Table 2.2 shows the within, between, and overall variation of the variables included in the analysis. Except of drinking water quality and unemployment rate, all the other variables have low within variation. Hahn et al. (2011) show that the Hausman (1978) test is not appropriate when some or all of the explanatory variables have little within variable variation. Therefore, we present the results from both models and compare them.

It follows from the model description above that:

$$y_{it} = x_{it}\beta + a_i + \lambda_t + \varepsilon_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (2.1)$$

where y_{it} is the state's per capita health care expenditures, x_{it} is $K \times 1$ and contains our variable of interest and other control variables, a_i is the state's fixed or random effect to account for the unobservable characteristics, λ_t is the time fixed effect, and ε_{it} is the error term. Based on the epidemiological evidence found in many studies (see Villanueva et al. 2014), we hypothesize a positive association such that an increase in the percentage of the population exposure to

¹ Following Cameron and Trivedi (2009), we examine the within and between standard deviations to determine which variables have low within variation. The results indicate that most of variables in our sample have low within variation.

drinking water violations within a state will result in an increase in state level per capita health care expenditures.

In addition to using basic panel estimation methods, LaSage and Pace (2009) and Elhorst (2014) state that use of a general non-spatial estimation is based upon observed values being independent of location when there is no correlation between neighbors. In other words, in a non-spatial model, each observation has a mean of $x_i\beta$ and a random component ε_i . The observation i represents a region or point in space, which is considered to be independent of its neighboring regions or points j , i.e., $E(\varepsilon_i\varepsilon_j) = E(\varepsilon_i)E(\varepsilon_j) = 0$.

However, in many cases, the assumption of observations' independency is not applicable. In other words, observations at different points or regions are dependent (LeSage and Pace, 2009). Pollution levels and health outcomes are examples of such a dependency assumption between the variable of interest and an outcome. For example, the pollution levels in region i may influence health outcomes in a neighboring region j (Chen et al., 2017; Erfanian and Collins, 2019).

With spatial interdependence, we suppose two neighbors (regions) i and j which are spatially correlated with normality being assumed for the error terms:

$$y_i = \rho_{ij}y_j + x_i\beta + \varepsilon_i \quad (2.2)$$

$$y_j = \rho_{ji}y_i + x_j\beta + \varepsilon_j \quad (2.3)$$

where the dependent variable in neighbor j influences the dependent variable in neighbor i and the reverse also holds true. Once a spatial component (whether this component is from the dependent variable, control variables, or the error term) is found to be statistically significant, then any coefficients estimated by a non-spatial model may be biased. In addition, by applying a non-spatial model when the spatial component is significant, variances may be non-efficient

(Griffith, 2005; LeSage and Pace, 2009). Accordingly, statistical tests (t-test and F-test) may be invalid, leading economists to interpret their results improperly.

Given that state level real per capita health expenditures show visual evidence of clustering (Figure 2.1), we test for spatial autocorrelation among states with a Moran's I (see Anselin, 1988, p.101). The global Moran's I is statistically significant (Moran's I index for 2000 = 0.16, P-value = 0.02; Moran's I index for 2011 = 0.21, P-value = 0.004) demonstrating that spatial interrelationships exist for per capita health care expenditures and the need to apply spatial econometrics modeling. We also report the scatter plot of Moran's I to be sure that the positive spatial correlation for some observations and negative spatial correlation for other observations do not cancel out each other. Figure 2.3 provides these results and illustrates that both at the start and end of the data, most of the states with high real per capita healthcare expenditures are adjacent to states with high real per capita health care expenditures. This also is true for the states with low real per capita health care expenditures. Thus, we have ample evidence to apply a spatial econometrics model in our analysis.

There are five possible spatial models. The first is a Spatial Autoregressive (SAR) Lag Model as shown in equations (2.2) and (2.3). A Spatial Error Model (SEM) has dependency in the error term, while a SLX model (Spatial Lag of Explanatory variables) assumes that only explanatory variables play a direct role in determining dependent variables. A Spatial Durbin Model (SDM) includes spatial lags of explanatory variables as well as the dependent variable, while a Spatial Error Durbin Model (SDEM) includes these lags along with spatially dependent disturbances.

To observe dependence between neighboring observations, spatial econometric models differentiate between direct and indirect effects. Direct effects show how changes in a variable

for the i^{th} state influences the i^{th} state's dependent variable (in-state impacts). Indirect effects explain the effects of a variable in j^{th} state on i^{th} state's dependent variable (regional impacts). LeSage (2008) discusses that since the impacts of a variable are different among observations, it is desirable to have a measurement of overall and average impacts. Thus, these measurements are divided into the concepts of average direct, indirect, and total effects (LeSage and Pace, 2014).

Parameters in a general, non-spatial linear regression are interpreted as a partial derivative of the dependent variable with respect to the explanatory variable. An assumption of independence between observations serves as the basis for this interpretation. In a spatial model, however, interpretation of the parameters becomes more complicated. As numerous economists (Anselin and Le Gallo, 2006; Kelejian et al., 2006; Kim et al., 2003; Le Gallo et al., 2003; LeSage and Pace, 2009) point out a model with a spatial lag of the dependent variable requires special interpretation of the parameters. Elhorst (2014) calculated the direct, indirect and the total effect in a general nesting spatial model as

$$Y = (I - \delta W)^{-1}(X\beta + WX\theta) + R \quad (2.4)$$

where W is the spatial weight matrix, δ is called the spatial autoregressive coefficient, θ represents a $K \times 1$ vector of fixed but unknown parameters to be estimated, and R represents the intercept and error terms.

The matrix of partial derivatives of the expected dependent variable with respect to changes in explanatory variables becomes:

$$\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdot \frac{\partial E(Y)}{\partial x_{Nk}} \right] = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1k}} & \cdot & \frac{\partial E(y_1)}{\partial x_{Nk}} \\ \frac{\partial E(y_N)}{\partial x_{1k}} & \cdot & \frac{\partial E(y_N)}{\partial x_{Nk}} \end{bmatrix}$$

$$= (1 - \delta W)^{-1} \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdot & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \cdot & w_{2N}\theta_k \\ \cdot & \cdot & \cdot & \cdot \\ w_{N1}\theta_k & w_{N2}\theta_k & \cdot & \beta_k \end{bmatrix} \quad (2.5)$$

where w_{ij} is the $(i, j)^{th}$ element of W . Every diagonal element of the partial derivative matrix in equation (2.5) shows the direct effect while the indirect effects are shown by every off-diagonal element. Since the direct and indirect effects are unique for each observation, LeSage and Pace (2009) suggest reporting the summary indicators (the average of the diagonal elements for the direct effect and the average of either the row sums or the column sums of the off-diagonal elements for indirect effects). Since θ in a SAR model is equal to zero, indirect effect would be equal to the off-diagonal elements of $(1 - \delta W)^{-1}\beta_k$.

The weight matrix W describes the interrelationships between observations. According to Elhorst (2014), the weight matrix can be thought of as a tool to define the neighbors for any given region. This definition can be in a geographical dimension or in another framework such as the share of trade or transportation. Various units of measurement for spatial dependencies such as cities, counties, states, and countries are available for spatial analysis (Getis, 2007).

Our spatial weight matrix is based on the distance between the center of states and we applied a three nearest-neighbors weight matrix. We chose the most representative weight matrix for the analysis by testing for different nearest neighbors. The weight matrix based on three nearest neighbors had the highest log likelihood value, which indicates that a weight matrix consisting of three nearest neighbors for the analysis is the most representative weight matrix for the analysis. In addition, we tested between SDM and SDEM model by using a Bayesian posterior probability model and the result confirmed that the most appropriate model to capture

the spillover effect for our model is the SDM model.² Spatial econometric models are estimated using Matlab software codes provided by Lacombe (2016).

Following previous literature which examines determinants of health care expenditures, all variables are converted to logarithmic form for estimation, so that regression coefficients are interpreted as elasticity estimates. Moreover, we evaluate these data using the extended projection (P_E) test from MacKinnon et al. (1983) to compare the log-log and linear model specifications. The results indicate that the log-log model is more appropriate. With the SDM, we estimate the marginal effects (direct, indirect, and total) of the independent variables on per capita health care expenditures using 2000-2011 data.

2.5. Results

Table 2.3 reports the regression results for the non-spatial models. In most models, our coefficient estimates for drinking water quality violations are positive and statistically significant, but they become insignificant when we include time fixed effects. In terms of the expected signs for the other explanatory variables, RE model coefficient estimates are similar to those for the FE models. Comparing the 95% confidence intervals for the drinking water quality coefficients in models (2) with (4) and those of models (3) with (5), we find that the estimates are within the 95% confidence intervals of each other.³ Since there are no large differences between the estimates of FE and RE, we continue and use the RE as the preferred approach.

Table 2.4 reports the results of the direct, indirect, and total effects from the Spatial Durbin Model (SDM) with RE and year fixed effects. The coefficient of spatially lagged

² SDM probs = 0.69, SDEM probs = 0.31

³ The confidence intervals for the drinking water quality variable coefficients are: model 2: (-0.0002, 0.0169), model 4: (0.0011, 0.0174), model 3: (-0.0032, 0.0036), and model 5: (-0.0027, 0.0040).

dependent variable is 0.149 and statistically significant at a 1% level, which indicates that the regression coefficient estimates from Table 2.3 are likely biased. This result also reveals that state level per capita health care expenditures tend to increase in response to higher per capita health care spending in neighboring states. This is expected since state level health care expenditures and health policy decisions depend on the surrounding states (Bose et al., 2015). Therefore, this prior research suggests that per capita health care expenditures follow the same path as state level health care expenditures.

With respect to the drinking water quality variable, the results show that this variable has a positive and statistically significant impact on per capita health care expenditures both within the state itself as well as in neighboring states. Relative to the direct effect, the magnitude of the average indirect effect of drinking water quality violations in state i is fairly large. Specifically, a 1% decrease in the population served by public water systems that experience violations of SDWA's health-based standards in state i , on average, would decrease annual per capita health care expenditures by 0.005% (\$0.32) in state i , and by 0.035% (\$2.26) in its three neighboring states.⁴ The direct effect of drinking water quality is small compared to other variables with statistically significant, but larger direct impacts. For example, a 1% increase in health status would result in a decrease of annual per capita health care expenditures in state i by 0.053% (\$3.42), about ten times the impact of drinking water quality violations on per capita health care expenditures.

The large difference between the direct (in-state) and indirect (regional) effects of drinking water quality on per capita health care expenditures is unexpected since water quality

⁴ Dollar values are based on the average per capita health care expenditures reported in Table 2.1.

contamination episodes are generally viewed as local problems as evidenced by the discussion in section 2.1. There are two possible explanations for such a disparity between direct and indirect effects. The first is that population movement between states so that exposed persons to a water contamination episode in state i have actually traveled from adjacent j states. Such spillover impact can be small if we look at one region but if we cumulate these small impacts on all neighbors it may lead to situations where the spillover impacts are much larger in magnitude than the direct impact (LeSage and Dominguez, 2012). The second is that changes in the percentage of population exposed to contaminants in one state are indicative of a larger regional problem with water quality contamination. One example is extreme weather events (Curriero et al., 2001). Such an explanation warrants a more coordinated regional approach across states when addressing water quality problems related to drinking water quality violations as is practiced by entities such as river basin commissions (Abdalla et al., 2011).

To illustrate the extent of this decrease on a state's total health care expenditures, we choose the state of Montana. This state represents the average of our sample, where the percentages of population exposed to violations is 6.67% in 2011 compared to an average of 6.37% for the other 47 states. We calculate the estimated decrease in total health care expenditures resulting from a 1% decrease in the population experiencing violations in drinking water quality. We obtain this value by multiplying \$0.32 by Montana's 2011 population. Therefore, a 1% decrease in the population exposed to drinking water quality violations would result in an estimated \$319,302 decrease in annual health care expenditures within the state of Montana. For Montana's three nearest neighbors (Idaho, North Dakota, and Wyoming), however, this 1% reduction would, on average, result in about a \$6.41 million reduction in annual health care expenditures. Further, we examine the in-state and regional impacts of a 1%

reduction across all 48 contiguous states. Multiplying the dollar values by the 2011 state populations, we find that, on average, this will lead to \$98.9 million and \$698.2 million reductions in annual health care expenditures for in-state and regional impacts, respectively.

The public water system costs to achieve a 1% reduction in the number of violations across all 48 states are uncertain. These costs will be largely passed on to the water system's customers and will depend on many factors such as system size and type of contaminant. According to Auerbach (1994), cost increases to comply with SDWA standards range from 2% of water charges for households served by large public water systems to 55% for households served by small systems. A more recent estimate of the costs associated with compliance to SDWA standards over the next 20 years is provided by the U.S. EPA's (2018c) Drinking Water Infrastructure Needs Survey and Assessment. The U.S. EPA estimates that out of total national needs (\$472.6 billion), about 12% (\$57 billion) is related to violations of SDWA regulations. It is unclear how much of this \$57 billion would be required to achieve a 1% reduction.

Comparing drinking water quality with air quality, we find that drinking water quality violations have a larger impact on health care expenditures than air quality violations, which have a statistically insignificant impact. This result is in contrast with other findings which have examined the impact of air quality on health care expenditures (examples include Narayan and Narayan (2008) and Yahaya et al. (2016)). Our result shows that when exposure to environmental contamination is measured as violation of a standard plus along with being aggregated across multiple pollutants, then exposure to drinking water quality violations has a larger impact on health care expenditures than exposure to air quality violations.

For the other control variables, the direct effect of income is positive and statistically significant as expected. Our estimates, however, are much lower in magnitude than the estimates

found in other studies. Wang (2009) and Bose (2015) found income to have impacts over twice as high (0.71 and 0.64, respectively). For access to health care variables, the unemployment rate is statistically insignificant in all effects. The indirect effect of uninsured rate is positive and statistically significant, which indicates that an increase in the uninsured rate in state i will result in an increase in per capita health care expenditures in neighboring states.

Examining the variables for consumption of health care services, the health status variable has a statistically significant, negative direct effect as expected. Medicare enrollment, similar to CMS (2017), is positive and statistically significant for both the direct and indirect effects so that increases in Medicare enrollment not only increases in state, but also the neighboring three states' per capita health care expenditures. This variable has the largest impact of any variable on per capita health care expenditures in our model. This impact is expected since per capita health expenditures for people age 65 or older, on average, are three to five times higher than spending by young people (Reinhardt, 2003).

Finally, environmental expenditures per square mile have positive and statistically significant direct effects on health care expenditures. This result indicates that higher expenditures reflect the existence of more environmental problems, leading to higher per capita health care expenditures due to the population facing more health risks related to environmental quality.

For the supply of health care variable, only the indirect effect for number of hospital beds is negative and statistically significant. A possible explanation for this result is that hospitals in state i compete with hospitals in neighboring states by improving quality of the services, and therefore, lower the cost of health care for patients from neighboring states (Bose et al., 2015). Thus, a higher supply of health care services benefits consumers in neighboring states by

reducing their per capita health care expenditures rather than in the state where more hospital beds are provided.

2.6. Conclusions

The impacts of drinking water quality violations on state level per capita health care expenditures are estimated using a proxy variable of the percentage of population served by public water systems that experienced violations of SDWA's health-based standards. We estimate both spatial and non-spatial models and control for factors that reflect air pollution as well as ability to pay plus consumption of along with supply of health care services using data from 48 contiguous states for the period 2000 – 2011.

We find a positive and statistically significant relationship between drinking water quality violations and state level per capita health care expenditures. Specifically, the results from the Spatial Durbin Model indicate that a 1% decrease in the percentage of population exposed to violations is associated with reductions in direct and indirect effects equal to 0.005% (\$0.32) and 0.035% (\$2.26) of per capita health care expenditures.

It is important to note that reductions in per capita health expenditures stemming from lowering drinking water quality violations is just one benefit that arises from drinking water quality improvement. Other, more localized benefits from fewer violations include real estate value impacts from correcting source water contamination problems. Examples of this research include Liu et al. (2017), Tuttle and Heintzelman (2015), and Leggett and Bockstael (2000). Given the high investment costs associated with lowering of drinking water quality violations, a full accounting of all benefits from these reductions will be needed to offset these costs.

Limitations of this research relate primarily to the data that are used. First, using an aggregated data at the state level may average out the effects at the local level where drinking

water quality violations are occurring, therefore resulting in biased estimates. Lindo (2015) provides a discussion on how the results may change based on the level of geographic aggregation of the data used in the analysis. Since per capita health care expenditures data are only available at the state level we could not explore any other options.

Second, sometimes people get exposed to contaminants in drinking water multiple times a year. However, our analysis does not account for this. Therefore, including some kind of an intensity treatment in the analysis may result in different conclusions. Third, our data only covers public water systems, thereby excluding about 45 million people who use private wells for their drinking water and thus are not regulated under the SDWA (U.S. Geological Survey, 2009). Considering this population in future research would expand results to consider the implications of drinking water violations to more rural areas.

Fourth, the proxy variable that we used to reflect exposure to drinking water contamination also has its flaws. These data include multiple types of contaminants that affect human health differently (i.e. short- and long-run health impacts). However, we did not include a lag system for population exposure to drinking water violations in our model to account for a range of temporal health impacts from contaminant exposures.

Finally, water systems have financial incentives not to comply with all the U.S. EPA regulations due to the higher costs that it will impose on these systems (Bennewell et al. 2009). Therefore, there is a higher probability that false or missing data are being reported. For example, the agency estimated that states were not reporting 40% of all health-based violations (U.S. EPA, 2004). Employing these changes in the drinking water quality variable may yield different results from our current models.

2.7. References

- Abdalla, C. W., Drohan, J. R., and Becker, J. C. (2011). *River basin approaches to water management in the Mid-Atlantic states*. PennState Extension. Retrieved from <https://extension.psu.edu/river-basin-approaches-to-water-management-in-the-mid-atlantic-states>
- Allaire, M., Wu, H., and Lall, U. (2018). National trends in drinking water quality violations. *Proceedings of the National Academy of Sciences*, 115(9), 2078–83. <http://doi.org/10.1073/pnas.1719805115>
- Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht, Netherlands: Springer Science+Business Media.
- Anselin, L., and Le Gallo, J. (2006). Interpolation of air quality measures in hedonic house price models: Spatial aspects. *Spatial Economic Analysis*, 1(1), 31–52. <http://doi.org/10.1080/17421770600661337>
- Auerbach, J. (1994). Costs and benefits of current SDWA regulations. *Journal of American Water Works Association*, 86(2), 69–78. <http://doi.org/https://www.jstor.org/stable/41292652>
- Baltagi, B. H., and Moscone, F. (2010). Health care expenditure and income in the OECD reconsidered: Evidence from panel data. *Economic Modelling*, 27(4), 804–811. <http://doi.org/10.1016/j.econmod.2009.12.001>
- Benedict, K. M., Reses, H., Vigar, M., Roth, D. M., Roberts, V. A., Mattioli, M., et al. (2017). Surveillance for waterborne disease outbreaks associated with drinking water — United States, 2013 – 2014 waterborne disease and outbreak surveillance system. *Morbidity and Mortality Weekly Report.*, 66(44), 1216–1221. <http://doi.org/10.15585/mmwr.mm6644a3>
- Bose, S. (2015). Determinants of per capita state-level health expenditures in the United States: A spatial panel analysis. *Journal of Regional Analysis and Policy*, 45(1), 93–107.
- Bose, S., Gebremedhin, T. G., and Sambamoorthi, U. (2015). State-level variations in hospital expenditures: An application of spatial regression. *Journal of Health Care Finance*, 42(2), 1–35.
- Cameron, A. C., and Trivedi, P. K. (2009). *Microeconometrics using STATA*. College Station, TX: StataCorp LP.
- Cantarero, D., and Lago-Peñas, S. (2010). The determinants of health care expenditure: A reexamination. *Applied Economics Letters*, 17(7), 723–726. <http://doi.org/10.1080/13504850802314437>
- Catlin, A., and Cowan, C. A. (2015). *History of health spending in the United States, 1960-2013*. Centers for Medicare and Medicaid Services. Retrieved from <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/HistoricalNHEPaper.pdf>

- Centers for Medicare and Medicaid Services. (2015). *National health expenditure accounts: Methodology paper, 2015*. Retrieved from <https://www.cms.gov/NationalHealthExpendData/>
- Centers for Medicare and Medicaid Services. (2017). Econometric analysis of state health expenditures: Methodology and model specification. Retrieved from <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/State-Model-14.pdf>
- Centers for Medicare and Medicaid Services. (2018). Historical national health expenditure data. Retrieved August 20, 2012, from <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/index.html>
- Chen, T.-M., Kuschner, W. G., Gokhale, J., and Shofer, S. (2007). Outdoor air pollution: Nitrogen dioxide, sulfur dioxide, and carbon monoxide health effects. *The American Journal of the Medical Sciences*, 333(4), 249–256. <http://doi.org/10.1097/MAJ.0b013e31803b900f>
- Chen, X., Shao, S., Tian, Z., Xie, Z., and Yin, P. (2017). Impacts of air pollution and its spatial spillover effect on public health based on China's big data sample. *Journal of Cleaner Production*, 142, 915–925. <http://doi.org/10.1016/j.jclepro.2016.02.119>
- Crivelli, L., Filippini, M., and Mosca, I. (2006). Federalism and regional health care expenditures: An empirical analysis for the Swiss cantons. *Health Economics*, 15(5), 535–541. <http://doi.org/10.1002/hec.1072>
- Cuckler, G., Martin, A., Whittle, L., Heffler, S., Sisko, A., Lassman, D., and Benson, J. (2011). Health spending by state of residence, 1991–2009. *Medicare and Medicaid Research Review*, 1(4), E1–E31. <http://doi.org/http://dx.doi.org/10.5600/mmrr.001.04.a03>
- Currie, J., Zivin, J. G., Meckel, K., Neidell, M., and Schlenker, W. (2013). Something in the water: Contaminated drinking water and infant health. *Canadian Journal of Economics*, 46(3), 791–810.
- Curriero, F. C., Patz, J. A., Rose, J. B., and Lele, S. (2001). The association between extreme precipitation and waterborne disease outbreaks in the United States, 1948 – 1994. *American Journal of Public Health*, 91(8), 1194–1199.
- Duggal, A., Frede, S., and Kasky, T. (2015). *A public health legal guide to safe drinking water*. Carey School of Law, University of Maryland. Retrieved from <http://www.astho.org/Public-Policy/Public-Health-Law/Public-Health-Authority-Over-Drinking-Water-Quality-Overview/>
- Dunn, A., Grosse, S. D., and Zuvekas, S. H. (2016). Adjusting health expenditures for inflation: A review of measures for health services research in the United States. *Health Services Research*, 53(1), 175–196. <http://doi.org/10.1111/1475-6773.12612>

- Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. New York, NY: Springer.
- Erfanian, E., and Collins, A. R. (2019). *Air quality and Asthma hospitalization: Evidence of PM2.5 concentrations in Pennsylvania counties* (Working Paper No. 2019-01). Regional Research Institute, West Virginia University. Retrieved from <http://rri.wvu.edu/wp-content/uploads/2019/03/Asthma.pdf>
- Frech, H. E. (1996). *Competition and monopoly in medical care*. Washington, D. C.: The AEI Press.
- Fredriksson, P. G., Wang, L., and Mamun, K. A. (2011). Are politicians office or policy motivated? The case of U.S. governors' environmental policies. *Journal of Environmental Economics and Management*, 62(2), 241–253. <http://doi.org/10.1016/j.jeem.2011.03.005>
- Gbesemete, K. P., and Gerdtham, U.-G. (1992). Determinants of health care expenditure in Africa: A cross-sectional study. *World Development*, 20(2), 303–308. [http://doi.org/10.1016/0305-750X\(92\)90108-8](http://doi.org/10.1016/0305-750X(92)90108-8)
- Gerdtham, U.-G., and Jönsson, B. (2000). International comparisons of health expenditure: Theory, data and econometric analysis. *Handbook of Health Economics, Volume 1*, 11–53. [http://doi.org/10.1016/s1574-0064\(00\)80160-2](http://doi.org/10.1016/s1574-0064(00)80160-2)
- Gerdtham, U.-G., Sjøgaard, J., Jönsson, B., and Andersson, F. (1992). A pooled cross-sectional analysis of the health care expenditure of the OECD countries. In P. Zweifel and H. E. Frech III (Eds.), *Health Economics Worldwide* (pp. 287–310). Springer-Science+Business Media.
- Getis, A. (2007). Reflections on spatial autocorrelation. *Regional Science and Urban Economics*, 37(4), 491–496. <http://doi.org/10.1016/j.regsciurbeco.2007.04.005>
- Griffith, D. A. (2005). Establishing qualitative geographic sample size in the presence of spatial autocorrelation. *Annals of the Association of American Geographers*, 95(4), 740–760. <http://doi.org/10.1080/00045608.2013.776884>
- Grossman, D. S., and Slusky, D. J. G. (2017). *The effect of an increase in lead in the water system on fertility and birth outcomes: The case of Flint, Michigan* (Working Paper No. 17-25). Department of Economics, West Virginia University. Retrieved from http://busecon.wvu.edu/phd_economics/pdf/17-25.pdf
- Guilfoos, T., Kell, D., Boslett, A., and Hill, E. L. (2018). The economic and health effects of the 2014 chemical spill in the Elk River, West Virginia. *American Journal of Agricultural Economics*, 100(2), 609–624. <http://doi.org/10.1093/ajae/aax089>
- Hausman, J. A. (1978). Specification test in econometrics. *Econometrica*, 46(6), 1251–1271. Retrieved from <http://www.jstor.org/stable/1913827>

- Hunter, P. R., MacDonald, A. M., and Carter, R. C. (2010). Water supply and health. *PLoS Medicine*, 7(11), 1–9. <http://doi.org/10.1371/journal.pmed.1000361>
- Jerrett, M., Eyles, J., Dufournaud, C., and Birch, S. (2003). Environmental influences on healthcare expenditures: An exploratory analysis from Ontario, Canada. *Journal of Epidemiology and Community Health*, 57(5), 334–338. <http://doi.org/10.1136/jech.57.5.334>
- Katsouyanni, K. (2003). Ambient air pollution and health. *British Medical Bulletin*, 68, 143–156. <http://doi.org/10.1093/bmb/ldg028>
- Kelejian, H. H., Tavlas, G. S., and Hondroyiannis, G. (2006). A spatial modelling approach to contagion among emerging economies. *Open Economies Review*, 17, 423–441. <http://doi.org/10.1007/s11079-006-0357-7>
- Kim, C. W., Phipps, T. T., and Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management*, 45(1), 24–39. [http://doi.org/10.1016/S0095-0696\(02\)00013-X](http://doi.org/10.1016/S0095-0696(02)00013-X)
- Kleiman, E. (1974). The determinants of national outlay on health. *The Economics of Health and Medical Care*, 66–88. http://doi.org/10.1007/978-1-349-63660-0_5
- Lacombe, D. J. (2016). MATLAB code. Texas Tech University. Retrieved from <http://myweb.ttu.edu/dolacomb/matlab.html>
- Le Gallo, J., Ertur, C., and Baumont, C. (2003). A spatial econometric analysis of convergence across european regions, 1980-1995. In B. Fingleton (Ed.), *European Regional Growth* (pp. 99–129). Berlin, Heidelberg: Springer. <http://doi.org/10.1007/978-3-662-07136-6>
- Leggett, C. G., and Bockstael, N. E. (2000). Evidence of the effects of water quality on residential land prices. *Journal of Environmental Economics and Management*, 39(2), 121–144. <http://doi.org/10.1006/jeem.1999.1096>
- LeSage, J. P. (2008). An introduction to spatial econometrics. *Revue d'économie Industrielle*, 123(3), 19–44. <http://doi.org/10.4000/rei.3887>
- LeSage, J. P., and Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton: CRC Press. <http://doi.org/10.1007/BF02646613>
- LeSage, J.P., and Dominguez, M. (2012). The importance of modeling spatial spillovers in public choice analysis. *Public Choice* 150(1), 525–545. <http://doi.org/10.1007/s11127-010-9714-6>
- LeSage, J. P., and Pace, R. K. (2014). Interpreting spatial econometric models. In M. M. Fischer and P. Nijkamp (Eds.), *Handbook of Regional Science*. New York, NY: Springer.

- List, J. A., and Sturm, D. M. (2006). How elections matter: Theory and evidence from environmental policy. *Quarterly Journal of Economics*, 121(4), 1249–1281. <http://doi.org/10.1162/qjec.121.4.1249>
- Liu, T., Opaluch, J. J., and Uchida, E. (2017). The impact of water quality in Narragansett Bay on housing prices. *Water Resources Research*, 53(8), 6454–6471. <http://doi.org/10.1002/2016WR019606>
- MacKinnon, J. G., White, H., and Davidson, R. (1983). Tests for model specification in the presence of alternative hypotheses. *Journal of Econometrics*, 21, 53–70. Retrieved from <http://www.jstor.org/stable/1911522>
- Martin, A. B., Whittle, L., Heffler, S., Barron, M. C., Sisko, A., and Washington, B. (2007). Health spending by state of residence, 1991–2004. *Health Affairs*, 26(6), 651–663. <http://doi.org/10.1377/hlthaff.26.6.w651>
- Martín, J. J. M., del Amo Gonzalez, M. P. L., and Dolores Cano Garcia, M. (2011). Review of the literature on the determinants of healthcare expenditure. *Applied Economics*, 43(1), 19–46. <http://doi.org/10.1080/00036841003689754>
- McGuire, T. G. (2000). Physician agency. In A. J. Culyer and J. P. Newhouse (Eds.), *Handbook of Health Economics* (pp. 461–536). Elsevier.
- Messner, M., Shaw, S., Regli, S., Rotert, K., Blank, V., and Soller, J. (2006). An approach for developing a national estimate of waterborne disease due to drinking water and a national estimate model application. *Journal of Water and Health*, 4(SUPPL. 2), 201–240. <http://doi.org/10.2166/wh.2006.024>
- Muennig, P. (2016). The social costs of lead poisonings. *Health Affairs*, 35(8), 1545. <http://doi.org/10.1377/hlthaff.2016.0661>
- Murthy, N. R. V., and Ukpolo, V. (1994). Aggregate health care expenditure in the United States: Evidence from cointegration tests. *Applied Economics*, 26(8), 797–802. <http://doi.org/10.1080/00036849400000094>
- Narayan, P. K., and Narayan, S. (2008). Does environmental quality influence health expenditures? Empirical evidence from a panel of selected OECD countries. *Ecological Economics*, 65(2), 367–374. <http://doi.org/10.1016/j.ecolecon.2007.07.005>
- Naumova, E. N., Liss, A., Jagai, J. S., Behlau, I., and Griffiths, J. K. (2016). Hospitalizations due to selected infections caused by opportunistic premise plumbing pathogens (OPPP) and reported drug resistance in the United States older adult population in 1991–2006. *Journal of Public Health Policy*, 37(4), 500–513. <http://doi.org/10.1057/s41271-016-0038-8>
- Newhouse, J. P. (1977). Medical-care expenditure: A cross-national survey. *Journal of Human Resources*, 12(1), 115–125.

- Organization for Economic Co-operation and Development. (2017). *Health at a glance 2017: OECD indicators*. Retrieved from http://www.oecd-ilibrary.org/social-issues-migration-health/health-at-a-glance-2017_health_glance-2017-en
- Pope, C. A., and Dockery, D. W. (2006). Health effects of fine particulate air pollution: Lines that connect. *Journal of the Air and Waste Management Association*, 56(6), 709–742. <http://doi.org/10.1080/10473289.2006.10464485>
- Prieto, D. C., and Lago-Peñas, S. (2012). Decomposing the determinants of health care expenditure: The case of Spain. *European Journal of Health Economics*, 13(1), 19–27. <http://doi.org/10.1007/s10198-010-0276-9>
- Qureshi, M. I., Khan, N. U., Rasli, A. M., and Zaman, K. (2015). The battle of health with environmental evils of Asian countries: Promises to keep. *Environmental Science and Pollution Research*, 22(15), 11708–11715. <http://doi.org/10.1007/s11356-015-4440-8>
- Raub, J. A., Mathieu-Nolf, M., Hampson, N. B., and Thom, S. R. (2000). Carbon monoxide poisoning - A public health perspective. *Toxicology*, 145(1), 1–14. [http://doi.org/10.1016/s0300-483x\(99\)00217-6](http://doi.org/10.1016/s0300-483x(99)00217-6)
- Reich, O., Weins, C., Schusterschitz, C., and Thöni, M. (2012). Exploring the disparities of regional health care expenditures in Switzerland: Some empirical evidence. *European Journal of Health Economics*, 13(2), 193–202. <http://doi.org/10.1007/s10198-011-0299-x>
- Reinhardt, U. E. (2003). Does the aging of the population really drive the demand for health care? *Health Affairs*, 22(6), 27–39. <http://doi.org/10.1377/hlthaff.22.6.27>
- Sawyer, B., and Cox, C. (2018). How does health spending in the U.S. compare to other countries? Retrieved August 20, 2012, from <https://www.healthsystemtracker.org/chart-collection/health-spending-u-s-compare-countries/#item-start>
- Sullivan, T. J., Driscoll, C. T., Beier, C. M., Burtraw, D., Fernandez, I. J., Galloway, J. N., et al. (2018). Air pollution success stories in the United States: The value of long-term observations. *Environmental Science and Policy*, 84, 69–73. <http://doi.org/10.1016/j.envsci.2018.02.016>
- Thornton, J. A., and Rice, J. L. (2008). Determinants of healthcare spending: A state level analysis. *Applied Economics*, 40(22), 2873–2889. <http://doi.org/10.1080/00036840600993973>
- Tuttle, C. M., and Heintzelman, M. D. (2015). A loon on every lake: A hedonic analysis of lake water quality in the Adirondacks. *Resource and Energy Economics*, 39, 1–15. <http://doi.org/10.1016/j.reseneeco.2014.11.001>
- U.S. Environmental Protection Agency. (2004). *EPA claims to meet drinking water goals despite persistent data quality shortcomings* (Report No. 2004-P-0008). Retrieved from <https://www.epa.gov/sites/production/files/2015-12/documents/20040305-2004-p-0008.pdf>

- U.S. Environmental Protection Agency. (2010). *Revised total coliform rule: A quick reference guide*. Retrieved from <https://nepis.epa.gov/Exe/ZyPDF.cgi/3000663W.PDF?Dockey=3000663W.PDF>
- U.S. Environmental Protection Agency. (2013). *Providing safe drinking water in America: 2013 national public water systems compliance report*. Retrieved from <https://www.epa.gov/sites/production/files/2015-06/documents/sdwacom2013.pdf>
- U.S. Environmental Protection Agency. (2014). Speech: Administrator Gina McCarthy, remarks celebrating the 40th anniversary of the Safe Drinking Water Act, as prepared. Retrieved from https://archive.epa.gov/epapages/newsroom_archive/speeches/21a0a07494e97f3985257da9006ad9d0.html
- U.S. Environmental Protection Agency. (2018a). Drinking water contaminant human health effects information. Retrieved from <https://www.epa.gov/dwstandardsregulations/drinking-water-contaminant-human-health-effects-information>
- U.S. Environmental Protection Agency. (2018b). Progress cleaning the air and improving people's health. Retrieved from <https://www.epa.gov/clean-air-act-overview/progress-cleaning-air-and-improving-peoples-health>
- U.S. Environmental Protection Agency. (2018c). *Drinking water infrastructure needs survey and assessment*. Retrieved from https://www.epa.gov/sites/production/files/2018-10/documents/corrected_sixth_drinking_water_infrastructure_needs_survey_and_assessment.pdf
- U.S. Geological Survey. (2009). Contamination in U.S. private wells. Retrieved from <https://water.usgs.gov/edu/gw-well-contamination.html>
- Villanueva, C. M., Kogevinas, M., Cordier, S., Templeton, M. R., Vermeulen, R., Nuckols, J. R., et al. (2014). Assessing exposure and health consequences of chemicals in drinking water: Current state of knowledge and research needs. *Environmental Health Perspectives*, 122(3), 213–221. <http://doi.org/10.1289/ehp.1206229>
- Wallsten, S., and Kosec, K. (2008). The effects of ownership and benchmark competition: An empirical analysis of U.S. water systems. *International Journal of Industrial Organization*, 26(1), 186–205. <http://doi.org/10.1016/j.ijindorg.2006.11.001>
- Wang, Z. (2009). The determinants of health expenditures: Evidence from US state-level data. *Applied Economics*, 41(4), 429–435. <http://doi.org/10.1080/00036840701704527>
- Wilson, R. M. (1999). Medical care expenditures and GDP growth in OECD nations. *American Association of Behavioral and Social Sciences Journal*, 2(3), 159–171.
- Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press. <http://doi.org/10.1515/humr.2003.021>

- World Health Organization. (2018). The determinants of health. Retrieved from <https://www.who.int/hia/evidence/doh/en/index3.html>
- Xu, K., Priyanka, S., and Holly, A. (2011). *The determinants of health expenditure: A country-level panel data analysis*. World Health Organization. Retrieved from https://www.who.int/health_financing/documents/report_en_11_deter-he.pdf?ua=1
- Yahaya, A., Nor, N. M., Habibullah, M. S., Ghani, J. A., and Noor, Z. M. (2016). How relevant is environmental quality to per capita health expenditures? Empirical evidence from panel of developing countries. *SpringerPlus*, 5(1), 1–14. <http://doi.org/10.1186/s40064-016-2505-x>
- Zou, X., Azam, M., Islam, T., and Zaman, K. (2016). Environment and air pollution like gun and bullet for low-income countries: War for better health and wealth. *Environmental Science and Pollution Research*, 23(4), 3641–3657. <http://doi.org/10.1007/s11356-015-5591-3>

2.8. Tables and Figures

Figure 2.1. Average real per capita health care expenditures between 2000 and 2011 (\$2009)

Figure 2.2. Percentage of population served by PWSs that violated health-based standards (2000 – 2011 average)

Figure 2.3. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 1: CT, ME, MA, NH, RI, and VT

Figure 2.4. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 2: NY and NJ

Figure 2.5. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 3: DE, MD, PA, VA, and WV

Figure 2.6. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 4: AL, GA, KY, MS, NC, TN, FL, and SC

Figure 2.7. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 5: IL, IN, MI, MN, OH, and WI

Figure 2.8. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 6: AR, LA, OK, NM, and TX

Figure 2.9. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 7: IA, MO, KS, and NE

Figure 2.10. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 8: CO, MT, ND, SD, UT, WY

Figure 2.11. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 9: AZ, CA, and NV

Figure 2.12. Average per capita health care expenditures and percentage of population exposed to health-based violations – Region 10: ID, OR, and WA

Figure 2.13. Scatter plots of Moran's I for 2000 and 2011

Table 2.1. Summary statistics of annual, state-level data for the contiguous 48 states, 2000 to 2011

Variable	Unit	Mean	Std. Dev.	Min	Max
Health care expenditures	2009 dollars	6451.47	973.48	4003.96	9417
Drinking water quality	%	7.33	7.72	0.01	78.56
Air quality	%	39.97	36.98	0	100
Income	Thousand 2009 dollars	48.94	9.25	29.73	86.20
Environmental expenditures per sq/mi	Thousand 2009 dollars	10.56	12.21	0.91	74.07
Medicare enrollment	%	14.88	1.98	9.18	20.81
Health status	%	20.90	2.78	13.40	28.80
Number of hospital beds		2.95	0.90	1.70	6.10
Uninsured rate	%	14.80	4.30	4.30	29.80
Unemployment rate	%	5.73	2.12	2.30	13.70

Table 2.2. Within, between, and overall variations of the variable used in the analysis

Variable	Standard Deviation		
	Within	Between	Overall
Health care expenditures	568.55	797.87	973.48
Drinking water quality	0.06	0.05	0.08
Air quality	0.11	0.36	0.37
Income	3.57	8.61	9.25
Environmental expenditures	2.57	12.05	12.21
Medicare enrollment	0.65	1.89	1.98
Health status	1.45	2.40	2.78
Number of hospital beds	0.17	0.90	0.90
Uninsured rate	1.61	4.03	4.30
Unemployment rate	1.84	1.05	2.12

Table 2.3. Non-spatial regression results, dependent variable of annual, state level per capita health care expenditures

	(1) Pooled	(2) FE	(3) FE	(4) RE	(5) RE
Drinking water quality	0.016*** (0.000)	0.008* (0.055)	0.000 (0.910)	0.009** (0.026)	0.001 (0.705)
Air quality	0.000 (0.938)	-0.001 (0.526)	-0.001 (0.176)	-0.001 (0.688)	-0.001 (0.432)
Income	0.323*** (0.000)	0.058 (0.596)	0.271*** (0.000)	0.212** (0.017)	0.305*** (0.000)
Environmental expenditures	0.015*** (0.005)	0.047* (0.073)	0.008 (0.481)	0.021 (0.165)	0.018** (0.043)
Medicare enrollment	0.721*** (0.000)	1.212*** (0.000)	0.443*** (0.007)	1.130*** (0.000)	0.521*** (0.000)
Health status	-0.038 (0.281)	-0.168*** (0.001)	-0.042** (0.050)	-0.214*** (0.000)	-0.031 (0.134)
Number of hospital beds	-0.018 (0.305)	-0.463*** (0.000)	0.077 (0.109)	-0.262*** (0.000)	0.061* (0.055)
Uninsured rate	-0.114*** (0.000)	0.004 (0.885)	-0.043*** (0.001)	-0.028 (0.374)	-0.052*** (0.000)
Unemployment rate	0.107*** (0.000)	0.009 (0.526)	-0.001 (0.902)	0.052*** (0.000)	0.006 (0.545)
Constant	3.515*** (0.000)	5.448*** (0.001)	4.563*** (0.000)	4.177*** (0.000)	3.895*** (0.000)
Year Fixed Effect	No	No	Yes	No	Yes
N	576	576	576	576	576
R-sq	0.662	0.754	0.959	0.516	0.868

Note: Numbers in the parentheses represent p-values.

* p<0.1, ** p<0.05, *** p<0.01

Table 2.4. Spatial Durbin model with random effects regression results, dependent variable of annual, state level per capita health care expenditures

	(1) Direct effect	(2) Indirect effect	(3) Total effect
Drinking water quality	0.005*** (0.008)	0.035*** (0.003)	0.040*** (0.003)
Air pollution	-0.002 (0.379)	-0.002 (0.850)	-0.004 (0.755)
Income	0.253*** (0.000)	0.078 (0.209)	0.331*** (0.000)
Environmental expenditures	0.013** (0.028)	-0.018 (0.518)	-0.005 (0.882)
Medicare enrollment	0.606*** (0.000)	1.374*** (0.000)	1.979*** (0.000)
Health status	-0.053** (0.019)	0.125 (0.296)	0.072 (0.598)
Number of hospital beds	-0.001 (0.953)	-0.438*** (0.000)	-0.439*** (0.000)
Uninsured rate	-0.010 (0.379)	0.126** (0.014)	0.116** (0.048)
Unemployment rate	0.001 (0.875)	-0.018 (0.460)	-0.017 (0.533)
Rho	0.149*** (0.000)		
Year Fixed Effects	Yes		
Observations	576		
R-sq	0.983		

Note: Numbers in the parentheses represent p-values.

* p<0.1, ** p<0.05, *** p<0.01

CHAPTER 3

Essay 2: The Impact of Public Water Supply Unreliability on Residential Property Prices in Marion County, West Virginia

3.1. Introduction

Lack of access to a reliable water supply is usually perceived as an issue that is faced mainly by developing countries.⁵ However, recent studies and reports show that developed countries, especially the United States, are also facing similar challenges due to problems associated with affordability, demographic change, high environmental quality expectations, and aging water infrastructure (Wescoat et al., 2007; OECD, 2016; Mack & Wrase, 2017; Allaire et al., 2018; Allen et al., 2018). For example, the Flint, Michigan crisis in 2014 brought increased attention to water supply reliability issues in the U.S.

Aging water infrastructure coupled with major funding shortfalls are threatening the nation's water security (Alfredo et al., 2016).⁶ Many of the pipes and main lines that deliver water across the country are more than 100 years old and subject to variety of stressors (American Society of Civil Engineers [ASCE], 2017). Aging water infrastructure leads to a higher rate of main breaks that result in lower water quantity and quality due to leaks and flowing contaminants into the water supply. An estimated 40% of the water distribution network's valves in the U.S. are not functioning properly (Baird, 2011). According to the ASCE (2017), an estimated 240,000 water main breaks occur each year, wasting over two trillion gallons of treated drinking water. In terms of quality, previous research has linked water system

⁵ There is no unified definition of water supply reliability (Majuru et al., 2018). Here, we follow the definition given by Zérah (2000): "a service is reliable if it is provided in time, and with the quality and the quantity required."

⁶ Water infrastructure involves what is constructed to pump, divert, transport, treat, store, and deliver water, as well as to collect, treat and discharge storm and wastewater.

deficiencies (e.g. loss of pressure caused by main breaks or maintenance work) to an increase in the flow of contaminants, in which result in more gastrointestinal illness incidents among the exposed households (Nygård et al., 2007; Ercumen et al., 2014).

The costs associated with replacing outdated water infrastructure are large. The American Water Works Association (2012) has estimated \$1 trillion in water infrastructure needs just to maintain current levels of water service over the next 25 years. West Virginia, being one of the most rural states in the country, faces many challenges related to water supply reliability due to the aging or non-existent water infrastructure (Levêque & Burns, 2018). Statewide, there have been an increasing number of boil water notices related to water main breaks and other contamination episodes (Figure 3.1). In addition, more than 55% of the treated water produced by public water systems in West Virginia is considered non-revenue water due to leaks in the distribution network (Coyne, 2019). The WVIJDC (2017) has estimated that \$17 billion is needed to connect all state residents to public water and to rehabilitate the existing water infrastructure.

In addition to public infrastructure costs, health and safety concerns lead some residents to incur defensive expenditures in order to avoid contamination from public water. For example, some West Virginia residents have been reported to pay up to \$200 per month for bottled water and water filters above their public water bill and to drive for one to three hours each week to fill up water jugs from a mountain spring (West Virginia Public Broadcasting, 2019).

Most of the needed improvements in water infrastructure are funded by local governments and public water systems revenues generated by ratepayers (ASCE, 2017). Since it is not optimal for a water system to achieve 100% reliability, decision makers need to make decisions that require a trade-off between cost and risk (Howe et al., 1994). In such cases, the

required investment costs are usually known, but the risk preferences of the affected consumers are not. A large literature exists that examines consumers' willingness to pay (WTP) for different levels of public water supply reliability (e.g. Howe et al., 1994; Griffin & Mjelde, 2000; Koss & Khawaja, 2001). However, the majority of these studies use stated preference approaches to conduct their analysis with a focus on developing countries. Other studies, using revealed preference approach (averting behavior), have found that an unreliable water supply also can alter consumer's behavior leading to additional costs to the affected households (e.g. Pattanayak et al., 2005; Jakus et al., 2009; Vásquez, 2012).

Since water service is location specific, access to a reliable and safe water supply should be an important public infrastructure attribute in determining residential property values. Therefore, the objective of this research is to examine the impact of water supply unreliability on residential property values. We examine this impact using a hedonic property model and measure this unreliability with boil water notices (BWN) in Marion County, West Virginia. Since water service reliability has been found to be associated with sociodemographic characteristics of communities (see VanDerslice, 2011), we utilize a quantile regression approach to estimating the impact of water supply unreliability on residential home values. This allows us to gain information on the property value impact of unreliable water supply across the distribution of home prices. We find statistically significant, negative relationships and that the estimated price impacts are not uniform across the distribution of housing prices. Specifically, we find that BWNs have a larger impact on low-price compared to high-price houses.

The rest of this essay is organized as follows. Section 2 provides an overview of four strands of literature related to water supply unreliability and their impacts on consumers. Section 3 describes the model that combines hedonic property price and averting behavior

theories, while section 4 covers the data utilized in analyses. Section 5 provides information about the empirical model and estimation strategy. Finally, results are discussed in section 6 and conclusions in section 7.

3.2. Literature Review

The literature review is divided into four sections concerning studies that: (1) investigate the economic impacts of water supply unreliability on domestic users; (2) examine the effect of boil water notices on consumers; (3) examine the impact of investments in water infrastructure on economic growth; and (4) investigate the impact of water supply unreliability on consumers' risk perceptions.

3.2.1. Economic impacts of water supply unreliability on domestic users

Previous research on the economic impacts of water supply unreliability on domestic users can be categorized in two general groups of studies. The first group have examined the economic and social losses caused by interruptions or restrictions in the service, mainly due to extreme weather events such as drought. The second group, which is the most common, has utilized non-market valuation methods to estimate the willingness to pay (WTP) (accept) for increasing (decreasing) water supply reliability. We discuss the first group briefly, then focus more on the second group.

In the first group, Russell et al. (1970) was one of the first studies that examined the economic impact of water shortages. They estimated the losses to public and private parties from the 1962–1966 drought in three towns in Massachusetts. They found that the economic losses inflicted upon these communities were surprisingly small (between \$5 and \$13 per capita, in 1970 dollars). A more recent example is Valiñas (2006) where she examined the welfare losses caused by rationing policies between 1992–1996 for a drought in Seville, Spain. By estimating

water demand functions of residential and commercial/industrial users, the WTP for a service without restrictions during the drought was obtained. Then, consumer surplus was used as a measure of welfare to calculate the welfare losses suffered by different users. On average, welfare losses, in 2001 Euros, were €138 and €62 per user/quarter for households and industrial/commercial firms, respectively.

In the second group, several studies have attempted to place a value on the reliability of the water supply using non-market valuation methods. For example, Howe et al. (1994) created a framework to obtain the optimal level of reliability, where the marginal benefits from increased reliability equal the marginal costs of achieving such a level. In this research, contingent valuation method was used to estimate the WTP for increased reliability in water supply (less probability of shortages) and the WTA for lower levels of reliability in three Colorado cities: Boulder, Longmont, and Aurora. They found, based upon the scenario of imposing higher bills to customers, that no changes in reliability could be justified for either Aurora and Longmont. For the city of Boulder, however, based on customers' WTA, a reduction in reliability could be justified due to a very high level of reliability as a starting point.

Other studies also used contingent valuation to estimate the WTP for more reliable water supply in both developed and developing countries (e.g. California Urban Water Agencies, 1994; Piper & Martin, 1997; Griffin & Mjelde, 2000; Koss & Khawaja, 2001; Genius & Tsagarakis, 2006; Genius et al., 2008; Vásquez et al., 2009; Vásquez, 2014; Vásquez & Espallat, 2016; Rodríguez-Tapia et al., 2017; Appiah et al., 2018). Other research has utilized choice experiments for value estimation (e.g. Powe et al., 2004; Hensher et al., 2005; MacDonald et al., 2005; Tarfasa & Brouwer, 2013; Latinopoulos, 2014).

Some studies have used revealed preference approaches to explore the same issue. Two main methods have been used: averting expenditures and hedonic property price methods. In the studies that have used averting expenditures, the goal is to estimate the costs related to unreliable and unsafe water supply, such as purchasing bottled water or installing filtering system in the house (e.g. Larson & Gnedenko, 1999; McConnell & Rosado, 2000; Um et al., 2002; Pattanayak et al., 2005; Vásquez, 2012). Following similar methodology, Jakus et al. (2009) and Vásquez et al. (2015) also examined the impact of perceived risk on avoidance behavior .

There are relatively few studies that used the hedonic property price method to examine the issues that are directly related to water supply reliability since this method requires more data. This literature can be divided into two subgroups: (1) studies that have examined the impact of different water supply sources on residential property values, and (2) studies that examined the impact of water quality from both public water systems and private wells on residential property values.

Within the first subgroup, research is based on different water sources offering in various levels of reliability and has focused mainly on developing countries. North and Griffin (1993) examined the impact of different water sources (i.e. piped in the house, a deep well or tap in the yard, or a communal source such as a shared well or tap) on residential rental values in the Bicol Region, Philippines. Their sample consisted of 1,597 transactions, and they found households value an in-house piped water source more highly relative to other characteristics of their homes. They also found that households in all income ranges are willing to pay about half their monthly imputed rent to have piped water in the house. Vasquez (2013a) examine the impact of different forms of water service management (municipal, private, and community-managed) on rental prices in urban Guatemala. He used data from 998 households who rented a housing unit from

the 2006 Living Standards Measurement Survey. To account for the endogeneity that may arise between rental price and household choice of water service, an instrumental variable approach was taken. The findings from this study indicate that households assign higher values to municipal services (at least \$38.92 per month) than to private and community-managed water supplies. Other studies utilize similar approaches with different datasets and estimation strategies (e.g. Anselin et al., 2010; Vásquez, 2013b; Berg & Nauges, 2012).

For the second subgroup, early hedonic studies examined the impact of groundwater contamination on residential property values and found no significant relationship between water quality and residential property prices (Malone & Barrows, 1990; Page & Rabinowitz, 1993; Dotzour, 1997). These outcomes have been attributed to the simple and outdated econometric identification strategies employed in these studies (Guignet et al., 2016).

More recently, Case et al. (2006) used a hybrid of hedonic and repeat-sales methods to examine the impact of groundwater contamination on residential condominium prices in Scottsdale, Arizona. Using data from 13,612 transactions, they found that, on average, properties affected by groundwater contamination decreased by 4.7% in value, but only after knowledge of the contamination was public. McLaughlin (2011) examined the impact of information level regarding groundwater contamination event on residential property values in Washington County, Minnesota. He finds that homeowners were initially well-informed about the contamination risk but were later somewhat misinformed by a government disclosure law that created an imperfect geographic boundary for the contamination areas. He concludes that this policy resulted in a negative effect on residential property values within the boundary, even for houses that were not actually at risk from groundwater contamination.

Another type of study under this subgroup relied on spatial hedonic models to examine the impact of groundwater contamination and residential property values. Boyle et al. (2010) looked at the impact of arsenic contamination of groundwater on house sale prices and bare land transactions in two Maine towns, Buxton and Hollis. They find that the discovery of arsenic contamination in 1993 led to significant, but temporary (two years) decreases in property prices. More specifically, they find that property values declined by 0.5% to 1% for each 0.01 mg/l of arsenic above the U.S. Environmental Protection Agency standards.

Unlike previous studies that used an aggregate spatial measure for groundwater contamination (e.g. at the neighborhood level), Guignet (2013) and Guignet et al. (2016) used a specific measure for each property. Guignet (2013) examined the impact of groundwater quality on residential property values in three Maryland counties (Baltimore, Frederick, and Baltimore City) from 1996 to 2007 using property-specific well water tests. He found that simply testing a home's well for contamination reduced its value by an average of 11%. A 13% depreciation was found when the tests revealed levels of contamination that are higher than the standards. Guignet et al. (2016) examined the impact of groundwater quality on property values in Lake County, Florida, where pollution concerns relate primarily to agricultural run-off. They found that a positive contamination test results in the three years prior to a transaction results, on average, in a decline of 2% to 6% in property values. Focusing on nitrogen-based contamination, they found that prices decline by 15% when the concentrations exceed the standards.

For water supply provided by public systems, Des Rosiers et al. (1999) investigated the impact of drinking water quality on housing prices. They used data for 800 houses in Charlesbourg municipality in Quebec City, Canada between 1990 and 1991, and employed OLS to estimate the coefficients. To measure water quality, they used public warnings that were

issued during the study period (23 warnings) affecting properties and the warnings duration (in days). They grouped these warnings into 17 spatial sectors, each of which experienced one or more warnings. They found that house buyers are sensitive to the quality of the water they drink, and the problems related to water quality are being capitalized into property values with average duration of the warning period per sector as a dominant factor. Also, market segmentation suggests that higher price property buyers are much more responsive to this issue, where they experienced value losses between 5.2% – 10.3% of mean sale price.

3.2.2. Boil water notices impact on consumers

Most of the research related to BWNs concerns the effectiveness of these notices as a tool for communicating water-related health risks and how people behave after receiving such a notice. In a meta-analysis study, Vedachalam et al. (2016) identified 11 studies over a 30-year period that examined public compliance to BWNs. They found that the median compliance rate with BWNs for drinking and non-drinking activities in those studies was 68%. Three reasons were identified for this non-compliance behavior: forgetting, not believing the notice, and choosing not to boil water. Overall, they conclude that a BWN is an effective tool to communicate with the public regarding problems related to the water supply.

Few studies have used surveys to estimate the costs incurred by consumers when a BWN is issued. For example, Laughland et al. (1993) estimated the cost of boiling, hauling, or purchasing water to avoid infection caused by drinking water outbreak in the Village of Milesburg and surrounding Boggs Township in Pennsylvania in 1989. Using three approaches (family income, minimum wage, and zero opportunity cost of time) to the valuation of time, they found that mean monthly household averting costs were \$33.47 using family income, \$13.07 using minimum wage, and \$5.60 using zero opportunity cost of time (in 1989 dollars). More

recently, Ailes et al. (2013) estimated the total costs of an outbreak in Alamosa, CO for residents, businesses, schools, and health care facilities and governmental plus non-governmental parties in 2008 to be approximately \$2.6 million. Finally, Heflin et al. (2014) improved on the methodology used by Ailes et al. (2013) by expanding the cost categories and found that economic impacts caused by disruptions in water service in Ithaca, NY and Somerset, MA ranged from over \$1,400 in savings to a loss of over \$1,000 with an overall average of \$93.96 per household.

Finally, Vedachalam et al. (2014) used a logistic regression model to identify the factors that affect the probability of a BWN being issued from water systems located around the Mohawk-Hudson watershed during extreme weather event in New York in 2011. Their results indicate that the probability of a BWN being issued increase with higher precipitation during the storm, high density of septic systems, lack of recent maintenance, and low population density.

3.2.3. The impact of investments in water infrastructure on economic growth

Many studies have shown that improvements in water infrastructure have significant impacts on economic growth in an area. For example, Janeski and Whitacre (2014) examined the long-term economic impacts of USDA water and sewer infrastructure investments in Oklahoma and found that median house values increased by 5% to 13% points in communities that obtained a water infrastructure project compared to communities without a water infrastructure project. McIntosh et al. (2018) also looked at the impact of a large infrastructure investment (including water and sewer) experiment implemented in low-income neighborhoods across 60 municipalities in Mexico. They found that the program increased the aggregate real estate value in those neighborhoods by \$2 for every \$1 spent on the program. Furthermore, water infrastructure availability, capacity, and reliability can be sources for regional competitiveness of

a region that attract new businesses (Center for Public Management, 2014; Munnell & Cook, 1990). This attractiveness can be attributed to the fact that water disruptions have a large impact on businesses. For example, every day of water service disruption results in average losses of about \$230 in sales per employee for U.S. businesses (Value of Water Campaign, 2017).

In terms of the costs of these investments, Bagi (2002) examined the economic costs and benefits of water and sewer investments in 54 rural and 33 urban communities across 30 states. He found that these investments generate benefits in both rural and urban areas and, on average, urban water or sewer facilities cost about 30% more than rural facilities. However, urban facilities create about twice the number of permanent jobs, induce three times more private investment, leverage twice as much in public funds, and add three times more to the local property tax base. He argues that these differences are due to the small size and remoteness of rural communities.

3.2.4. The impact of water supply unreliability on consumers' risk perceptions

Multiple studies have investigated the determinants of consumers' risk perceptions regarding public water supplies. The findings from these studies show that there are various factors that affect consumers' perceptions about public water supply including knowledge about water testing results, local experience with water systems, sociocultural beliefs about tap water, and the sensory qualities of water, with this final factor being the most important (Doria et al., 2009; Doria 2010). Other studies focused more on the impact of demographic and socioeconomic factors on risk perceptions about public water and found that race, ethnicity, nativity, income, age, and education influence individuals' risk perception of drinking water (Pierce & Gonzalez, 2017; Javidi & Pierce, 2018).

Anadu and Harding (2000) looked at the differences in risk perception about public drinking water and the use of bottled water in four Oregon communities. They compared responses from residents in two communities that have experienced water safety violations with responses from residents of two communities that did not have these problems. They found that individuals in communities with persistent drinking water problems have higher risk perceptions than those individuals in communities with no problems.

3.3. Theoretical Framework

The basic framework for hedonic property price model was provided by Rosen (1974), where consumers choose between differentiated products with multiple attributes or characteristics to maximize their utility. In applying this model to housing markets, let $Z = (z_1, z_2, \dots, z_n)$ be a vector of observable attributes where z_i measures the amount of the i^{th} attribute of a house which includes property attributes (such as age, square footage, number of bedrooms, etc.), neighborhood attributes (such as distance to schools and highways), and environmental attributes. Water supply unreliability (WSR) is included as a separate attribute which combines neighborhood and environmental elements. Here, we assume that information about WSR is obtained by consumers of housing from boil water notices (BWN_0) that have been issued prior to the sale.

Assuming a single competitive housing market and full information, the consumer decision problem is described as:

$$\max U\{X, Z, WSR\{E(BWN_0), DE[E(BWN_0)]\}\} \quad (1)$$

$$\text{subject to } Y = X + P\{Z, WSR[E(BWN_0)]\} + DE[E(BWN_0)] \quad (2)$$

where X is the numeraire good, WSR is a measure of water supply unreliability which is a positively related to consumer expectations as derived BWN_0 , Y is income, P is the hedonic

price schedule, and DE represents the associated defensive expenditures incurred (i.e. bottled water, water filter, etc.) when the water supply is unreliable so that $\frac{dDE}{dBWN_0} > 0$.

Furthermore, we assume an expectation function:

$$E(BWN_0) = 0 \quad \forall \quad BWN_0 \leq \pi_i \quad (3)$$

$$E(BWN_0) > 0 \quad \forall \quad BWN_0 > \pi_i \quad (4)$$

where π_i represents a threshold on the number of BWN that housing consumers use when deciding whether water service provided to the house is deemed unreliable. When the number of boil water notices issued prior the sale are higher than π , then expectations of unreliable water supply are formed about the impacted property. Water supply unreliability will generate negative utility to the consumer leading to a decrease in the price of the house.

Assuming that $E(BWN_0) > 0$, then the Lagrangian function and the first order conditions are:

$$L = U\{X, Z, WSR\{E(BWN_0), DE[E(BWN_0)]\}\} + \lambda\{Y - X - P\{Z, WSR[E(BWN_0)]\} - DE[E(BWN_0)]\} \quad (5)$$

$$\frac{\partial U}{\partial Z} = \lambda \frac{\partial P}{\partial Z} \quad (6)$$

$$\frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial E(BWN_0)} + \frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial DE} \cdot \frac{dDE}{dE(BWN_0)} = \lambda \left(\frac{\partial P}{\partial WSR} \cdot \frac{dWSR}{dE(BWN_0)} + \frac{dDE}{dE(BWN_0)} \right) \quad (7)$$

$$\frac{\partial U}{\partial X} = \lambda \quad (8)$$

where λ is the Lagrange multiplier on the budget constraint. Focusing on the condition for WSR and substituting out for λ we obtain:

$$\underbrace{\frac{\frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial E(BWN_0)} + \frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial DE} \cdot \frac{dDE}{dE(BWN_0)}}{\frac{\partial U}{\partial X}}}_{\text{Marginal rate of substitution}} - \underbrace{\frac{\frac{\partial DE}{\partial E(BWN_0)}}{\frac{\partial P}{\partial WSR} \cdot \frac{dWSR}{dE(BWN_0)}}}_{\text{Marginal cost of DE}} = \underbrace{\frac{\frac{\partial P}{\partial WSR} \cdot \frac{dWSR}{dE(BWN_0)}}{\frac{\partial P}{\partial WSR} \cdot \frac{dWSR}{dE(BWN_0)}}}_{\text{Marginal implicit price}} \quad (9)$$

Equation (9) shows that, at the optimum, the marginal implicit price of BWN_0 from a hedonic property price model (RHS) reflects both the marginal rate of substitution between water supply unreliability and defensive expenditures in relation to BWN_0 and the numeraire good X along with a second term that measures the marginal cost of defensive expenditures associated with BWN_0 due to water supply unreliability (LHS).

Rosen (1974) also described the consumer's maximum 'bid' function for a house $\theta(Z; U, Y)$, where utility and income are fixed. This function represents the amount a consumer is willing to pay for different attribute vectors for a given utility-income index. Substituting the budget constraint into the utility function we obtain:

$$U\{Y - \theta\{Z, WSR[E(BWN_0)]\} - DE[E(BWN_0)], Z, WSR\{E(BWN_0), DE[E(BWN_0)]\}\} = \bar{u} \quad (10)$$

If we implicitly differentiate $\theta(\cdot)$ with respect to BWN_0 , we obtain:

$$\frac{\frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial E(BWN_0)} + \frac{\partial U}{\partial WSR} \cdot \frac{\partial WSR}{\partial DE} \cdot \frac{dDE}{dE(BWN_0)}}{\frac{\partial U}{\partial X}} - \frac{\partial DE}{\partial E(BWN_0)} = \frac{\partial \theta}{\partial WSR} \cdot \frac{dWSR}{dE(BWN_0)} \quad (11)$$

Combining conditions (9) and (11) we find that the marginal bid or the marginal willingness to pay (MWTP) for a housing characteristic is equal to its equilibrium marginal price. The first stage hedonic property price function $P(\cdot)$ represents an envelope of consumer's bid functions in equilibrium. Therefore, it can be used to obtain the marginal value that consumers place on housing attributes. This means that the marginal price of an attribute is equal to the MWTP for that attribute (Taylor, 2003). Econometrically, we can obtain the marginal price of any attribute by regressing the price of the house on the attributes that we are interested in, in this case being WSR.

3.4. Study Area and Data

3.4.1. Study area

Located in the north central region of West Virginia, Marion County is a largely rural county with a population of nearly 56,000 (Figure 3.2). The county encompasses an area of 312 square miles and contains two cities (Fairmont and Mannington) and nine towns. Fairmont is the county's seat and the most populated city in the county. According to the Census Bureau (2018), median household income in Marion County is \$48,158, which is about 10% higher than the West Virginia median, but 20% lower than the U.S median. There are about 37,753 structures in Marion County in which 17% are unserved by public water services (WVIJDC, 2017). Out of these structures, there are about 19,839 owner occupied-housing units in Marion County with a median value of \$110,100 (Census Bureau, 2018). The largest employers in the county are Fairmont State University and Fairmont Regional Medical Center.

One indication of problems with public water supplies is evidenced by water systems issuance of a Boil Water Notice (BWN) to alert their customers. A BWN, also known as a Boil Water Advisory, is issued when there is an identified or suspected microbial contaminant in the water distribution system. A BWN often occurs due to water main breaks. In Marion County, for example, water systems reported 255 water main breaks and issued 79 BWNs in 2017. The BWN will instruct consumers to boil all water used for drinking, cooking, food preparation, brushing teeth, and making ice (Water Quality Research Foundation, 2018).

Currently, there are 31 public water systems in Marion County with the city of Fairmont Water Department being by far the largest, serving about half of the county's population (Table 3.1). About 5% of the county's population use private wells for their water (U.S. Geological Survey [USGS], 2015). In 2017, water systems in Marion County produced nearly 3.1 million gallons of treated drinking water but lost about 33.8% of it due to leaks into the water

distribution network. Marion County is one of 10 counties in West Virginia that face major challenges related to water supply reliability based upon BWNs per 10,000 people (Figure 3.3). In addition, about 20% of the county's population were served by public water systems that violated the health-based standards of the Safe Drinking Water Act (SDWA). Finally, using water system's net income per service connection as a proxy for resources available for the system, 19 systems are designated as under-resourced (Table 3.1). These facts indicate that most water systems in Marion County are facing financial difficulties that may restrict service improvements and compliance with the SDWA standards.

3.4.2. Data

Our analysis is based on two main sources of data. The first is West Virginia Office of Environmental Health Services (OEHS). The second is Marion County Assessor. Below is a description of these data.

3.4.2.1. Boil water notices (BWNs)

To measure water supplier unreliability, we use BWNs issued by either public water systems or the Marion County Health Department. The OEHS provides information on all BWNs in West Virginia starting from 2012. Between January 2012 and December 2017, the total number of BWNs in West Virginia was 6,980 with the annual number almost doubling between 2012 and 2017 (Figure 3.1). For each notice, the provided information includes: when the notice is issued and lifted, the name of the public water system plus its PWSID⁷, the public health sanitation district where the notice is issued, the reason for the notice, and details about the

⁷ PWSID is an identification code that starts with the state's initials and followed by seven numbers. These codes can be used to find more information about the water system (e.g. city and county served, or the source of the primary water) in the Safe Drinking Water Information System/Federal Warehouse (SDWIS/Fed).

affected areas or street names. Using information from the SDWIS/Fed database and details from each notice, we obtained city and county affected by each notice.⁸

3.4.2.2. Housing data

The Marion County Assessor provides data for all residential property sales between January 2012 and December 2017. This data set contains 7,972 residential property transactions. By dropping all property sales without structures, the number of transactions declined to 5,525. To ensure only arm's length sales in our analysis, a process following Herriges et al. (2005) is used to drop all properties that were less than 50% of their assessed values and/or sold for less than \$5,000. Therefore, after eliminating these sales, the total number of transactions included in our analysis is 1,985 single-family residential properties.

To capture housing attributes previously found in the literature to influence housing prices, we include variables for housing characteristics in the hedonic model such as size, story height, age, numbers of bedrooms plus bathrooms, and presence of house amenities (e.g. air conditioning and fireplace). In addition, we control for two variables that have been consistently neglected in hedonic property price models: (1) house physical condition, and (2) material and workmanship quality. Based upon assessor data for physical condition, we rank houses from Unsound = 1 to Excellent = 6. For quality, we use the quality grade factor provided by the county's assessor ranging from E = Poor (0.5) to X = Excellent (2.5). These two variables are unrelated as the first one only measures the physical condition and the second measures the quality of the building regardless of the physical condition.

⁸ Some water systems were not available on SDWIS/Fed, so we used the WV Drinking Water Watch to obtain the necessary information. Available at <http://129.71.204.189:1977/DWWpublic/index.jsp>

All property sales are geocoded using house's street address with ArcGIS to measure neighborhood and proximity characteristics such as crime, school quality, distance to Fairmont State University, and to the nearest highway interchange⁹. For crime, we use total crime index that compares the average local crime level to that of the entire U.S. (an index of 100 is average). This index includes both property and violent crimes for 2010 at the block group level and it is obtained from ArcGIS database. For school quality, we follow the literature and use proficiency tests as a proxy (Brasington, 1999). Specifically, we use the percentage of students in elementary school that scored at or above proficiency levels in math tests. We obtain these shapefiles for attendance zones in the county from the National Center for Education Statistics (NCES) and the data for math tests from the GreatSchools website. For distance variables, we obtain the shapefiles for Fairmont State University and highway interchange locations from the Census Bureau TIGER/Line database.

3.4.2.3. Linking BWNs to house sale observations

There were 440 BWNs in Marion County between 2012 and 2017, but 90 BWNs could not be used due to insufficient information about the affected locations (54 BWNs) or because the date when the BWNs were lifted are unavailable (36 BWNs). Thus, the total number of BWNs used in the analysis is 350. Then, based upon the details provided for each BWN along home addresses for each property transaction, West Virginia Property Viewer was used to allocate properties and BWNs among the 22 tax districts in Marion County (Figure 3.4).¹⁰

⁹ This variable was included since Fairmont serves a “bedroom” community for the more prosperous communities of Morgantown to the north and Clarksburg to the south (Trach 2019)

¹⁰ WV Property Viewer is an online interactive GIS map that provides information on all properties in West Virginia and their owners. Also, it provides information on tax district boundaries in each county.
<https://www.mapwv.gov/parcel/>

Following this, the details of each BWN are linked to all affected houses based on street addresses or affected areas. For example, if a BWN affects Street A and is issued in January 1, 2014 and lifted on January 5, 2014, houses located at Street A and sold between January 1, 2014 and January 1, 2015 were assigned the appropriate values for each BWN variable as described below.

Tables 3.2 and 3.3 show the distribution of property transactions, BWNs, and properties affected by BWNs in each tax district in Marion County between 2012 and 2017. Over the entire county from 2013 to 2017, about 35% of residential property transactions are affected by a BWN, and as expected Fairmont has the largest number of transactions and BWNs. Specifically, about 41.6% of the transactions happen in Fairmont with 34% of these transactions being affected by BWNs. Table 3.4 provides information about the reasons behind the issuance of BWNs in Marion County. About 80% of the BWNs were issued due to breaks or leaks, and it is the same in both Fairmont and the rest of the county. We transfer the information in Table 3.2 into a map (Figure 3.5) showing the locations of the affected and unaffected properties in Marion County. As demonstrated in Figure 3.5, problems of water supply reliability are spread across Marion County and not limited to a single location.

Four variables were used to measure water supply unreliability: (a) number of BWNs affecting a sold house a year before its sale date; (b) number of days a sold house is under BWNs a year before its sale date; (c) average duration under BWNs a year before a house sale date ((b) divided by (a)); and (d) a binary variable indicating that if a sold house is affected by BWN or

not for a year prior to its sale date.¹¹ For these variables, property sales from January 1, 2013 to December 31, 2017 were used in the analysis and BWNs from January 1, 2012 to December 31, 2016. Therefore, our analysis will rely on a total of 1,985 observations.

Table 3.5 provides summary statistics and description for all variables included in the analysis. Explanatory variables are grouped into four categories. The first category consists of focus variables related to BWNs as proxy measures of water supply unreliability. We expect these variables to have negative impacts on housing prices. The second category is structural variables that include building characteristics and house amenities. Except for story height, construction material, and house age, all the other variables are expected to have positive impacts on housing prices. Property variables are the third category. These include parcel characteristics of lot size and fencing with positive impacts and sidewalks with a negative impact since it is associated with cleaning responsibilities. Finally, there are neighborhood and proximity variables. For crime level and distance variables to highway and a major employer (Fairmont State University), negative impacts are expected whereas school quality should have a positive impact on housing prices.

3.5. Empirical Models

There are four main empirical issues for which hedonic property price theory provides no or little guidance. The first is selecting a functional form, the second is geographic coverage of the data, the third is dealing with omitted variable bias, and the fourth is spatial dependence.

¹¹ Hedonic property models with monthly variables (i.e. number of BWNs and days a month before the sale) also were estimated, but the results were statistically insignificant coefficients for BWN variables in all specifications and we do not report them here.

For the first issue, two main types of functional forms are available: (a) simple choices such as linear, log-linear (semi-log), and log-log; and (b) more flexible options include quadratic specifications such as Box-Cox transformations and nonparametric approaches (Phaneuf & Requate, 2016). In a simulation-based experimental design, Cropper et al. (1988) showed that when all housing characteristics are included in the hedonic property price function, linear and quadratic forms of the Box-Cox transformations provided the most accurate estimates of the marginal implicit prices. However, when some characteristics are unobserved or are replaced by proxies, simple forms and linear Box-Cox performed better than the quadratic Box-Cox model. Based on these results, researchers in the last 20 years have relied on relatively simple functional forms when estimating the hedonic price functions (especially the log-linear form) (Freeman et al., 2014; Taylor, 2003, 2008).

A more recent study by Kuminoff et al. (2010) used the same methodology employed by Cropper et al. (1988) but increased the sample size (200 vs 2,000) and focused more on the omitted variable bias issue. Overall, they found similar results to Cropper et al. (1988) when there are no omitted variables. However, when there are omitted variables and enough variation in the variable of interest to permit the use of a combination of spatial fixed effects, quasi-experimental methods, and temporal controls, their results suggest that the quadratic Box-Cox functional form outperforms other simple forms.

Since we are not employing a quasi-experimental identification strategy in this study, we follow the results found by Cropper et al. (1988) and use a simple functional form. Also, we follow the literature and use the log-linear functional form (Taylor, 2003) as it allows the housing characteristics to impact the house's price non-linearly, and unlike the log-log form, is more accommodating for the use of binary variables.

The second issue arises due to the underlying assumption that the study area under consideration represents a single housing market in which all properties are part of the same housing market. If the sample consists of properties from different housing markets, then estimating one hedonic property price function is inappropriate (Schnare & Struyk, 1976). Thus, it is important to make sure that Marion County represents a single housing market (i.e. there are no submarkets in our sample) if we were to estimate one hedonic property price model. Theoretically, researchers agree on the existence of submarkets, however, in practice there is little consensus as to how sub-markets should be identified (Xiao, 2017).

The most common method to identifying sub-markets involves three main steps introduced by Schnare and Struyk (1976) (Keskin & Watkins, 2017). First, data are partitioned to delineate potential sub-markets. Second, hedonic property price regressions are estimated for each sub-market. Third, statistical techniques, such as Chow test, are used to determine whether significant differences exist between the sub-market specific coefficient estimates. For the first step, different ways are available to partition the data, but in most cases, researchers use either prior knowledge or other information in the data to address this challenge.

In our case, we are interested to see if there are differences between the city of Fairmont and other areas in the county. Thus, residential property transactions are split into two data sets: (1) all transactions in Fairmont, and (2) all transactions in the rest of Marion County. A Chow test is used to determine if there are significant differences in regression coefficient estimates between Fairmont and the rest of county data. Upon finding no significant difference between

the two subsamples¹², we proceed to estimate one hedonic property price regression model for Marion County.

For the third issue, as with any regression model, the goal is to balance between the variance and bias of the estimates. With inclusion of many variables, multicollinearity may result, leading to imprecise estimated coefficients. On the other hand, not including some variables may lead to biased estimates due to omitted variable bias (Taylor, 2003). Since it is difficult to have a fully specified model with all neighborhood characteristics, most hedonic models suffer from the problem of omitted variables. Different studies use varying methods to account for the unobservable variables such as spatial fixed effects, quasi-experimental designs, and/or repeated sales (Freeman et al., 2014; Kuminoff et al., 2010). Here, we use both spatial and year fixed effects to control for unobservable characteristics for different tax districts and for different years of house sales. The OLS model is thus written as

$$\ln(P) = \beta_0 + \beta Z + \alpha_{tax\ district} + \gamma_{year} + \varepsilon \quad (12)$$

where $\ln(P)$ is the natural log of the transaction price for the property, Z represents a vector of house-related characteristics including the variable of interest related to water supply unreliability, $\alpha_{tax\ district}$ and γ_{year} are the tax district and year fixed effects, and ε is the error term.

The fourth issue is spatial dependence, i.e. the existence of a functional relationship between what happens at one location and what happens elsewhere (Anselin, 1988). This issue may occur in hedonic property price models when houses in one location are impacted by prices or characteristics of nearby houses compared to houses that are farther apart (Anselin & Lozano-

¹² Chow statistic = 2.153, p-value = 0.116

Gracia, 2009). Also, spatial dependence may occur in hedonic property price models as a result of the presence of common practical issues such as measurement errors in explanatory variables, omitted variables, and other forms of model misspecification (Baumont, 2004). Traditional OLS hedonic property price models do not consider the spatial dimension of housing price data and ignoring spatial dependence may result in biased and inconsistent, or inefficient estimates depending on the type of spatial process involved with the model (LeSage & Pace, 2009). Therefore, the use of spatial econometric techniques is utilized to address this problem and to obtain reliable estimates of the coefficients plus standard errors.

Two common models are used to incorporate spatial dependence into empirical hedonic property price models: spatial lag and spatial error specifications (Anselin & Lozano-Gracia, 2009). The spatial lag model (SLM) accounts for spatial dependence by introducing a spatially lagged dependent variable (a weighted average of observations on the dependent variable in neighboring locations) into the model, whereas the spatial error model (SEM) includes a spatially correlated error term. Following Anselin (1988), a general model of housing price determination including both spatial effects can be written as:

$$\begin{aligned}
 \ln(P) &= \rho W_1 \ln(P) + ZB + \varepsilon \\
 \varepsilon &= \lambda W_2 \varepsilon + \mu \\
 \mu &\sim N(0, \sigma^2 I)
 \end{aligned} \tag{13}$$

where $\ln(P)$ is the natural log of sale price, Z is a $N \times K$ matrix of property characteristics, B is a $K \times 1$ vector of coefficients, W_1 and W_2 are $N \times N$ spatial weight matrices associated with autoregressive process in house prices and in the error term, ε is a $N \times 1$ spatial autoregressive error, μ is a $N \times 1$ normally distributed random error term with a zero mean and variance σ^2 , and ρ and λ are coefficients on the spatially lagged variables, $\ln(P)$ and ε . In equation (13), ρ , B ,

and λ are estimated and W_1 and W_2 are chosen by the researcher based on the research objective and the data. If ρ and λ are estimated to be statistically equal to zero, then equation (13) reduces to the classical linear regression model with no spatial effects. When $\rho \neq 0$, then the model will include a spatial lag specification and when $\lambda \neq 0$, then the model will include a spatial error specification.

Since the spatial lag model includes a spatially lagged dependent variable among the explanatory variables, the regression coefficients from this model cannot be interpreted as simple partial derivatives. Therefore, special interpretation is required that takes into account the spatial spillovers in the model (Golgher & Voss, 2016). Basically, with spatial lag models, not only are we able to observe the impact of a variation in z_i on P for house i , but also the impact on P observed for other houses (for details, see LeSage & Pace (2009)). Therefore, using this model, three summary measures of effects are obtained: (1) the direct effect representing the average impact of a one unit change in z_i on P for house i ; (2) the indirect effect representing the average impact of a one unit change in z_i on P for neighboring houses; and (3) the total effect showing the average total impact of a one unit increase in z_i on all houses (direct plus indirect effects).

In choosing between SLM and SEM, empirical research utilizing spatial hedonic property price models rely on a data-driven approach as provided by Anselin (1988), also known as the forward specification analysis.¹³ In this specification search, an OLS model is first estimated, then two Lagrange Multiplier (LM) test statistics and their robust forms are used to test the OLS residuals for the presence of spatial dependence in the lag and error terms. Based on the results

¹³ Florax et al. (2003) compared the two methods of specification searches in spatial econometrics (forward vs backward specification analyses) and found that forward specification analysis outperforms the backward method in terms of finding the true data generating process as well as in the observed accuracy of the estimators for spatial and non-spatial parameters.

of these tests, an appropriate model is then selected. Most hedonic studies have followed this approach (e.g. Kim et al., 2003; Anselin et al., 2010; Boyle et al., 2010; Liu et al., 2017).

Another important decision to be made before testing for spatial dependence is what specification to use for the spatial weight matrix W . A spatial weight matrix defines the relationship between neighbors in the model (i.e. how the value in one location in the system is affected by the values in other locations). This relationship can either be based on distance or contiguity between observations (Anselin, 2001). More formally, $w_{ij} = 1$ when i and j are adjacent neighbors, and $w_{ij} = 0$ otherwise. There is no formal guidance on the choice of spatial weight matrix since it depends on the available data and researcher preference.

In this research, a distance-based spatial weight matrix is appropriate because we are using point coordinates to indicate the location of each house. Common approaches to defining a spatial weight matrix based on distance are: nearest neighbor, cutoff distance, and nearest neighbor within a cutoff distance. We use K-Nearest Neighbor (KNN) weights, in which all observations have the same numbers of neighbors (K) irrespective of distance. This method is recommended to avoid the possibility of islands (i.e. observations without neighbors), which may result in loss of degrees of freedom since all unconnected observations will be eliminated in the spatial model (Anselin & Bera, 1998). Also, this type of spatial weight matrix has been used frequently in other hedonic studies (e.g. Mueller & Loomis, 2008; Pandit et al., 2013; Netusil et al., 2014; Liu et al., 2017). For the number of neighbors K , we follow LeSage and Pace (2009) and we choose the number that maximizes the value of a log-likelihood function. The LM tests for spatial dependence indicate that the SLM is the more appropriate specification (Table 3.6). Moreover, using the log-likelihood function criterion, we find that using five nearest neighbors result in the maximum log-likelihood value.

Finally, BWNs in our data are not equally distributed across housing price transactions (Table 3.7). On average, properties transacted at the lower price quantiles experience more water supply reliability problems compared to the properties sold at the higher price quantiles. Therefore, we extend our analysis and look at the impact of water supply unreliability across the price distribution instead of assessing its impact with a focus on the mean. As explained below, a quantile regression approach is utilized to accomplish this analysis. This approach also will be used to estimate a threshold value π discussed in section 3.3.

3.5.1. Quantile regression

The two models discussed above (OLS and SLM) specify the change in the conditional mean of the housing price associated with a change in the housing characteristics z_i . We extend our analysis and employ quantile regression approach (see Koenker & Bassett, 1978; Koenker & Hallock, 2001; Hao & Naiman, 2007) to examine the impact of housing characteristics at different points (quantiles) across the distribution of housing prices. Unlike OLS, quantile regression specifies changes in the conditional quantile, which allows us to observe how housing characteristics are valued differently by consumers of housing at different price ranges.

Using equation (12) as a reference, quantile regression model is expressed as:

$$\ln(P) = \beta_0(\tau) + \beta Z(\tau) + \varepsilon(\tau) \quad (14)$$

where $0 < \tau < 1$ indicates the proportion of the population having scores below the quantile at τ , i.e. the corresponding quantile of housing price distribution and β are the quantile-specific parameters to be estimated. Similar to equation (14), the spatial quantile lag model is expressed as:

$$\ln(P) = \rho(\tau)W \ln(P) + ZB(\tau) + \varepsilon(\tau) \quad (15)$$

which will result in estimates based on the conditional quantile and take account of the spatial effect at the same time.

To estimate the spatial quantile model, two-stage quantile regression approach proposed by Kim and Muller (2004) is used to account for the endogeneity in the spatially lagged variable. In the first stage, the spatially lagged exogenous variables WZ and Z are used to predict the spatially lagged endogenous variable $W \ln(P)$ at an individual quantile. The predicted $\widehat{W \ln(P)}$, is substituted for $W \ln(P)$ in the spatial lag model to eliminate the correlation between the spatially lagged endogenous variable and the error term. Then, the second stage regression for that quantile is performed to obtain $\rho(\tau)$ and $\beta(\tau)$. This two-stage procedure is then repeated for each quantile.

3.6. Results

An overview of the models estimated is shown in Figure 3.6. The discussion in this section will focus on the important findings with results of all models estimated reported in Appendices A through D. Table 3.8 reports OLS regression model results for each of the four BWN variables with spatial (tax district) and year fixed effects.¹⁴ Overall, there are statistically significant, negative impacts found for BWN variables during the sale or in the year prior to the sale on residential property values.¹⁵ The magnitude of the coefficients ranges from -0.0065 to -0.1904, meaning that a one unit change in BWNs as an indicator of unreliable water supply can depreciate housing prices between 0.65% and 19%, depending upon how unreliability is

¹⁴ As a robustness check we also estimated the models with census block groups spatial fixed effects with the results being similar to the tax district fixed effects. These model results are shown in Appendix Table 1A.

¹⁵ To ensure that BWNs variables are not picking up impacts related to rural areas, we examined separate models for Fairmont only vs other areas (i.e. urban vs rural). The results are consistent between both models and are reported in Appendix Tables 2A and 3A.

measured (i.e. in either days, BWN episodes, or presence versus absence). Examining the other control variables, we see that most of them have statistically significant impacts with the expected signs. Among all variables, the quality grade factor has the largest impact on house sale prices with a coefficient estimate of about 0.48. However, these OLS coefficient estimates results are likely to be biased as discussed in section 3.5.

Table 3.9 shows the regression results from the four spatial lag models. All estimates for the spatial autoregressive coefficient (ρ) are positive and statistically significant, meaning that a positive spatial similarity exists between residential property sale prices. To interpret the results from the spatial lag model, we report the direct, indirect, and total effects for the four BWN variables in Table 3.10.¹⁶ A Bayesian Monte Carlo Markov Chain (MCMC) estimation procedure involving 1,000 draws is used to calculate the standard errors and p-values for these effects. Examining the average direct effects of the variables, they are similar to the estimated coefficients from Table 3.8 in terms of sign and statistical significance, but with a lower magnitude as expected.

For interpretation, we examine the direct impact from the BWNs_year variable. This impact is that the issuance of one more BWN, on average, depreciates residential property values by 7%. In addition, the average indirect effect from this additional issuance of a BWN will result in a 1.3% decrease in value of the neighboring properties. One more day under a BWN during the year prior to the sale date has the smallest impact on residential property values with a less than 1% decrease for an additional day of BWN. However, the average duration of BWNs (i.e. number of days divided by number of BWNs in the past year) has a much larger magnitude, such

¹⁶ See Appendix B for the full models.

that a one day increase in the average duration will result, on average, in a 2.7% decrease in house value and 0.6% decline in the neighboring property values. Finally, the results from the last variable (BWN) show that regardless of the number of BWNs or number of days under BWNs, being simply affected by a BWN is estimated to depreciate housing prices by 18% and neighboring residential prices by 3.5%.

Examining the results reported in Appendix Tables 1B through 4B, core housing characteristics that have statistically significant coefficients with their expected signs include: square footage, physical condition, building quality, age of house, number of bedrooms, and other property amenities such as the presence of AC, fire place, basement garage, and fence. These results are in line with what other studies have found using hedonic property price models for residential properties (e.g. Pandit et al., 2013; McLaughlin, 2011). Similar to OLS coefficient results, building quality has the largest effect on housing price. Houses built with Alum/Vinyl materials and older houses, on average, have lower prices. For indirect effects, these variables have similar signs and statistical significance but with much smaller magnitudes indicating that similar houses will have similar characteristics.

To examine the changing impact of water supply unreliability over the distribution of housing prices, quantile regression model results are reported for BWN variables from spatial quantile regressions (Table 3.11). To facilitate the interpretation of these coefficient estimates, quantile level estimates and their 95% confidence intervals are presented in Figure 3.7. The straight lines represent the estimates of the 2SLS model, which show the average impact of water

supply unreliability on housing values.¹⁷ Focusing on coefficients that are statistically different from zero, it is clear from Figure 3.7 and Table 3.11 that water supply unreliability has more negative impacts on house sales at the lower quantiles of the house price distribution compared to houses priced at the high quantiles. For example, the BWNs_year variable has negative, statistically significant impacts for quantiles 0.1 to 0.6, but no statistically significant impacts at quantiles 0.7 or greater (Table 3.11).

Finally, we examine the valuation of water supply unreliability computed using the estimates from the first-stage hedonic property price model. As mentioned in the section 3.3, the marginal willingness to pay (MWTP) is defined as the derivative of the hedonic price equilibrium equation with respect to the characteristics of interest. Following Muller and Loomis (2008) and Anselin et al. (2010), the MWTP from the OLS model equals the estimated coefficient for the BWN variable multiplied by the price, or

$$MWTP_{OLS} = \frac{\partial \ln P(Z)}{\partial z_i} = \hat{\beta} \bar{P} \quad (16)$$

where $\hat{\beta}$ is the coefficient and $\bar{P}$ is the mean housing price. For the SLM, the total effect consists of coefficient and a spatial multiplier because impacts from a change in one household's water supply unreliability spills over to neighbors. This spatial multiplier effect needs to be accounted for to accurately compute the MWTP. Following Kim et al. (2003), we calculate the SLM MWTP for a change in BWNs variables as:

$$MWTP_{Lag} = \frac{\partial \ln P(Z)}{\partial z_i} = \hat{\beta} \bar{P} \left(\frac{1}{1 - \hat{\rho}} \right) \quad (17)$$

¹⁷ There are two common ways to estimate spatial lag models: (1) using maximum likelihood or (2) two-stage least squares. Table 3.9 shows the results using the first method, whereas Table 3.11 shows the results from the second method.

where $\hat{\rho}$ is the estimated spatial autoregressive coefficient. It is important to note that these marginal benefits estimates represent a capitalized rather than the annual impact from water supply unreliability. As such, the marginal benefit estimates are influenced both by the length of time the buyer of the house expects to reside in the house, the amount the buyer expects to receive for this attribute when he sells the house, the discount rate, and the projected improvements in water infrastructure. Table 3.12 shows the MWTP calculations for the BWN variables with statistically significant coefficients from the estimated spatial models. As it can be seen, on average, the MWTP for improving water supply reliability ranges from \$1,160 to \$35,116 depending upon how unreliability is measured – in either days, BWN episodes, or presence versus absence.

Since the number of days in which the house is expected to be under BWNs over a year represents a clear and known marginal change, we use it as the preferred measure for water supply unreliability. Thus, by reducing the expected number of BWN by one day per year per house, the total effect of this change, on average, would be an improvement by \$1,160 in housing prices when including the impacted house itself and its neighbors. This impact represents 0.86% of the average house price in Marion County.

Furthermore, we see that the MWTP values for consumers of low-price houses are greater than consumers of high-price houses. That is, a reduction of one day under BWN per year will increase housing prices at the lower end of the housing price distribution by \$2,100 to \$2,700, whereas houses at the mid-range of the distribution will increase by \$850 to \$1,000 (Table 3.12). Houses at the 0.7 quantile and above of the price distribution show no statistically significant impacts from the days of BWN variable.

We interpret these results to mean that these differences stem from differing risk perceptions and awareness about public water supply problems between housing consumers. Previous studies have shown that consumers who experience more problems with their water supply perceive the associated health risks differently and are were willing to pay more to fix water supply problems than those consumers who experience water supply problems infrequently (Anadu & Harding, 2000; Genius & Tsagarakis, 2006). Thus, the quantile regression results indicate the existence of a threshold for BWN of perhaps one day of BWN per year. If the average BWN is greater than one day per year, then expectations of reduced water supply reliability are included in housing prices. Below this average, then expectations for water supply reliability are such that the house purchaser MWTP for improving water supply reliability is zero as very few houses under one day per year experience water reliability issues.

Overall, water supply unreliability has a substantial impact on the value of residential properties in Marion county. To calculate the aggregate MWTP for a one-day reduction of BWN, three factors are multiplied together: (1) the average value of statistically significant coefficients from the spatial quantile regression, (2) the average percentage of households that would be expected to be affected by BWN in Marion County between 2013-2017 (35%), and (3) from the quantile regression results, only 40% of the houses would incur a price impact from these notices. Following this procedure, we obtain an aggregate MWTP value of \$4.60 million for a one-day reduction of the annual BWN throughout Marion County. It is important to note that this is a large improvement in terms of BWNs if we look at the average of 1.4 days in Table 3.5.

3.7. Conclusions

Aging water infrastructure combined with funding shortfalls represent serious challenges to local governments and water systems across the United States. The number of water main

breaks has been increasing every year resulting in more interruptions in public water service (Folkman 2018). Since achieving full reliability in water service is most likely not an optimal policy, decision makers at local water utilities attempt to balance between cost and risk associated with their policies (Howe et al., 1994). However, water customers' perceptions of the risk associated with supply disruptions is usually unknown to decision makers. Therefore, studies have attempted to examine the WTP for water supply reliability using stated preference approaches (Genius & Tsagarakis, 2006; Vásquez & Espaillet, 2016).

In this research, we examine the impact of water supply unreliability on single-family, residential property sales in Marion County, WV using spatial and non-spatial hedonic property price models. To measure the impact of water supply unreliability, we define four variables based on issuance of boil water notices (BWNs) one year prior to the sale and link them to house sale transactions. Our analysis is based on 1,985 housing transactions and 350 BWNs throughout the county between 2012-2017. Important factors that affect observed house prices are controlled for including house size, age, number of bedrooms plus bathrooms, construction quality, and presence of house amenities (air conditioning, fireplace, and fence). In addition, ArcGIS is used to measure neighborhood and proximity characteristics such as school quality and distance to the nearest highway interchange. Finally, our models include fixed effects for both time and tax district.

We find that there are statistically significant, negative impacts on house prices from prior issuances of BWNs. Depending upon the model and how unreliability is measured, BWNs can depreciate housing prices at the margin from 0.57% to 18%. Furthermore, by using a quantile regression approach, we find that water supply unreliability has a larger impact on low-price houses compared to high-price houses. Based on what we would judge as the best estimate

of water supply unreliability, the marginal willingness-to-pay (MWTP) for a reduction in one day under a BWN per year will increase housing values at the lower end of the housing price distribution by \$2,100 to \$2,700, whereas houses at the mid-range of the distribution will increase by \$850 to \$1,000. However, house transactions at the higher end of the housing price distribution show no statistically significant impacts from the days of BWN variable.

The results from the quantile regression models can be interpreted as an inconvenience measure, where consumers will be willing to pay to fix water supply reliability problems until a certain threshold in which after that point their MWTP will be zero. Our results indicate that consumers' MWTP will be positive if the house is expected to experience, on average, one day or more under BWNs annually. Since many houses in Marion County (particularly lower priced houses) experience more than one day of BWNs, water supply unreliability has a substantial impact on the value of residential properties in this county. Aggregated throughout Marion County, a MWTP value of \$4.60 million is computed for a one-day reduction of the annual BWN.

Comparing our BWN impact estimate to the results found by Des Rosiers et al. (1999), these authors found a larger magnitude of impact for the measure (Duration BWNs_year). We find that reducing the average duration of BWNs by one day per year will result, on average, in about a 3% improvement in housing prices, whereas Des Rosiers et al. found that this same change led to a 5% to 10% improvement in upper priced houses. This difference is to be expected since we are using a larger sample size and different methodology of linking BWNs to sale observations. For linking BWNs to sale observations, they used aggregated measures and grouped the BWNs into multiple 'spatial sectors' where each of them had one or more warnings

and any house that was located in those sectors was considered having problems with water quality. On the other hand, we use specific measure for each house as explained in section 4.

Our estimates indicate that some households in Marion County have a positive MWTP for a greater reliability in their water supply. The aggregated value of MWTP to reduce BWN of \$4.60 million may help to guide water systems in their decisions regarding water pricing and investments in the water distribution network. In addition, since an unreliable water supply has a negative impact on property valuation and therefore property tax revenues collected by the county. Thus, these estimates can help inform water infrastructure investments at the local government level. In addition to these impacts, as discussed in the literature review, studies have shown that improvements in water infrastructure have positive and significant impacts on economic growth in an area and, in general, these investments generate benefits in both urban and rural areas.

Finally, it is important to note, however, that our findings reflect the specific nature of our data. The area of study is a relatively small geographical area. Also, due to missing data we had to drop a relatively large number of BWNs (90) from our analysis. In addition, when allocating BWNs to house sale observations, most BWNs affect one or multiple streets in addition to surrounding areas. Due to limited knowledge, we were unable to include those surrounding areas in our analysis. Therefore, not all house sale transactions affected by BWN were included in this analysis so that our monetary estimates of BWN impacts should be regarded as conservative.

3.8. References

- Ailes, E., Budge, P., Shankar, M., Collier, S., Brinton, W., Cronquist, A., ... Brunkard, J. M. (2013). Economic and health impacts associated with a *Salmonella* Typhimurium drinking water outbreak-Alamosa, CO, 2008. *PLoS ONE*, 8(3), 1–10. <http://doi.org/10.1371/journal.pone.0057439>
- Alfredo, K., Allaire, M., Becker, W., Boyle, C., Cho, A., Deane, M., ... Lall, U. (2016). America's water: Developing a road map for the future of our nation's infrastructure. Retrieved from <http://water.columbia.edu/files/2016/03/Developing-a-Water-Road-Map-Whitepaper.pdf>
- Allaire, M., Wu, H., & Lall, U. (2018). National trends in drinking water quality violations. *Proceedings of the National Academy of Sciences*, 115(9), 2078–2083. <http://doi.org/10.1073/pnas.1719805115>
- Allen, M., Clark, R., Cotruvo, J. A., & Grigg, N. (2018). Drinking water and public health in an era of aging distribution infrastructure. *Public Works Management and Policy*, 23(4), 301–309. <http://doi.org/10.1177/1087724X18788368>
- American Society of Civil Engineers. (2017). Infrastructure report card: Drinking water. Retrieved from <https://www.infrastructurereportcard.org/cat-item/drinking-water/>
- American Water Works Association. (2012). Buried no longer: Confronting America's water infrastructure challenge. Retrieved from <http://www.climateneeds.umd.edu/reports/American-Water-Works.pdf>
- Anadu, E. C., & Harding, A. K. (2000). Risk perception and bottled water use. *American Water Works Association Journal*, 92, 82–92.
- Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Dordrecht, Netherlands: Springer Science+Business Media.
- Anselin, L. (2001). Spatial econometrics. In B. H. Baltagi (Ed.), *A Companion to Theoretical Econometrics* (pp. 310–330). Malden, MA: Blackwell Publishing Ltd.
- Anselin, L., & Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah & D. E. Giles (Eds.), *Handbook of Applied Economic Statistics* (pp. 237–289). New York, NY: Marcel Dekker, INC. <http://doi.org/10.5860/choice.34-4512>
- Anselin, L., & Lozano-Gracia, N. (2009). Spatial hedonic models. In T. C. Mills & K. Patterson (Eds.), *Palgrave Handbook of Econometrics* (Volume 2, pp. 1213–1250). New York, NY: Palgrave Macmillan.
- Anselin, L., Lozano-Gracia, N., Deichmann, U., & Lall, S. (2010). Valuing access to water—A spatial hedonic approach, with an application to Bangalore, India. *Spatial Economic Analysis*, 5(2), 161–179. <http://doi.org/10.1080/17421771003730703>
- Appiah, A., Adamowicz, W., Lloyd-Smith, P., & Dupont, D. (2018). Reliability of drinking water: Risk perceptions and economic value. *Water Economics and Policy*, 1850020, 1–27. <http://doi.org/10.1142/S2382624X18500200>

- Bagi, F. S. (2002). Economic impact of water/sewer facilities on rural and urban communities. *Rural America*, 17(4), 44–49.
- Baird, G. M. (2011). Fasten your seat belts: Main breaks and the issuance of precautionary boil-water notices. *Journal of American Water Works Association*, 103(3), 24–28.
- Baumont, C. (2004). Spatial effects in housing price models: Do housing prices capitalize urban development policies in the agglomeration of Dijon (1999)? Retrieved from <https://hal.archives-ouvertes.fr/hal-01525664/document>
- Berg, C. Van Den, & Nauges, C. (2012). The willingness to pay for access to piped water: A hedonic analysis of house prices in Southwest Sri Lanka. *Letters in Spatial and Resource Sciences*, 5, 151–166. <http://doi.org/10.1007/s12076-012-0079-y>
- Boyle, K. J., Kuminoff, N. V., Zhang, C., Devanney, M., & Bell, K. P. (2010). Does a property-specific environmental health risk create a “neighborhood” housing price stigma? Arsenic in private well water. *Water Resources Research*, 46(3), 1–10. <http://doi.org/10.1029/2009WR008074>
- Brasington, D. M. (1999). Which measures of school quality does the housing market value? *Journal of Real Estate Research*, 18(3), 395–413.
- California Urban Water Agencies. (1994). The value of water supply reliability: Results of a contingent valuation survey of residential customers. Retrieved from <https://www.cuwa.org/publications-archive/yg34aaefy4ap3bypfhtx3khpmt66b>
- Case, B., Colwell, P. F., Leishman, C., & Watkins, C. (2006). The impact of environmental contamination on condo prices: A hybrid repeat-sale/hedonic approach. *Real Estate Economics*, 34(1), 77–107. <http://doi.org/10.1111/j.1540-6229.2006.00160.x>
- Census Bureau. (2018). Quick facts: Marion County, West Virginia. Retrieved from <https://www.census.gov/quickfacts/fact/table/marioncountywestvirginia/PST045218#>
- Center for Public Management. (2014). *Study on investment in water and wastewater infrastructure and economic development*. Retrieved from https://scholarworks.umb.edu/cgi/viewcontent.cgi?article=1022&context=cpm_pubs
- Coyne, C. (2019). Money down the drain: WV losing most of water it produces. Retrieved from https://www.wvgazettemail.com/report_for_america/money-down-the-drain-wv-losing-most-of-water-it/article_40dbcf49-2f61-56d6-8146-ae088fa2d436.html
- Cropper, M. L., Deck, L. B., & McConnell, K. E. (1988). On the choice of functional form for hedonic price functions. *The Review of Economics and Statistics*, 70(4), 668–675.
- Des Rosiers, F., Bolduc, A., & Theriault, M. (1999). Environment and value: Does drinking water quality affect house prices? *Journal of Property Investment & Finance*, 17(5), 444–463.
- Doria, M. D. F., Pidgeon, N., & Hunter, P. R. (2009). Perceptions of drinking water quality and risk and its effect on behaviour: A cross-national study. *Science of the Total Environment*, 407(21), 5455–5464. <http://doi.org/10.1016/j.scitotenv.2009.06.031>

- Doria, M. D. F. (2010). Factors influencing public perception of drinking water quality. *Water Policy*, 12, 1–19. <http://doi.org/10.2166/wp.2009.051>
- Dotzour, M. (1997). Groundwater contamination and residential property values. *The Appraisal Journal*, 65(3), 279–285.
- Ercumen, A., Gruber, J. S., & Colford Jr, J. M. (2014). Water distribution system deficiencies and gastrointestinal illness: A systematic review and meta-analysis. *Environmental Health Perspectives*, 122(7), 651–660.
- Freeman III, A. M., Herriges, J. A., & Kling, C. L. (2014). *The measurement of environmental and resource values*. New York, NY: RFF Press.
- Genius, M., & Tsagarakis, K. P. (2006). Water shortages and implied water quality: A contingent valuation study. *Water Resources Research*, 42(12), 1–8. <http://doi.org/10.1029/2005WR004833>
- Genius, M., Hatzaki, E., Kouromichelaki, E. M., Kouvakis, G., Nikiforaki, S., & Tsagarakis, K. P. (2008). Evaluating consumers' willingness to pay for improved potable water quality and quantity. *Water Resources Management*, 22(12), 1825–1834. <http://doi.org/10.1007/s11269-008-9255-7>
- Golgher, B. A., & Voss, P. R. (2016). How to interpret the coefficients of spatial models: Spillovers, direct and indirect effects. *Spatial Demography*, 4, 175–205. <http://doi.org/10.1007/s40980-015-0016-y>
- Griffin, R. C., & Mjelde, J. W. (2000). Valuing water supply reliability. *American Journal of Agricultural Economics*, 82(2), 414–426.
- Guignet, D. (2013). What do property values really tell us? A hedonic study of underground storage tanks. *Land Economics*, 89(2), 211–226. <http://doi.org/10.3368/le.89.2.211>
- Guignet, D., Walsh, P. J., & Northcutt, R. (2016). Impacts of ground water contamination on property values: Agricultural run-off and private wells. *Agricultural and Resource Economics Review*, 45(2), 293–318. <http://doi.org/10.1017/age.2016.16>
- Hao, L., & Naiman, D. Q. (2007). *Quantile Regression*. Thousand Oaks, CA: Sage Publications, Inc.
- Heflin, C., Jensen, J., & Miller, K. (2014). Understanding the economic impacts of disruptions in water service. *Evaluation and Program Planning*, 46, 80–86. <http://doi.org/10.1016/j.evalprogplan.2014.05.003>
- Hensher, D., Shore, N., & Train, K. (2005). Households' willingness to pay for water service attributes. *Environmental and Resource Economics*, 32(4), 509–531. <http://doi.org/10.1007/s10640-005-7686-7>
- Herriges, J. A., Secchi, S., & Babcock, B. A. (2005). Living with hogs in Iowa: The impact of livestock facilities on rural residential property values. *Land Economics*, 81(4), 530–545.
- Howe, C. W., Smith, M. G., Bennett, L., Brendeeke, C. M., Flack, J. E., Hamm, Robert, M., ...

- Wunderlich, K. (1994). The value of water supply reliability in urban water systems. *Journal of Environmental Economics and Management*, 26(1), 19–30.
- Jakus, P. M., Shaw, W. D., Nguyen, T. N., & Walker, M. (2009). Risk perceptions of arsenic in tap water and consumption of bottled water. *Water Resources Research*, 45(5), 1–8. <http://doi.org/10.1029/2008WR007427>
- Janeski, I., & Whitacre, B. E. (2014). Long-term economic impacts of USDA water and sewer infrastructure investments in Oklahoma. *Journal of Agricultural and Applied Economics*, 46(01), 21–39. <http://doi.org/10.1017/s1074070800000614>
- Javidi, A., & Pierce, G. (2018). U.S. households' perception of drinking water as unsafe and its consequences: Examining alternative choices to the tap. *Water Resources Research*, 54, 6100–6113. <http://doi.org/10.1029/2017WR022186>
- Keskin, B., & Watkins, C. (2017). Defining spatial housing submarkets: Exploring the case for expert delineated boundaries. *Urban Studies*, 54(6), 1446–1462. <http://doi.org/10.1177/0042098015620351>
- Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management*, 45, 24–39.
- Kim, T. H., & Muller, C. (2004). Two-stage quantile regression when the first stage is based on quantile regression. *Econometrics Journal*, 7, 218–231.
- Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, 46(1), 33–50.
- Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives*, 15(4), 143–156.
- Koss, P., & Khawaja, M. S. (2001). The value of water supply reliability in California: A contingent valuation study. *Water Policy*, 3(2), 165–174. [http://doi.org/10.1016/S1366-7017\(01\)00005-8](http://doi.org/10.1016/S1366-7017(01)00005-8)
- Kuminoff, N. V., Parmeter, C. F., & Pope, J. C. (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? *Journal of Environmental Economics and Management*, 60(3), 145–160.
- Larson, B. A., & Gnedenko, E. (1999). Avoiding health risks from drinking water in Moscow: An empirical analysis. *Environment and Development Economics*, 4, 565–581.
- Latinopoulos, D. (2014). Using a choice experiment to estimate the social benefits from improved water supply services. *Journal of Integrative Environmental Sciences*, 11(3–4), 187–204. <http://doi.org/10.1080/1943815X.2014.942746>
- Laughland, A. S., Musser, L. M., Musser, W. N., & Shortle, J. S. (1993). The opportunity cost of time and averting expenditures for safe drinking water. *Journal of American Water Resources Association*, 29(2), 291–299.

- LeSage, J. P., & Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Boca Raton, FL: CRC Press.
- Levêque, J. G., & Burns, R. C. (2018). Drinking water in West Virginia (USA): Tap water or bottled water - What is the right choice for college students? *Journal of Water and Health*, 16(5), 827–838. <http://doi.org/10.2166/wh.2018.129>
- Liu, T., Opaluch, J. J., & Uchida, E. (2017). The impact of water quality in Narragansett Bay on housing prices. *Water Resources Research*, 53(8), 6454–6471. <http://doi.org/10.1002/2016WR019606>
- MacDonald, D. H., Barnes, M., Bennett, J., Morrison, M., & Young, M. D. (2005). Using a choice modelling approach for customer service standards in urban water. *Journal of the American Water Resources Association*, 41(3), 719–728. <http://doi.org/10.1111/j.1752-1688.2005.tb03766.x>
- Mack, E. A., & Wrase, S. (2017). A burgeoning crisis? A nationwide assessment of the geography of water affordability in the United States. *PLoS ONE*, 12(1), 1–19. <http://doi.org/10.1371/journal.pone.0169488>
- Majuru, B., Suhrcke, M., & Hunter, P. R. (2018). Reliability of water supplies in low and middle-income countries: A structured review of definitions and assessment criteria. *Journal of Water, Sanitation and Hygiene for Development*, 8(2), 142–164. <http://doi.org/10.2166/washdev.2018.174>
- Malone, P., & Barrows, R. (1990). Groundwater pollution's effects on residential property values, Portage County, Wisconsin. *Journal of Soil and Water Conservation*, 45(2), 346–348.
- McConnell, K. E., & Rosado, M. A. (2000). Valuing discrete improvements in drinking water quality through revealed preferences. *Water Resources Research*, 36(6), 1575–1582.
- McIntosh, C., Alegría, T., Ordóñez, G., & Zenteno, R. (2018). The neighborhood impacts of local infrastructure investment: Evidence from urban Mexico. *American Economic Journal: Applied Economics*, 10(3), 263–286.
- McLaughlin, P. A. (2011). Something in the water? Testing for groundwater quality information in the housing market. *Journal of Agricultural and Resource Economics*, 36(2), 375–394. <http://doi.org/10.2139/ssrn.1395008>
- Mueller, J. M., & Loomis, J. B. (2008). Spatial dependence in hedonic property models: Do different corrections for spatial dependence result in economically significant differences in estimated implicit prices? *Journal of Agricultural and Resource Economics*, 33(2), 212–231.
- Munnell, A. H., & Cook, L. M. (1990). How does public infrastructure affect regional economic performance? *New England Economic Review*, September, 11–33.
- Netusil, N. R., Kincaid, M., & Chang, H. (2014). Valuing water quality in urban watersheds: A comparative analysis of Johnson Creek, Oregon, and Burnt Bridge Creek, Washington. *Water Resources Research*, 50, 4254–4268.

<http://doi.org/10.1002/2013WR014546>.Received

- North, J. H., & Griffin, C. C. (1993). Water source as a housing characteristic: Hedonic property valuation and willingness to pay for water. *Water Resources Research*, 29(7), 1923–1929.
- Nygård, K., Wahl, E., Krogh, T., Tveit, O. A., Bøhleng, E., Tverdal, A., & Aavitsland, P. (2007). Breaks and maintenance work in the water distribution systems and gastrointestinal illness: A cohort study. *International Journal of Epidemiology*, 36(4), 873–880.
<http://doi.org/10.1093/ije/dym029>
- OECD. (2016). Water, growth and finance: Policy perspectives. Retrieved from <https://www.oecd.org/environment/resources/Water-Growth-and-Finance-policy-perspectives.pdf>
- Page, G. W., & Rabinowitz, H. (1993). Groundwater contamination: Its effects on property values and cities. *Journal of the American Planning Association*, 59(4), 473–481.
<http://doi.org/10.1080/01944369308975901>
- Pandit, R., Polyakov, M., Tapsuwan, S., & Moran, T. (2013). The effect of street trees on property value in Perth, Western Australia. *Landscape and Urban Planning*, 110, 134–142.
<http://doi.org/10.1016/j.landurbplan.2012.11.001>
- Pattanayak, S. K., Yang, J. C., Whittington, D., & Bal Kumar, K. C. (2005). Coping with unreliable public water supplies: Averting expenditures by households in Kathmandu, Nepal. *Water Resources Research*, 41(2), 1–11. <http://doi.org/10.1029/2003WR002443>
- Phaneuf, D. J., & Requate, T. (2016). *A Course in Environmental Economics: Theory, Policy, and Practice*. Cambridge, UK: Cambridge University Press.
- Pierce, G., & Gonzalez, S. (2017). Mistrust at the tap? Factors contributing to public drinking water (mis)perception across US households. *Water Policy*, 19, 1–12.
<http://doi.org/10.2166/wp.2016.143>
- Piper, S., & Martin, W. E. (1997). Household willingness to pay for improved rural water supplies: A comparison of four sites. *Water Resources Research*, 33(9), 2153–2163.
- Powe, N. A., Garrod, G. D., McMahon, P. L., & Willis, K. G. (2004). Assessing customer preferences for water supply options using mixed methodology choice experiments. *Water Policy*, 6(5), 427–441.
- Rodríguez-Tapia, L., Revollo-Fernández, D., & Morales-Novelo, J. (2017). Household's perception of water quality and willingness to pay for clean water in Mexico City. *Economies*, 5(2), 1–14. <http://doi.org/10.3390/economies5020012>
- Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, 82(1), 34–55.
- Russell, C. S., Arey, D. G., & Kates, R. W. (1970). *Drought and Water Supply: Implications of the Massachusetts Experience for Municipal Planning*. Baltimore, MD: John Hopkins Press.

- Schnare, A. B., & Struyk, R. J. (1976). Segmentation in urban housing markets. *Journal of Urban Economics*, 3(2), 146–166. [http://doi.org/10.1016/0094-1190\(76\)90050-4](http://doi.org/10.1016/0094-1190(76)90050-4)
- Tarfasa, S., & Brouwer, R. (2013). Estimation of the public benefits of urban water supply improvements in Ethiopia: A choice experiment. *Applied Economics*, 45(9), 1099–1108. <http://doi.org/10.1080/00036846.2011.613793>
- Taylor, L. O. (2003). The hedonic method. In P. A. Champ, K. J. Boyle, & C. Brown, Thomas (Eds.), *A Primer on Nonmarket Valuation* (pp. 331–393). New York, NY: Springer Science+Business Media.
- Taylor, L. O. (2008). Theoretical foundations and empirical developments in hedonic modeling. In A. Baranzini, J. Ramirez, C. Schaerer, & P. Thalmann (Eds.), *Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation* (pp. 15–34). New York, NY: Springer Science+Business Media.
- Trach, M. 2019. Personal interview on June 24. Marion County Assessor, Fairmont WV.
- VanDerslice, J. (2011). Drinking water infrastructure and environmental disparities: Evidence and methodological considerations. *American Journal of Public Health*, 101(S1), S109–S114.
- U.S. Geological Survey. (2015). USGS water use data for West Virginia. Retrieved from <https://waterdata.usgs.gov/wv/nwis/wu>
- Um, M. J., Kwak, S. J., & Kim, T. Y. (2002). Estimating willingness to pay for improved drinking water quality using averting behavior method with perception measure. *Environmental and Resource Economics*, 21(3), 287–302. <http://doi.org/10.1021/es990728j>
- Valiñas, M. de los A. G. (2006). Analysing rationing policies: Drought and its effects on urban users' welfare (Analysing rationing policies during drought). *Applied Economics*, 38(8), 955–965.
- Value of Water Campaign. (2017). The economic benefits of investing in water infrastructure. Retrieved from [http://thevalueofwater.org/sites/default/files/Economic Impact of Investing in Water Infrastructure_VOW_FINAL_pages.pdf](http://thevalueofwater.org/sites/default/files/Economic%20Impact%20of%20Investing%20in%20Water%20Infrastructure_VOW_FINAL_pages.pdf)
- Vásquez, W. F. (2012). Reliability perceptions and water storage expenditures: Evidence from Nicaragua. *Water Resources Research*, 48(10), 1–8. <http://doi.org/10.1029/2011WR011024>
- Vásquez, W. F. (2013a). A hedonic valuation of residential water services. *Applied Economic Perspectives and Policy*, 35(4), 661–678. <http://doi.org/10.1093/aep/ppt022>
- Vásquez, W. F. (2013b). An economic valuation of water connections under different approaches of service governance. *Water Resources and Economics*, 2–3, 17–29. <http://doi.org/10.1016/j.wre.2013.10.001>
- Vásquez, W. F. (2014). Willingness to pay and willingness to work for improvements of municipal and community-managed water services. *Water Resources Research*, 50(10), 8002–8014. <http://doi.org/10.1002/2013WR014910>.Received

- Vásquez, W. F., & Espailat, R. (2016). Willingness to pay for reliable supplies of safe drinking water in Guatemala: A referendum contingent valuation study. *Urban Water Journal*, 13(3), 284–292. <http://doi.org/10.1080/1573062X.2014.991741>
- Vásquez, W. F., Mozumder, P., & Franceschi, D. (2015). Water Quality, Household Perceptions and Averting Behavior: Evidence from Nicaragua. *Water Economics and Policy*, 1(4), 1–21. <http://doi.org/10.1142/S2382624X15500113>
- Vásquez, W. F., Mozumder, P., Hernández-Arce, J., & Berrens, R. P. (2009). Willingness to pay for safe drinking water: Evidence from Parral, Mexico. *Journal of Environmental Management*, 90(11), 3391–3400. <http://doi.org/10.1016/j.jenvman.2009.05.009>
- Vedachalam, S., John, M. E., & Riha, S. J. (2014). Spatial analysis of boil water advisories issued during an extreme weather event in the Hudson River Watershed, USA. *Applied Geography*, 48, 112–121. <http://doi.org/10.1016/j.apgeog.2014.02.001>
- Vedachalam, S., Spotte-Smith, K. T., & Riha, S. J. (2016). A meta-analysis of public compliance to boil water advisories. *Water Research*, 94, 136–145. <http://doi.org/10.1016/j.watres.2016.02.014>
- Water Quality Research Foundation. (2018). Boil water notice toolkit. Retrieved from http://www.wqrf.org/uploads/8/3/5/5/83551838/2018_wqrf_bwn_final.pdf
- Wescoat, J. L., Headington, L., & Theobald, R. (2007). Water and poverty in the United States. *Geoforum*, 38(5), 801–814. <http://doi.org/10.1016/j.geoforum.2006.08.007>
- West Virginia Infrastructure and Jobs Development Council. (2017). Needs assessment. Retrieved from <https://assets.documentcloud.org/documents/5396603/2017NeedsAssessment-IJDC.pdf>
- West Virginia Public Broadcasting. (2019). 2 bills aim to address water, sewer infrastructure issues. Retrieved from <http://www.wvpublic.org/post/2-bills-aim-address-water-sewer-infrastructure-issues#stream/0>
- WV Office of Environmental Health Services. (2019). Public boil water notices. Retrieved from <http://www.wvdhhr.org/oehs/oehs-eed/boilwater.cfm>
- Xiao, Y. (2017). *Urban Morphology and Housing Market*. Shanghai, China: Springer and Tongji University Press. <http://doi.org/10.1007/978-981-10-2762-8>
- Zérah, M. (2000). Household strategies for coping with unreliable water supplies: The case of Delhi. *Habitat International*, 24, 295–307.

3.9. Tables and Figures

Figure 3.1. Total number of boil water notices in West Virginia between 2012 and 2017

Figure 3.2. Study area – Marion County, West Virginia

Figure 3.3. Average number of boil water notices per 10,000 by County between 2012 and 2017 (WV Office of Environmental Health Services [OEHS], 2019)

Figure 3.4. Tax districts in Marion County

Figure 3.5. Residential property transactions affected by boil water notices in Marion County, West Virginia between 2012 and 2017

Figure 3.6. Schematic of the models estimated in the analysis

Figure 3.7. Spatial quantile model coefficients for BWN variables and their 95% confidence intervals

Table 3.1. Public water systems serving residential areas in Marion County, West Virginia 2017

PWS Name	City Served	Population Served	Service Connections	# BWNs	# Health based Violations	Water Pumped into Distribution System (gal)	Water Lost (accounted for) *	Water Lost (unaccounted for)**	Water Main Breaks	Water Charge (\$/4,500 gal)	Net Income/Service Connections (\$)
City of Fairmont	Fairmont	29,179	13,457	36	0	2,067,884	46,718 (2.26)	737,293 (35.65)	127	39.92	62.41
Valley Falls PSD	Fairmont	4,027	1,699	5	1	96,041	0	26,730 (27.83)	0	44.31	31.18
Monongah Water Works	Monongah	3,214	1,418	5	1	227,579	19,820 (8.71)	98,200 (43.15)	26	49.82	-334.41
Tri-County Water Association - Fairmont	Bridgeport	2,522	1,080	2	1	89,199	0	20,811 (23.33)		45.59	-134.49
Little Creek PSD	Fairmont	2,029	900	1	0	71,487	0	23,057 (32.25)	0	40.01	-130.71
City of Mannington	Mannington	2,003	936	2	0	98,358	430 (0.44)	10,694 (10.87)	1	43.76	3.72
Monumental PSD	Fairmont	1,946	825	3	0	54,193	6,200 (11.44)	10,958 (20.22)	13	54.32	-23.18
Rivesville Water System	Rivesville	1,372	616	6	0	33,634	45 (0.13)	8,050 (23.93)	3	44.73	-56.99
Paw Paw Route 19 PSD	Morgantown	1,249	536	1	2	34,247	0	13,005 (37.97)	0	66.53	-75.03
Grant Town Water System ***	Grant Town	1,240	524	1	0						
Bingamon PSD	Wyatt	1,213	538	3	0	47,361	1,827 (3.86)	19,163 (40.46)	21	45.53	-53.49
Ice's Run PSD	Fairmont	1,109	486	1	0	29,393	3,848 (13.09)	4,710 (16.02)	9	54.67	-45.20
Downs PSD	Fairmont	1,007	450	2	0	31,041	5,250 (16.91)	5,783 (18.63)	10	57.93	132.91
Fairview Water System	Fairview	806	357	2	0	28,314	796 (2.81)	8,607 (30.40)	1	62.50	-471.13
Farmington Water	Farmington	692	208	1	0	19,642	0	3,877 (19.74)	0	50.21	-82.32
Montana Water Association	Fairmont	692	301	1	0	16,973	0	3,292 (19.40)	1	54.94	14.54
Worthington Municipal Water	Worthington	680	299	1	0	24,559	2,273 (9.26)	1,276 (5.20)	4	34.97	-134.50
Mannington PSD	Mannington	590	249	1	0	48,118	10,102 (20.99)	8,057 (16.74)	31	71.69	-174.98
Sugar Lane Water Association	Rivesville	410	84	1	0	3,774	150 (3.97)	244 (6.47)	0	54.84	-89.76
Four States PSD ***	Worthington	380	160	2	0						
Hutchinson Community Water Association	Worthington	370	157	0	0	38,940	0	31,845 (81.78)	5	24.55	-54.73
Minister's Run Water Association	Rivesville	348	147	1	1	9,967	0	3,938 (39.51)	0	49.01	17.01
Mannington PSD - Logansport	Mannington	310	131	0	0						
Mannington PSD - Metz	Mannington	232	98	0	0						
Lincoln Heights Improvement Association	Farmington	197	84	0	0	1,507	0	289 (19.18)	2	50.93	34.32
Coon's Run PSD	Shinnston	178	75	1	0	25,501	0	7,466 (29.28)	1	43.52	141.37
Monumental PSD - Chesapeake	Fairmont	133	56	0	0						
Tri-County Water Association - Shinnston	Bridgeport	122	51	0	1						
Little Laurel Run Improvement Association	Farmington	73	30	0	0	2,531	0	284 (11.22)	0	40.37	-87.77
Rayford Acres ***	Fairmont	71	30	0	0						
Sunny View Acres Water Project	Farmington	69	29	0	1	888	0	28 (3.15)	0	49.73	-19.17
Total		58,463	26,011	79	8	3,101,131	97,459 (3.14%)	1,047,657 (33.78%)	255		

* Include: (a) mains, plant, filters, flushing, etc; (b) fire department use; (c) main leaks; (d) backwashing; and (e) blowing setting basins.

** Due to leaks in the water distribution system (non-revenue water)

*** reports are unavailable; empty cells indicate missing data

Systems with multiple branches prepare only one report for their water and cost statistics (e.g. Tri-County and Mannington PSD).

Percentage of total in parentheses

Sources: Safe Drinking Water Information System (SDWIS/Fed); WV Office of Environmental Health Services (OEHS); WV Drinking Water Watch; WV Public Service Commission

Table 3.2. Property transactions and boil water notices by tax districts in Marion County, West Virginia between 2012 and 2017

Number	District	Property Transactions	BWNs	Properties Affected by BWNs
1	BARRACKVILLE	53	4	30 (56.6)
2	FAIRMONT DISTRICT	78	20	23 (29.5)
3	FAIRMONT CITY **	485	51	138 (28.5)
4	GRANT ANNEX **	136	20	45 (33.1)
5	UNION CITY **	177	11	34 (19.2)
6	WINFIELD CITY **	28	4	21 (75)
7	FAIRVIEW	9	3	1 (11.1)
8	FARMINGTON	14	5	10 (71.4)
9	GRANT DISTRICT	236	20	32 (13.6)
10	GRANT TOWN	19	2	12 (63.2)
11	LINCOLN DISTRICT	133	37	69 (51.9)
12	MANNINGTON DISTRICT	17	3	11 (64.7)
13	MANNINGTON CITY	75	7	59 (78.7)
14	MONONGAH-GRANT *	24	0	14 (58.3)
15	MONONGAH-LINCOLN *	19	0	12 (63.2)
16	PAW PAW DISTRICT	59	31	41 (69.5)
17	RIVESVILLE	50	24	37 (74)
18	UNION DISTRICT	113	12	29 (25.7)
19	WINFIELD DISTRICT	86	11	22 (25.6)
20	WORTHINGTON	5	1	4 (80)
21	WHITE HALL	25	2	11 (44)
22	PLEASANT VALLEY	144	17	45 (31.3)
	Multiple Districts	-	65	-
	Total	1,985	350	700 (35.3)

* BWNs that affect districts 14 and 15 usually affect other districts as well

** Part of Fairmont City

Percentage of total in parentheses

Table 3.3. Property transactions and boil water notices in Fairmont City vs. rest of the county

Area	Property Transactions	BWNs	Properties Affected by BWNs
Fairmont City	826 (41.6)	86 (24.6)	238 (34)
Other	1,159 (58.4)	264 (75.4)	462 (66)
Total	1,985 (100)	350 (100)	700 (100)

Percentage of total in parentheses

Table 3.4. Reasons for issuing a BWN in Marion County

Reason	Marion County		Fairmont		Rest of the county	
	Number of BWNs	Percentage of total	Number of BWNs	Percentage of total	Number of BWNs	Percentage of total
Break or leak	279	79.7%	69	80.2%	210	79.5%
Water main break/repair	90	25.7%	22	25.6%	68	25.8%
Water line break/repair	171	48.9%	47	54.7%	124	47.0%
Water leak	18	5.1%	0	0%	18	6.8%
Water valve repair	9	2.6%	5	5.8%	4	1.5%
Fire hydrant replacement	13	3.7%	7	8.1%	6	2.3%
Low chlorine	9	2.6%	0	0%	9	3.4%
Maintenance and improvements	25	7.1%	3	3.5%	22	8.3%
Unspecified/missing	15	4.3%	2	2.3%	13	4.9%
Total	350	100%	86	100%	264	100%

Note that all of the 65 BWNs that affect multiple districts were accounted under rest of the county even if some of them affect parts of Fairmont.

Table 3.5. Summary statistics and variable descriptions

Variable	Description	Unit	Average	Std. Dev.	Min	Max
Dependent variable						
House price	House's sale price	\$	135,338	81,082	6,000	650,000
Independent variables						
Focus variables						
BWNs_year	Number of BWNs affecting the house a year before the sale	Number	0.46	0.85	0	13
Days BWNs_year	Number of days the house was under BWNs a year before the sale	Days	1.40	5.52	0	116
Duration BWNs_year	Average duration under BWNs a year before the sale	Days	0.94	2.40	0	35
BWN	1 = if the house was affected by a BWN, 0 = otherwise	0/1	0.35	0.48	0	1
Structural variables						
SQFT	Building area in square feet	ft2	1,645.45	658.89	480	5,488
Story height	Story height	Number	1.27	0.42	1	3
Construction material	Material used in construction, 1 = if the material used is Alum/Vinyl, 0 = otherwise	0/1	0.63	0.48	0	1
Physical condition	Physical condition of the house (1-6, 1 = Unsound, 6 = Excellent)	Number	4.75	0.82	1	6
Quality grade factor	Quality of the material and workmanship (0.5-2.5, 0.5 = E, 2.5 = X+)	Number	8.37	2.69	2	18
Age	Age of the house	Years	63	36	0	167
Bedrooms	Number of bedrooms	Number	2.80	0.76	1	12
Total Bathrooms	Total number of bathrooms (full + half)	Number	1.88	0.81	1	6
AC	Heating system with AC, 1 = Central with A/C, 0 = otherwise	0/1	0.77	0.42	0	1
Fire place	1 = if there is a wood burning fire place, 0 = otherwise	0/1	0.31	0.46	0	1
Basement garage	1 = if there is basement garage, 0 = otherwise	0/1	0.29	0.45	0	1
Property variables						
Lot size	Lot size	Acres	0.96	5.30	0.01	130.28
Sidewalk	1 = if there is a sidewalk, 0 = otherwise	0/1	0.06	0.24	0	1
Fence	1 = if there is a fence around the property, 0 = otherwise	0/1	0.49	0.50	0	1
Neighborhood and proximity variables						
Crime	Total crime index	Number	54.05	24.28	19	101
School quality	Percentage of students scoring at or above proficiency levels in the math test	%	48.91	14.26	29	71
Distance to highway exit	Distance to the nearest highway interchange (I-79)	Miles	2.63	2.68	0.09	17.47
Distance to FSU	Distance to Fairmont State University	Miles	3.19	2.57	0.14	17.30

Observations = 1,985

Table 3.6. Lagrange Multiplier (LM) diagnostics for spatial dependence

Test	Statistic	P-value
LM _{Error}	48.3510	0.0000
LM _{Lag}	73.7100	0.0000
Robust LM _{Error}	3.1320	0.0768
Robust LM _{Lag}	28.4910	0.0000

Table 3.7. BWN variables means by price quantile

Price quantile	BWNs _{year}	Days BWNs _{year}	Duration BWNs _{year}	BWN
31,928.37	1.122	4.694	2.826	0.811
59,863.85	0.568	1.907	1.621	0.471
81,285.8	0.383	0.890	0.676	0.313
102,267.1	0.457	1.314	0.788	0.319
124,880.6	0.406	0.995	0.623	0.301
144,610.7	0.401	1.185	0.614	0.291
167,371.4	0.338	0.540	0.427	0.268
210,602	0.268	0.549	0.466	0.228
301,112.6	0.204	0.505	0.376	0.162

Table 3.8. OLS regression results, tax district and year fixed effects are included (dependent variable is ln (P))

	(1)	(2)	(3)	(4)
BWNs_year	-0.0741*** (0.0172)			
Days BWNs_year		-0.0065** (0.0031)		
Duration BWNs_year			-0.0280*** (0.0067)	
BWN				-0.1904*** (0.0235)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0310 (0.0277)	-0.0305 (0.0279)	-0.0316 (0.0276)	-0.0321 (0.0272)
Construction material	-0.0565*** (0.0181)	-0.0541*** (0.0182)	-0.0528*** (0.0182)	-0.0567*** (0.0179)
Physical condition	0.2153*** (0.0186)	0.2216*** (0.0186)	0.2203*** (0.0184)	0.2075*** (0.0181)
Quality grade factor	0.4787*** (0.0760)	0.4809*** (0.0771)	0.4749*** (0.0765)	0.4743*** (0.0742)
Age	-0.0016*** (0.0005)	-0.0017*** (0.0005)	-0.0017*** (0.0005)	-0.0015*** (0.0005)
Bedrooms	0.0307* (0.0161)	0.0310* (0.0165)	0.0331** (0.0164)	0.0326** (0.0156)
Total Bathrooms	0.0152 (0.0186)	0.0172 (0.0186)	0.0216 (0.0184)	0.0147 (0.0182)
AC	0.1844*** (0.0247)	0.1831*** (0.0248)	0.1817*** (0.0246)	0.1847*** (0.0243)
Fire place	0.1162*** (0.0197)	0.1164*** (0.0199)	0.1182*** (0.0199)	0.1178*** (0.0194)
Basement garage	0.0433** (0.0184)	0.0427** (0.0185)	0.0434** (0.0186)	0.0407** (0.0183)
Lot size	0.0077** (0.0034)	0.0076** (0.0035)	0.0076** (0.0034)	0.0078** (0.0033)
Sidewalk	-0.0509 (0.0387)	-0.0502 (0.0392)	-0.0510 (0.0390)	-0.0482 (0.0381)
Fence	0.0908*** (0.0187)	0.0945*** (0.0188)	0.0925*** (0.0186)	0.0879*** (0.0184)
Crime	-0.0012* (0.0006)	-0.0011* (0.0006)	-0.0011* (0.0006)	-0.0013** (0.0006)
School quality	0.0009 (0.0009)	0.0008 (0.0009)	0.0007 (0.0009)	0.0008 (0.0009)
Distance to highway exit	0.0176 (0.0141)	0.0182 (0.0142)	0.0161 (0.0138)	0.0144 (0.0136)
Distance to FSU	-0.0106 (0.0119)	-0.0109 (0.0120)	-0.0092 (0.0117)	-0.0075 (0.0116)
Constant	9.4583*** (0.1449)	9.3641*** (0.1460)	9.4009*** (0.1425)	9.5381*** (0.1383)
Observations	1,985	1,985	1,985	1,985
R-squared	0.7060	0.7013	0.7067	0.7132
Adj R-squared	0.6993	0.6946	0.7000	0.7067

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.9. Spatial lag model results (dependent variable is ln (P))

	(1)	(2)	(3)	(4)
BWNs_year	-0.0668*** (0.0171)			
Days BWNs_year		-0.0057* (0.0030)		
Duration BWNs_year			-0.0266*** (0.0066)	
BWN				-0.1806*** (0.0231)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0317 (0.0272)	-0.0312 (0.0274)	-0.0322 (0.0271)	-0.0327 (0.0267)
Construction material	-0.0476*** (0.0179)	-0.0452** (0.0180)	-0.0438** (0.0180)	-0.0477*** (0.0178)
Physical condition	0.2135*** (0.0184)	0.2192*** (0.0184)	0.2179*** (0.0182)	0.2058*** (0.0180)
Quality grade factor	0.3964*** (0.0753)	0.3949*** (0.0762)	0.3902*** (0.0757)	0.3926*** (0.0737)
Age	-0.0013*** (0.0005)	-0.0014*** (0.0005)	-0.0014*** (0.0005)	-0.0013*** (0.0005)
Bedrooms	0.0291* (0.0164)	0.0293* (0.0167)	0.0313* (0.0166)	0.0309* (0.0158)
Total Bathrooms	0.0139 (0.0183)	0.0155 (0.0182)	0.02 (0.0181)	0.0135 (0.0180)
AC	0.1744*** (0.0245)	0.1728*** (0.0246)	0.1715*** (0.0243)	0.1747*** (0.0240)
Fire place	0.1018*** (0.0194)	0.1013*** (0.0196)	0.1032*** (0.0195)	0.1034*** (0.0191)
Basement garage	0.0289 (0.0180)	0.0277 (0.0181)	0.0285 (0.0181)	0.0265 (0.0179)
Lot size	0.0081** (0.0034)	0.008** (0.0034)	0.0081** (0.0034)	0.0082** (0.0033)
Sidewalk	-0.0453 (0.0385)	-0.0444 (0.0389)	-0.0453 (0.0387)	-0.0429 (0.0379)
Fence	0.0882*** (0.0184)	0.0915*** (0.0186)	0.0894*** (0.0183)	0.0852*** (0.0182)
Crime	-0.0009 (0.0006)	-0.0008 (0.0006)	-0.0008 (0.0006)	-0.0010 (0.0006)
School quality	0.0003 (0.0009)	0.0003 (0.0009)	0.0002 (0.0009)	0.0003 (0.0009)
Distance to highway exit	0.0243* (0.0137)	0.0252* (0.0138)	0.023* (0.0134)	0.0212 (0.0132)
Distance to FSU	-0.0163 (0.0117)	-0.0168 (0.0118)	-0.0151 (0.0115)	-0.0133 (0.0114)
Constant	7.6052 (0.1428)	7.4412*** (0.1438)	7.4996*** (0.1408)	7.6969*** (0.1368)
ρ	0.1690***	0.1762***	0.1742***	0.1681***
Log likelihood	-790.7172	-804.1425	-786.4972	-765.7369
AIC	1675.4	1702.3	1667	1625.5
Observations	1,985	1,985	1,985	1,985

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.10. Direct, indirect, and total effects of boil water notices variables

	Direct	Indirect	Total
BWNs_year	-0.0699*** (0.0003)	-0.0134*** (0.0001)	-0.0803*** (0.0003)
Days BWNs_year	-0.0058*** (0.0001)	-0.0012*** (0.0000)	-0.0070*** (0.0001)
Duration BWNs_year	-0.0266*** (0.0001)	-0.0055*** (0.0000)	-0.0321*** (0.0002)
BWN	-0.1803*** (0.0006)	-0.0354*** (0.0002)	-0.2157*** (0.0007)

Simulated standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.11. 2SLS estimates for the spatial quantile models (dependent variable is ln (P))

	2SLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWNs_year	-0.0669*** (0.0104)	-0.3645*** (0.0777)	-0.1867*** (0.0322)	-0.0728*** (0.0252)	-0.0447*** (0.0114)	-0.0292*** (0.0101)	-0.0274*** (0.0094)	-0.0211 (0.0161)	0.0066 (0.0133)	0.0084 (0.0108)
Days BWNs_year	-0.0065*** (0.0016)	-0.0664*** (0.0173)	-0.0271** (0.0121)	-0.0155 (0.0095)	-0.0075 (0.0048)	-0.0064** (0.0033)	-0.0049** (0.0025)	-0.0048 (0.0034)	-0.0015 (0.0033)	0.0009 (0.0030)
Duration BWNs_year	-0.0291*** (0.0037)	-0.1189*** (0.0294)	-0.0598*** (0.0111)	-0.0432*** (0.0106)	-0.0345*** (0.0064)	-0.0316*** (0.0073)	-0.0204** (0.0098)	-0.0163** (0.0078)	-0.0056 (0.0056)	0.00002 (0.0049)
BWN	-0.1853*** (0.0186)	-0.5392*** (0.0653)	-0.2971*** (0.0483)	-0.1750*** (0.0265)	-0.1017*** (0.0209)	-0.0676*** (0.0171)	-0.0509*** (0.0185)	-0.0449** (-0.0449)	-0.0074 (0.0205)	0.0077 (0.0172)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.12. MWTP for a change in water supply reliability from the estimated spatial models

	2SLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWNs_year	11,788	14,823	14,067	6,943	5,356	4,398	4,819			
Days BWNs_year	1,160	2,679	2,093			982	868			
Duration BWNs_year	5,062	4,713	4,416	4,164	4,181	4,749	3,592	3,239		
BWN	35,116	28,690	24,746	18,304	12,875	10,421	9,090	9,129		

Note: The values represent coefficients that are statistically significant at 5%; empty cells are for insignificant coefficient.

Since BWN is a binary variable, its marginal impact is equal to:

Mean P in quantile * (exp(b)-1) * (1/1-rho).

3.10. Appendix A: OLS Models - Dependent Variable is ln (P)

Table 3.1A. OLS Regression Results (block groups spatial and year fixed effects are included)

	(1)	(2)	(3)	(4)
BWNs_year	-0.0671*** (0.0182)			
Days BWNs_year		-0.0064** (0.0031)		
Duration BWNs_year			-0.0312*** (0.0072)	
BWN				-0.1926*** (0.0259)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0142 (0.0301)	-0.0111 (0.0303)	-0.0147 (0.0298)	-0.0168 (0.0294)
Construction material	-0.0565** (0.0220)	-0.0537** (0.0221)	-0.0522** (0.0220)	-0.0577*** (0.0216)
Physical condition	0.2266*** (0.0207)	0.2314*** (0.0206)	0.2293*** (0.0204)	0.2177*** (0.0202)
Quality grade factor	0.5791*** (0.0985)	0.5859*** (0.0991)	0.5839*** (0.0981)	0.5712*** (0.0971)
Age	-0.0021*** (0.0005)	-0.0022*** (0.0005)	-0.0021*** (0.0005)	-0.0019*** (0.0005)
Bedrooms	0.0152 (0.0174)	0.0150 (0.0175)	0.0173 (0.0174)	0.0163 (0.0171)
Total Bathrooms	0.0131 (0.0220)	0.0137 (0.0220)	0.0182 (0.0218)	0.0154 (0.0216)
AC	0.1743*** (0.0279)	0.1736*** (0.0280)	0.1693*** (0.0274)	0.1701*** (0.0272)
Fire place	0.1006*** (0.0224)	0.1015*** (0.0226)	0.1051*** (0.0224)	0.1007*** (0.0221)
Basement garage	0.0380* (0.0206)	0.0393* (0.0208)	0.0392* (0.0207)	0.0353* (0.0205)
Lot size	0.0096* (0.0056)	0.0094* (0.0057)	0.0093 (0.0057)	0.0102* (0.0056)
Sidewalk	-0.0089 (0.0441)	-0.0092 (0.0445)	-0.0146 (0.0438)	-0.0053 (0.0432)
Fence	0.0819*** (0.0211)	0.0848*** (0.0213)	0.0814*** (0.0208)	0.0775*** (0.0207)
Crime	-0.0008 (0.0007)	-0.0005 (0.0007)	-0.0007 (0.0007)	-0.0008 (0.0007)
School quality	0.0008 (0.0011)	0.0009 (0.0011)	0.0007 (0.0011)	0.0009 (0.0011)
Distance to highway exit	-0.0398*** (0.0095)	-0.0380*** (0.0095)	-0.0343*** (0.0094)	-0.0391*** (0.0093)
Distance to FSU	0.0240** (0.0106)	0.0225** (0.0106)	0.0235** (0.0105)	0.0260** (0.0105)
Constant	9.5656*** (0.1753)	9.5042*** (0.1744)	9.5313*** (0.1692)	9.6281*** (0.1688)
Observations	1,985	1,985	1,985	1,985
R-squared	0.7651	0.7621	0.7682	0.7718
Adj R-squared	0.7146	0.7110	0.7184	0.7228

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.2A. OLS Regression Results – Fairmont

	(1)	(2)	(3)	(4)
BWNs_year	-0.0900*** (0.0296)			
Days BWNs_year		-0.0192 (0.0170)		
Duration BWNs_year			-0.0238 (0.0224)	
BWN				-0.1435*** (0.0352)
SQFT	0.0003*** (0.0000)	0.0003*** (0.0000)	0.0003*** (0.0000)	0.0003*** (0.0000)
Story height	0.0287 (0.0360)	0.0329 (0.0369)	0.0341 (0.0369)	0.0305 (0.0358)
Construction material	-0.0082 (0.0234)	-0.0065 (0.0234)	-0.0050 (0.0233)	-0.0047 (0.0231)
Physical condition	0.2069*** (0.0258)	0.2118*** (0.0264)	0.2117*** (0.0263)	0.2040*** (0.0252)
Quality grade factor	0.6758*** (0.1620)	0.6539*** (0.1667)	0.6484*** (0.1669)	0.6697*** (0.1590)
Age	-0.0015** (0.0007)	-0.0017** (0.0007)	-0.0017** (0.0007)	-0.0015** (0.0006)
Bedrooms	0.0071 (0.0213)	0.0059 (0.0216)	0.0060 (0.0214)	0.0084 (0.0209)
Total Bathrooms	0.0131 (0.0344)	0.0162 (0.0344)	0.0166 (0.0342)	0.0119 (0.0339)
AC	0.1803*** (0.0332)	0.1859*** (0.0341)	0.1875*** (0.0342)	0.1840*** (0.0332)
Fire place	0.1273*** (0.0331)	0.1280*** (0.0337)	0.1279*** (0.0336)	0.1265*** (0.0325)
Basement garage	0.0569** (0.0237)	0.0579** (0.0237)	0.0575** (0.0237)	0.0556** (0.0237)
Lot size	0.0295 (0.0355)	0.0274 (0.0370)	0.0289 (0.0368)	0.0363 (0.0342)
Sidewalk	-0.0685* (0.0398)	-0.0682* (0.0406)	-0.0675* (0.0405)	-0.0642 (0.0392)
Fence	0.0790*** (0.0214)	0.0806*** (0.0214)	0.0806*** (0.0214)	0.0796*** (0.0214)
Crime	-0.0003 (0.0010)	-0.0002 (0.0011)	-0.0002 (0.0011)	-0.0003 (0.0010)
School quality	0.0011 (0.0012)	0.0012 (0.0012)	0.0011 (0.0012)	0.0011 (0.0012)
Distance to highway exit	-0.0233 (0.0475)	-0.0268 (0.0481)	-0.0281 (0.0482)	-0.0257 (0.0472)
Distance to FSU	-0.0599*** (0.0222)	-0.0632*** (0.0220)	-0.0626*** (0.0221)	-0.0553** (0.0223)
Constant	9.3364*** (0.2504)	9.3021*** (0.2534)	9.3084*** (0.2537)	9.3706*** (0.2480)
Observations	826	826	826	826
R-squared	0.6783	0.6732	0.6738	0.6827
Adj R-squared	0.6678	0.6626	0.6632	0.6723

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.3A. OLS Regression Results – Other Areas

	(1)	(2)	(3)	(4)
BWNs_year	-0.0712*** (0.0202)			
Days BWNs_year		-0.0062* (0.0031)		
Duration BWNs_year			-0.0290*** (0.0067)	
BWN				-0.2283*** (0.0326)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0779** (0.0394)	-0.0790** (0.0397)	-0.0827** (0.0389)	-0.0799** (0.0387)
Construction material	-0.0763*** (0.0253)	-0.0734*** (0.0255)	-0.0725*** (0.0254)	-0.0807*** (0.0251)
Physical condition	0.2225*** (0.0249)	0.2286*** (0.0247)	0.2268*** (0.0243)	0.2115*** (0.0244)
Quality grade factor	0.3537*** (0.0889)	0.3694*** (0.0891)	0.3650*** (0.0879)	0.3410*** (0.0874)
Age	-0.0019*** (0.0007)	-0.0020*** (0.0007)	-0.0019*** (0.0007)	-0.0018*** (0.0007)
Bedrooms	0.0312 (0.0227)	0.0335 (0.0234)	0.0358 (0.0233)	0.0318 (0.0218)
Total Bathrooms	0.0242 (0.0222)	0.0249 (0.0218)	0.0335 (0.0218)	0.0286 (0.0220)
AC	0.1844*** (0.0343)	0.1801*** (0.0344)	0.1751*** (0.0339)	0.1843*** (0.0333)
Fire place	0.0908*** (0.0284)	0.0903*** (0.0287)	0.0935*** (0.0287)	0.0975*** (0.0279)
Basement garage	0.0240 (0.0278)	0.0220 (0.0282)	0.0255 (0.0283)	0.0242 (0.0276)
Lot size	0.0079** (0.0034)	0.0078** (0.0034)	0.0079** (0.0034)	0.0081** (0.0033)
Sidewalk	0.0041 (0.1143)	0.0006 (0.1143)	0.0017 (0.1143)	0.0067 (0.1137)
Fence	0.0878*** (0.0295)	0.0924*** (0.0296)	0.0900*** (0.0290)	0.0809*** (0.0290)
Crime	-0.0012 (0.0010)	-0.0010 (0.0010)	-0.0011 (0.0010)	-0.0014 (0.0010)
School quality	0.0030 (0.0022)	0.0028 (0.0022)	0.0026 (0.0021)	0.0029 (0.0022)
Distance to highway exit	0.0241 (0.0206)	0.0233 (0.0208)	0.0212 (0.0200)	0.0222 (0.0196)
Distance to FSU	-0.0193 (0.0200)	-0.0175 (0.0201)	-0.0159 (0.0194)	-0.0185 (0.0191)
Constant	9.5474*** (0.2062)	9.4527*** (0.2053)	9.4985*** (0.1964)	9.6653*** (0.1907)
Observations	1,159	1,159	1,159	1,159
R-squared	0.7228	0.7183	0.7254	0.7322
Adj R-squared	0.7129	0.7083	0.7156	0.7226

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.11. Appendix B: Spatial Lag Models (SLM) - Dependent Variable is ln (P)

Table 3.1B. Direct, Indirect, Total Effects for Model (1) – BWNs_year

	Direct		Indirect		Total	
	Estimate	SE	Estimate	SE	Estimate	SE
BWNs_year	-0.0669***	0.0003	-0.0134***	0.0001	-0.0803***	0.0003
SQFT	0.0002***	0.0000	0.00005***	0.0000	0.0003***	0.0000
Story height	-0.0314	0.0007	-0.0063	0.0002	-0.0377	0.0009
Construction material	-0.047**	0.0006	-0.0094**	0.0001	-0.0564**	0.0007
Physical condition	0.2153***	0.0004	0.0431***	0.0002	0.2584***	0.0005
Quality grade factor	0.3973***	0.0020	0.0793***	0.0005	0.4766***	0.0024
Age	-0.0013***	0.0000	-0.0003***	0.0000	-0.0016***	0.0000
Bedrooms	0.0294*	0.0005	0.0059*	0.0001	0.0353*	0.0006
Total Bathrooms	0.0139	0.0005	0.0028	0.0001	0.0167	0.0006
AC	0.1762***	0.0007	0.0353***	0.0003	0.2115***	0.0009
Fire place	0.1033***	0.0006	0.0206***	0.0002	0.1239***	0.0007
Basement garage	0.0284	0.0005	0.0057	0.0001	0.0341	0.0007
Lot size	0.0081***	0.0001	0.0016***	0.0000	0.0097***	0.0001
Sidewalk	-0.0447	0.0012	-0.0089	0.0002	-0.0536	0.0014
Fence	0.09***	0.0006	0.018***	0.0001	0.1081***	0.0007
Crime	-0.0009	0.0000	-0.0002	0.0000	-0.0011	0.0000
School quality	0.0003	0.0000	0.0001	0.0000	0.0004	0.0000
Distance to highway exit	0.0248*	0.0004	0.005*	0.0001	0.0298*	0.0005
Distance to FSU	-0.0165	0.0004	-0.0033	0.0001	-0.0199	0.0005

Table 3.2B. Direct, Indirect, Total Effects for Model (2) – Days BWNs_year

	Direct		Indirect		Total	
	Estimate	SE	Estimate	SE	Estimate	SE
Days BWNs_year	-0.0058***	0.0001	-0.0012***	0.0000	-0.0070***	0.0001
SQFT	0.0002***	0.0000	0.00005***	0.0000	0.0003***	0.0000
Story height	-0.0310	0.0008	-0.0064	0.0002	-0.0374	0.0009
Construction material	-0.0454**	0.0006	-0.0094**	0.0001	-0.0548**	0.0007
Physical condition	0.2203***	0.0004	0.0457***	0.0002	0.266***	0.0006
Quality grade factor	0.3959***	0.0021	0.0818***	0.0006	0.4777***	0.0026
Age	-0.0015***	0.0000	-0.0003***	0.0000	-0.0018***	0.0000
Bedrooms	0.0294**	0.0004	0.0061**	0.0001	0.0355**	0.0005
Total Bathrooms	0.0156	0.0004	0.0032	0.0001	0.0188	0.0005
AC	0.1736***	0.0007	0.0361***	0.0002	0.2097***	0.0008
Fire place	0.1013***	0.0006	0.021***	0.0002	0.1222***	0.0007
Basement garage	0.0293	0.0007	0.0061	0.0001	0.0354	0.0008
Lot size	0.0082***	0.0001	0.0017***	0.0000	0.0099***	0.0001
Sidewalk	-0.0445	0.0011	-0.0092	0.0002	-0.0537	0.0014
Fence	0.0928***	0.0006	0.0193***	0.0002	0.1121***	0.0007
Crime	-0.0008	0.0000	-0.0002	0.0000	-0.0009	0.0000
School quality	0.0002	0.0000	0.00005	0.0000	0.0003	0.0000
Distance to highway exit	0.0250*	0.0004	0.0052*	0.0001	0.0302*	0.0005
Distance to FSU	-0.0164	0.0004	-0.0034	0.0001	-0.0199	0.0005

Table 3.3B. Direct, Indirect, Total Effects for Model (3) – Duration BWNs_year

	Direct		Indirect		Total	
	Estimate	SE	Estimate	SE	Estimate	SE
Duration BWNs_year	-0.0266***	0.0001	-0.0055***	0.0000	-0.0321***	0.0002
SQFT	0.0002***	0.0000	0.00005***	0.0000	0.0003***	0.0000
Story height	-0.0328	0.0008	-0.0068	0.0002	-0.0396	0.0009
Construction material	-0.0439**	0.0006	-0.0091**	0.0001	-0.0529**	0.0007
Physical condition	0.2186***	0.0004	0.0452***	0.0002	0.2638***	0.0005
Quality grade factor	0.393***	0.0021	0.0809***	0.0005	0.474***	0.0023
Age	-0.0014***	0.0000	-0.0003***	0.0000	-0.0017***	0.0000
Bedrooms	0.0313**	0.0005	0.0065**	0.0001	0.0378**	0.0006
Total Bathrooms	0.0204	0.0005	0.0042	0.0001	0.0246	0.0007
AC	0.1718***	0.0007	0.0355***	0.0002	0.2073***	0.0009
Fire place	0.1034***	0.0006	0.0213***	0.0002	0.1248***	0.0007
Basement garage	0.0291	0.0006	0.0060	0.0001	0.0351	0.0007
Lot size	0.0081***	0.0001	0.0017***	0.0000	0.0097***	0.0001
Sidewalk	-0.0458	0.0011	-0.0094	0.0002	-0.0553	0.0013
Fence	0.0898***	0.0006	0.0186***	0.0002	0.1085***	0.0007
Crime	-0.0008	0.0000	-0.0002	0.0000	-0.001	0.0000
School quality	0.0002	0.0000	0.00004	0.0000	0.0002	0.0000
Distance to highway exit	0.0229*	0.0004	0.0048*	0.0001	0.0277*	0.0005
Distance to FSU	-0.0150	0.0004	-0.0031	0.0001	-0.0181	0.0005

Table 3.4B. Direct, Indirect, Total Effects for Model (4) – BWN

	Direct		Indirect		Total	
	Estimate	SE	Estimate	SE	Estimate	SE
BWN	-0.1803***	0.0006	-0.0354***	0.0002	-0.2157***	0.0007
SQFT	0.0002***	0.0000	0.00005***	0.0000	0.0003***	0.0000
Story height	-0.0338	0.0008	-0.0067	0.0002	-0.0405	0.0009
Construction material	-0.0481***	0.0006	-0.0095**	0.0001	-0.0576***	0.0008
Physical condition	0.2063***	0.0004	0.0406***	0.0002	0.2468***	0.0005
Quality grade factor	0.3948***	0.0020	0.0773***	0.0005	0.4721***	0.0024
Age	-0.0013***	0.0000	-0.0003***	0.0000	-0.0015***	0.0000
Bedrooms	0.0307**	0.0004	0.0061**	0.0001	0.0368**	0.0005
Total Bathrooms	0.0147	0.0005	0.0029	0.0001	0.0176	0.0006
AC	0.175***	0.0007	0.0344***	0.0002	0.2093***	0.0009
Fire place	0.1043***	0.0006	0.0205***	0.0002	0.1247***	0.0007
Basement garage	0.0267	0.0006	0.0052	0.0001	0.0319	0.0008
Lot size	0.0083***	0.0001	0.0016***	0.0000	0.0099***	0.0001
Sidewalk	-0.0423	0.0011	-0.0083	0.0002	-0.0507	0.0013
Fence	0.0861***	0.0005	0.0169***	0.0001	0.103***	0.0006
Crime	-0.0009	0.0000	-0.0002	0.0000	-0.0011	0.0000
School quality	0.0004	0.0000	0.0001	0.0000	0.0005	0.0000
Distance to highway exit	0.0219*	0.0004	0.0043	0.0001	0.0262*	0.0005
Distance to FSU	-0.014	0.0004	-0.0028	0.0001	-0.0168	0.0005

3.12. Appendix C: Quantile Regression Models - Dependent Variable is ln (P)

Table 3.1C. Non-Spatial Quantile Regression Results for Model (1) – BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWNs_year	-0.3150*** (0.0244)	-0.1889*** (0.0167)	-0.0668*** (0.0128)	-0.0480*** (0.0096)	-0.0440*** (0.0099)	-0.0277*** (0.0100)	-0.0150 (0.0101)	-0.0004 (0.0104)	0.0043 (0.0107)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0711 (0.0551)	-0.0379 (0.0377)	-0.0431 (0.0289)	-0.0419* (0.0217)	-0.0308 (0.0223)	-0.0268 (0.0226)	-0.0189 (0.0229)	0.0214 (0.0236)	0.0318 (0.0243)
Construction material	-0.1032** (0.0413)	-0.0537* (0.0283)	-0.0564*** (0.0217)	-0.0519*** (0.0163)	-0.0462*** (0.0167)	-0.0439*** (0.0170)	-0.0434** (0.0172)	-0.0279 (0.0177)	-0.0533*** (0.0182)
Physical condition	0.2518*** (0.0306)	0.2340*** (0.0210)	0.2282*** (0.0160)	0.2151*** (0.0121)	0.1934*** (0.0124)	0.1738*** (0.0126)	0.1530*** (0.0127)	0.1345*** (0.0131)	0.1258*** (0.0135)
Quality grade factor	0.5825*** (0.1443)	0.5209*** (0.0988)	0.5298*** (0.0756)	0.5217*** (0.0568)	0.4789*** (0.0585)	0.4561*** (0.0593)	0.5000*** (0.0599)	0.5115*** (0.0618)	0.5354*** (0.0635)
Age	-0.0023*** (0.0008)	-0.0025*** (0.0006)	-0.0023*** (0.0004)	-0.0023*** (0.0003)	-0.0023*** (0.0003)	-0.0021*** (0.0003)	-0.0018*** (0.0003)	-0.0018*** (0.0004)	-0.0017*** (0.0004)
Bedrooms	0.0375 (0.0330)	0.0161 (0.0226)	0.0352** (0.0173)	0.0454*** (0.0130)	0.0442*** (0.0134)	0.0403*** (0.0135)	0.0437*** (0.0137)	0.0370*** (0.0141)	0.0280* (0.0145)
Total Bathrooms	-0.0291 (0.0378)	0.0170 (0.0259)	0.0313 (0.0198)	0.0393*** (0.0149)	0.0418*** (0.0153)	0.0329** (0.0155)	0.0322** (0.0157)	0.0134 (0.0162)	0.0098 (0.0166)
AC	0.2109*** (0.0520)	0.2562*** (0.0356)	0.2443*** (0.0273)	0.2056*** (0.0205)	0.2045*** (0.0211)	0.1964*** (0.0214)	0.1844*** (0.0216)	0.1459*** (0.0223)	0.0876*** (0.0229)
Fire place	0.1460*** (0.0431)	0.1305*** (0.0295)	0.1275*** (0.0226)	0.1250*** (0.0170)	0.1144*** (0.0175)	0.0979*** (0.0177)	0.0777*** (0.0179)	0.0762*** (0.0184)	0.0765*** (0.0190)
Basement garage	0.0580 (0.0444)	0.0404 (0.0304)	0.0408* (0.0233)	0.0328* (0.0175)	0.0272 (0.0180)	0.0111 (0.0183)	0.0039 (0.0184)	0.0074 (0.0190)	-0.0045 (0.0196)
Lot size	0.0006 (0.0040)	0.0079*** (0.0027)	0.0096*** (0.0021)	0.0093*** (0.0016)	0.0084*** (0.0016)	0.0099*** (0.0016)	0.0164*** (0.0016)	0.0187*** (0.0017)	0.0220*** (0.0017)
Sidewalk	-0.0508 (0.0828)	-0.0860 (0.0567)	-0.0363 (0.0434)	-0.0104 (0.0326)	-0.0414 (0.0335)	-0.0517 (0.0340)	-0.0445 (0.0344)	-0.0620* (0.0354)	-0.0359 (0.0364)
Fence	0.1110*** (0.0400)	0.1076*** (0.0274)	0.1131*** (0.0210)	0.0936*** (0.0157)	0.0899*** (0.0162)	0.0865*** (0.0164)	0.0764*** (0.0166)	0.0722*** (0.0171)	0.0649*** (0.0176)
Crime	-0.0019 (0.0016)	-0.0017 (0.0011)	-0.0014* (0.0008)	-0.0013** (0.0006)	-0.0008 (0.0006)	-0.0007 (0.0006)	-0.0014** (0.0007)	-0.0018*** (0.0007)	-0.0016** (0.0007)
School quality	0.0008 (0.0022)	0.0007 (0.0015)	0.0003 (0.0012)	-0.0001 (0.0009)	0.0001 (0.0009)	0.0005 (0.0009)	-0.0003 (0.0009)	-0.0003 (0.0010)	-0.0002 (0.0010)
Distance to highway exit	0.0157 (0.0289)	0.0042 (0.0198)	0.0037 (0.0152)	-0.0007 (0.0114)	-0.0001 (0.0117)	0.0017 (0.0119)	0.0043 (0.0120)	-0.0011 (0.0124)	-0.0030 (0.0127)
Distance to FSU	-0.0220 (0.0295)	-0.0110 (0.0202)	-0.0131 (0.0154)	-0.0044 (0.0116)	-0.0002 (0.0119)	-0.0010 (0.0121)	-0.0009 (0.0122)	0.0000 (0.0126)	-0.0030 (0.0130)
Constant	9.0437*** (0.2636)	9.3823*** (0.1805)	9.4288*** (0.1381)	9.5746*** (0.1038)	9.7164*** (0.1068)	9.8205*** (0.1083)	9.9792*** (0.1094)	10.1811*** (0.1128)	10.3263*** (0.1160)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.2C. Non-Spatial Quantile Regression Results for Model (2) – Days BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Days BWNs_year	-0.0510*** (0.0034)	-0.0281*** (0.0023)	-0.0133*** (0.0020)	-0.0051*** (0.0014)	-0.0068*** (0.0015)	-0.0059*** (0.0015)	-0.0032** (0.0016)	-0.0026 (0.0016)	0.0004 (0.0017)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0843* (0.0495)	-0.0512 (0.0337)	-0.0499* (0.0288)	-0.0345 (0.0210)	-0.0261 (0.0215)	-0.0295 (0.0225)	-0.0181 (0.0232)	0.0220 (0.0240)	0.0308 (0.0251)
Construction material	-0.0711* (0.0371)	-0.0612** (0.0253)	-0.0623*** (0.0216)	-0.0530*** (0.0158)	-0.0433*** (0.0161)	-0.0437*** (0.0169)	-0.0380** (0.0174)	-0.0270 (0.0180)	-0.0494*** (0.0188)
Physical condition	0.2767*** (0.0274)	0.2507*** (0.0187)	0.2254*** (0.0160)	0.2193*** (0.0117)	0.1928*** (0.0119)	0.1750*** (0.0125)	0.1533*** (0.0128)	0.1324*** (0.0133)	0.1234*** (0.0139)
Quality grade factor	0.5237*** (0.1295)	0.4809*** (0.0883)	0.5152*** (0.0754)	0.4951*** (0.0551)	0.4908*** (0.0562)	0.4689*** (0.0589)	0.5132*** (0.0607)	0.5128*** (0.0627)	0.5449*** (0.0657)
Age	-0.0021*** (0.0007)	-0.0028*** (0.0005)	-0.0023*** (0.0004)	-0.0024*** (0.0003)	-0.0024*** (0.0003)	-0.0021*** (0.0003)	-0.0018*** (0.0003)	-0.0018*** (0.0004)	-0.0017*** (0.0004)
Bedrooms	0.0299 (0.0296)	0.0338* (0.0202)	0.0379** (0.0172)	0.0465*** (0.0126)	0.0475*** (0.0128)	0.0407*** (0.0134)	0.0430*** (0.0139)	0.0379*** (0.0143)	0.0284* (0.0150)
Total Bathrooms	0.0049 (0.0339)	0.0204 (0.0232)	0.0420** (0.0198)	0.0399*** (0.0144)	0.0383*** (0.0147)	0.0337** (0.0154)	0.0318** (0.0159)	0.0113 (0.0164)	0.0090 (0.0172)
AC	0.2587*** (0.0467)	0.2372*** (0.0318)	0.2388*** (0.0272)	0.2061*** (0.0199)	0.1970*** (0.0203)	0.1986*** (0.0212)	0.1827*** (0.0219)	0.1483*** (0.0226)	0.0908*** (0.0237)
Fire place	0.1328*** (0.0386)	0.1100*** (0.0264)	0.1282*** (0.0225)	0.1251*** (0.0164)	0.1140*** (0.0168)	0.0961*** (0.0176)	0.0766*** (0.0181)	0.0786*** (0.0187)	0.0784*** (0.0196)
Basement garage	0.0669* (0.0399)	0.0338 (0.0272)	0.0381 (0.0232)	0.0339** (0.0170)	0.0235 (0.0173)	0.0135 (0.0181)	0.0056 (0.0187)	0.0081 (0.0193)	-0.0066 (0.0202)
Lot size	-0.0005 (0.0036)	0.0087*** (0.0024)	0.0101*** (0.0021)	0.0092*** (0.0015)	0.0083*** (0.0015)	0.0085*** (0.0016)	0.0166*** (0.0017)	0.0192*** (0.0017)	0.0213*** (0.0018)
Sidewalk	-0.1414* (0.0742)	-0.0411 (0.0506)	-0.0548 (0.0432)	-0.0121 (0.0316)	-0.0403 (0.0322)	-0.0609* (0.0338)	-0.0377 (0.0348)	-0.0582 (0.0360)	-0.0305 (0.0377)
Fence	0.1498*** (0.0359)	0.1211*** (0.0245)	0.1032*** (0.0209)	0.0910*** (0.0153)	0.0921*** (0.0156)	0.0839*** (0.0163)	0.0778*** (0.0168)	0.0725*** (0.0174)	0.0656*** (0.0182)
Crime	-0.0011 (0.0014)	-0.0016 (0.0010)	-0.0014* (0.0008)	-0.0012* (0.0006)	-0.0006 (0.0006)	-0.0008 (0.0006)	-0.0011 (0.0007)	-0.0017** (0.0007)	-0.0015** (0.0007)
School quality	0.0018 (0.0020)	0.0010 (0.0014)	0.0002 (0.0012)	-0.0001 (0.0009)	0.0001 (0.0009)	0.0002 (0.0009)	0.0000 (0.0009)	-0.0002 (0.0010)	-0.0001 (0.0010)
Distance to highway exit	0.0253 (0.0259)	0.0066 (0.0177)	-0.0024 (0.0151)	-0.0053 (0.0110)	-0.0014 (0.0113)	0.0036 (0.0118)	0.0063 (0.0122)	-0.0008 (0.0126)	-0.0041 (0.0132)
Distance to FSU	-0.0241 (0.0264)	-0.0218 (0.0180)	-0.0070 (0.0154)	0.0017 (0.0112)	-0.0001 (0.0115)	-0.0020 (0.0120)	-0.0016 (0.0124)	0.0004 (0.0128)	-0.0024 (0.0134)
Constant	8.3390*** (0.2343)	9.3118*** (0.1598)	9.4426*** (0.1364)	9.5229*** (0.0997)	9.7028*** (0.1017)	9.8193*** (0.1065)	9.9302*** (0.1098)	10.1831*** (0.1135)	10.3312*** (0.1188)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.3C. Non-Spatial Quantile Regression Results for Model (3) – Duration BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Duration BWNs_year	-0.0918*** (0.0073)	-0.0599*** (0.0052)	-0.0469*** (0.0042)	-0.0364*** (0.0037)	-0.0273*** (0.0037)	-0.0135*** (0.0037)	-0.0076** (0.0038)	-0.0041 (0.0038)	0.0002 (0.0041)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0773* (0.0458)	-0.0390 (0.0325)	-0.0519** (0.0262)	-0.0413* (0.0233)	-0.0260 (0.0232)	-0.0254 (0.0234)	-0.0144 (0.0236)	0.0253 (0.0236)	0.0311 (0.0256)
Construction material	-0.0778** (0.0343)	-0.0598** (0.0244)	-0.0610*** (0.0197)	-0.0427** (0.0175)	-0.0420** (0.0174)	-0.0418** (0.0176)	-0.0378** (0.0177)	-0.0263 (0.0177)	-0.0468** (0.0192)
Physical condition	0.2603*** (0.0254)	0.2432*** (0.0180)	0.2217*** (0.0145)	0.2047*** (0.0129)	0.1922*** (0.0129)	0.1738*** (0.0130)	0.1521*** (0.0131)	0.1334*** (0.0131)	0.1236*** (0.0142)
Quality grade factor	0.5381*** (0.1198)	0.5147*** (0.0850)	0.5284*** (0.0687)	0.5345*** (0.0610)	0.4648*** (0.0608)	0.4652*** (0.0614)	0.5132*** (0.0618)	0.5144*** (0.0617)	0.5415*** (0.0671)
Age	-0.0021*** (0.0007)	-0.0027*** (0.0005)	-0.0023*** (0.0004)	-0.0024*** (0.0004)	-0.0024*** (0.0003)	-0.0022*** (0.0004)	-0.0018*** (0.0004)	-0.0018*** (0.0004)	-0.0017*** (0.0004)
Bedrooms	0.0298 (0.0274)	0.0261 (0.0194)	0.0376** (0.0157)	0.0533*** (0.0139)	0.0480*** (0.0139)	0.0392*** (0.0140)	0.0428*** (0.0141)	0.0383*** (0.0141)	0.0274* (0.0153)
Total Bathrooms	-0.0066 (0.0314)	0.0202 (0.0223)	0.0392** (0.0180)	0.0346** (0.0160)	0.0429*** (0.0160)	0.0377** (0.0161)	0.0311* (0.0162)	0.0109 (0.0162)	0.0082 (0.0176)
AC	0.2581*** (0.0432)	0.2494*** (0.0306)	0.2360*** (0.0248)	0.2235*** (0.0220)	0.2007*** (0.0219)	0.1917*** (0.0221)	0.1795*** (0.0223)	0.1505*** (0.0222)	0.0929*** (0.0242)
Fire place	0.1362*** (0.0358)	0.1058*** (0.0254)	0.1342*** (0.0205)	0.1195*** (0.0182)	0.1094*** (0.0182)	0.0978*** (0.0183)	0.0779*** (0.0184)	0.0801*** (0.0184)	0.0791*** (0.0200)
Basement garage	0.0578 (0.0369)	0.0291 (0.0262)	0.0359* (0.0211)	0.0351* (0.0188)	0.0304 (0.0187)	0.0148 (0.0189)	0.0049 (0.0190)	0.0083 (0.0190)	-0.0104 (0.0206)
Lot size	0.0002 (0.0033)	0.0083*** (0.0023)	0.0096*** (0.0019)	0.0098*** (0.0017)	0.0086*** (0.0017)	0.0075*** (0.0017)	0.0163*** (0.0017)	0.0192*** (0.0017)	0.0214*** (0.0018)
Sidewalk	-0.1393** (0.0687)	-0.0350 (0.0487)	-0.0461 (0.0394)	-0.0271 (0.0350)	-0.0399 (0.0349)	-0.0608* (0.0352)	-0.0420 (0.0354)	-0.0553 (0.0354)	-0.0323 (0.0385)
Fence	0.1348*** (0.0332)	0.1279*** (0.0235)	0.1020*** (0.0190)	0.0943*** (0.0169)	0.0907*** (0.0168)	0.0828*** (0.0170)	0.0764*** (0.0171)	0.0712*** (0.0171)	0.0663*** (0.0186)
Crime	-0.0015 (0.0013)	-0.0017* (0.0009)	-0.0015** (0.0008)	-0.0013* (0.0007)	-0.0006 (0.0007)	-0.0008 (0.0007)	-0.0010 (0.0007)	-0.0017** (0.0007)	-0.0013* (0.0007)
School quality	0.0018 (0.0018)	0.0009 (0.0013)	0.0000 (0.0011)	-0.0002 (0.0009)	0.0001 (0.0009)	0.0003 (0.0009)	0.0002 (0.0010)	-0.0003 (0.0010)	-0.0000 (0.0010)
Distance to highway exit	0.0239 (0.0240)	0.0053 (0.0170)	0.0001 (0.0138)	-0.0017 (0.0122)	0.0014 (0.0122)	0.0061 (0.0123)	0.0076 (0.0124)	0.0006 (0.0124)	-0.0025 (0.0134)
Distance to FSU	-0.0286 (0.0245)	-0.0210 (0.0174)	-0.0123 (0.0140)	-0.0021 (0.0124)	0.0027 (0.0124)	-0.0015 (0.0125)	-0.0022 (0.0126)	0.0002 (0.0126)	-0.0022 (0.0137)
Constant	8.5422*** (0.2170)	9.3099*** (0.1540)	9.5060*** (0.1244)	9.5415*** (0.1105)	9.7095*** (0.1102)	9.8365*** (0.1112)	9.9259*** (0.1120)	10.1653*** (0.1117)	10.3211*** (0.1215)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.4C. Non-Spatial Quantile Regression Results for Model (4) – BWN

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWN	-0.4666*** (0.0339)	-0.2672*** (0.0264)	-0.1697*** (0.0217)	-0.1236*** (0.0191)	-0.0992*** (0.0188)	-0.0752*** (0.0177)	-0.0529*** (0.0165)	-0.0286 (0.0184)	-0.0065 (0.0210)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0970** (0.0436)	-0.0326 (0.0339)	-0.0376 (0.0280)	-0.0445* (0.0246)	-0.0297 (0.0242)	-0.0284 (0.0227)	-0.0111 (0.0212)	0.0100 (0.0236)	0.0250 (0.0270)
Construction material	-0.0789** (0.0326)	-0.0622** (0.0254)	-0.0530** (0.0209)	-0.0565*** (0.0184)	-0.0526*** (0.0181)	-0.0537*** (0.0170)	-0.0356** (0.0158)	-0.0312* (0.0177)	-0.0434** (0.0202)
Physical condition	0.2251*** (0.0243)	0.2315*** (0.0189)	0.2209*** (0.0156)	0.2159*** (0.0137)	0.2007*** (0.0135)	0.1811*** (0.0127)	0.1642*** (0.0118)	0.1412*** (0.0132)	0.1188*** (0.0150)
Quality grade factor	0.5538*** (0.1141)	0.5454*** (0.0888)	0.5177*** (0.0732)	0.5163*** (0.0643)	0.5029*** (0.0633)	0.4932*** (0.0596)	0.5089*** (0.0554)	0.5261*** (0.0618)	0.5866*** (0.0707)
Age	-0.0021*** (0.0007)	-0.0024*** (0.0005)	-0.0026*** (0.0004)	-0.0021*** (0.0004)	-0.0021*** (0.0004)	-0.0018*** (0.0003)	-0.0019*** (0.0003)	-0.0017*** (0.0004)	-0.0018*** (0.0004)
Bedrooms	0.0349 (0.0261)	0.0217 (0.0203)	0.0271 (0.0167)	0.0323** (0.0147)	0.0412*** (0.0145)	0.0442*** (0.0136)	0.0465*** (0.0127)	0.0380*** (0.0141)	0.0140 (0.0161)
Total Bathrooms	0.0015 (0.0298)	0.0154 (0.0232)	0.0231 (0.0191)	0.0359** (0.0168)	0.0413** (0.0165)	0.0369** (0.0155)	0.0215 (0.0145)	0.0213 (0.0161)	0.0104 (0.0184)
AC	0.2263*** (0.0411)	0.2452*** (0.0320)	0.2513*** (0.0264)	0.2171*** (0.0232)	0.2089*** (0.0228)	0.1881*** (0.0214)	0.1687*** (0.0200)	0.1438*** (0.0223)	0.0956*** (0.0254)
Fire place	0.1465*** (0.0340)	0.1227*** (0.0265)	0.1196*** (0.0218)	0.1186*** (0.0192)	0.0994*** (0.0189)	0.0948*** (0.0178)	0.0898*** (0.0165)	0.0657*** (0.0184)	0.0795*** (0.0211)
Basement garage	0.0270 (0.0351)	0.0402 (0.0273)	0.0386* (0.0225)	0.0196 (0.0198)	0.0136 (0.0195)	0.0094 (0.0183)	0.0058 (0.0171)	0.0016 (0.0190)	0.0016 (0.0217)
Lot size	0.0000 (0.0031)	0.0071*** (0.0024)	0.0085*** (0.0020)	0.0098*** (0.0018)	0.0089*** (0.0017)	0.0092*** (0.0016)	0.0138*** (0.0015)	0.0207*** (0.0017)	0.0203*** (0.0019)
Sidewalk	-0.0135 (0.0653)	-0.0748 (0.0508)	-0.0353 (0.0419)	-0.0232 (0.0368)	-0.0283 (0.0362)	-0.0257 (0.0341)	-0.0338 (0.0317)	-0.0529 (0.0354)	-0.0448 (0.0404)
Fence	0.0805** (0.0316)	0.0981*** (0.0246)	0.1180*** (0.0203)	0.0849*** (0.0178)	0.0857*** (0.0175)	0.0891*** (0.0165)	0.0807*** (0.0154)	0.0764*** (0.0171)	0.0661*** (0.0196)
Total Crime Index	-0.0018 (0.0012)	-0.0018* (0.0010)	-0.0015* (0.0008)	-0.0012* (0.0007)	-0.0012* (0.0007)	-0.0014** (0.0007)	-0.0014** (0.0006)	-0.0014** (0.0007)	-0.0021*** (0.0008)
School quality	0.0002 (0.0018)	-0.0000 (0.0014)	0.0002 (0.0011)	0.0002 (0.0010)	0.0001 (0.0010)	0.0003 (0.0009)	-0.0004 (0.0009)	-0.0007 (0.0010)	-0.0020* (0.0011)
Distance to highway exit	0.0110 (0.0229)	-0.0008 (0.0178)	0.0006 (0.0147)	0.0082 (0.0129)	0.0052 (0.0127)	0.0044 (0.0119)	0.0092 (0.0111)	-0.0040 (0.0124)	0.0027 (0.0142)
Distance to FSU	-0.0116 (0.0233)	-0.0095 (0.0181)	-0.0129 (0.0149)	-0.0093 (0.0131)	-0.0023 (0.0129)	-0.0026 (0.0121)	-0.0050 (0.0113)	0.0001 (0.0126)	-0.0082 (0.0144)
Constant	9.0361*** (0.2061)	9.4443*** (0.1603)	9.5479*** (0.1323)	9.6324*** (0.1162)	9.7146*** (0.1144)	9.8799*** (0.1076)	10.0364*** (0.1002)	10.2573*** (0.1117)	10.5828*** (0.1276)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.13. Appendix D: Spatial Quantile Regression Models - Dependent Variable is ln (P)

Table 3.1D. Spatial Quantile Regression Results for Model (1) – BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWNs_year	-0.3645*** (0.0777)	-0.1867*** (0.0322)	-0.0728*** (0.0252)	-0.0447*** (0.0114)	-0.0292*** (0.0101)	-0.0274*** (0.0094)	-0.0211 (0.0161)	0.0066 (0.0133)	0.0084 (0.0108)
SQFT	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0263 (0.0360)	-0.0408 (0.0258)	-0.0438* (0.0264)	-0.0414** (0.0185)	-0.0339* (0.0177)	-0.031 (0.0209)	-0.0116 (0.0231)	0.0135 (0.0212)	-0.0062 (0.0204)
Construction material	-0.0917*** (0.0267)	-0.0654*** (0.0187)	-0.0638*** (0.0229)	-0.0578*** (0.0145)	-0.0393*** (0.0133)	-0.026* (0.0137)	-0.0335** (0.0168)	-0.0229 (0.0177)	-0.0269* (0.0143)
Physical condition	0.234*** (0.0270)	0.2375*** (0.0228)	0.2201*** (0.0188)	0.2005*** (0.0141)	0.1804*** (0.0165)	0.1597*** (0.0137)	0.1473*** (0.0148)	0.1364*** (0.0166)	0.1444*** (0.0185)
Quality grade factor	0.4941*** (0.0995)	0.3962*** (0.0643)	0.4356*** (0.0599)	0.41*** (0.0488)	0.3803*** (0.0585)	0.362*** (0.0474)	0.3536*** (0.0613)	0.4262*** (0.0538)	0.4462*** (0.0685)
Age	-0.0025*** (0.0008)	-0.0026*** (0.0004)	-0.0025*** (0.0004)	-0.0026*** (0.0004)	-0.0026*** (0.0003)	-0.0025*** (0.0004)	-0.0023*** (0.0004)	-0.0024*** (0.0004)	- (0.0003)
Bedrooms	0.0104 (0.0199)	0.0226 (0.0198)	0.0341* (0.0178)	0.0517*** (0.0166)	0.0466*** (0.0119)	0.0496*** (0.0145)	0.0342** (0.0134)	0.0384*** (0.0116)	0.0476*** (0.0140)
Total Bathrooms	-0.0165 (0.0276)	0.0201 (0.0175)	0.0402*** (0.0151)	0.0509*** (0.0141)	0.037*** (0.0135)	0.0258** (0.0127)	0.0367** (0.0145)	0.019 (0.0147)	0.0123 (0.0160)
AC	0.15*** (0.0469)	0.2181*** (0.0370)	0.2344*** (0.0315)	0.2277*** (0.0245)	0.2271*** (0.0241)	0.2084*** (0.0305)	0.1701*** (0.0249)	0.1485*** (0.0250)	0.0863*** (0.0317)
Fire place	0.1453*** (0.0330)	0.1276*** (0.0255)	0.1127*** (0.0193)	0.1081*** (0.0172)	0.0935*** (0.0116)	0.0838*** (0.0142)	0.08*** (0.0152)	0.0756*** (0.0146)	0.0588*** (0.0170)
Basement garage	0.0202 (0.0292)	0.0228 (0.0227)	0.0295 (0.0188)	0.0182 (0.0160)	0.0068 (0.0137)	0.0089 (0.0168)	0.0023 (0.0160)	0.0046 (0.0184)	-0.0081 (0.0188)
Lot size	0.0006 (0.0058)	0.0087 (0.0062)	0.0116*** (0.0042)	0.0106*** (0.0037)	0.0107* (0.0056)	0.0115 (0.0074)	0.0241*** (0.0077)	0.0215** (0.0100)	0.0373*** (0.0078)
Sidewalk	-0.0161 (0.0559)	-0.062 (0.0477)	-0.0434 (0.0399)	-0.0366 (0.0280)	-0.0572* (0.0343)	-0.0341 (0.0368)	-0.0568* (0.0308)	-0.0809** (0.0320)	-0.098** (0.0423)
Fence	0.1107*** (0.0289)	0.0925*** (0.0223)	0.1022*** (0.0186)	0.0974*** (0.0145)	0.0956*** (0.0140)	0.0954*** (0.0148)	0.0709*** (0.0170)	0.0671*** (0.0169)	0.0509*** (0.0142)
Crime	0.0001 (0.0009)	-0.0007 (0.0006)	-0.0009 (0.0006)	-0.0005 (0.0005)	-0.0002 (0.0004)	-0.0004 (0.0005)	-0.0006 (0.0005)	-0.0005 (0.0005)	-0.0005 (0.0005)
School quality	0.0016 (0.0013)	0.0001 (0.0011)	-0.0008 (0.0008)	-0.0014* (0.0008)	-0.0007 (0.0006)	-0.0006 (0.0008)	-0.0007 (0.0008)	-0.0003 (0.0007)	-0.0005 (0.0007)
Distance to highway exit	-0.017 (0.0118)	-0.0107 (0.0078)	-0.0208** (0.0086)	-0.0213*** (0.0055)	-0.0138** (0.0061)	-0.0105* (0.0062)	-0.0156** (0.0063)	-0.0149** (0.0062)	-0.0123** (0.0062)
Distance to FSU	-0.0019 (0.0110)	-0.0088 (0.0080)	-0.0045 (0.0068)	0.0007 (0.0056)	-0.0044 (0.0054)	-0.0046 (0.0052)	-0.0018 (0.0057)	0.0009 (0.0063)	0.0031 (0.0062)
ρ	0.2149*** (0.0445)	0.2055*** (0.0341)	0.1477*** (0.0272)	0.1465*** (0.0237)	0.1709*** (0.0280)	0.1777*** (0.0259)	0.1583*** (0.0252)	0.1556*** (0.0261)	0.168*** (0.0252)
Constant	6.8245*** (0.5332)	7.0918*** (0.3944)	7.8607*** (0.3409)	8.0012*** (0.2709)	7.8362*** (0.3149)	7.9136*** (0.3000)	8.3481*** (0.3047)	8.3872*** (0.3113)	8.2968*** (0.3034)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.2D. Spatial Quantile Regression Results for Model (2) – Days BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Days BWNs_year	-0.0664*** (0.0173)	-0.0271** (0.0121)	-0.0155 (0.0095)	-0.0075 (0.0048)	-0.0064** (0.0033)	-0.0049** (0.0025)	-0.0048 (0.0034)	-0.0015 (0.0033)	0.0009 (0.0030)
SQFT	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0575* (0.0306)	-0.0303 (0.0283)	-0.046* (0.0244)	-0.0413** (0.0192)	-0.0323* (0.0173)	-0.0266 (0.0198)	-0.0092 (0.0243)	0.0052 (0.0225)	-0.0063 (0.0222)
Construction material	-0.0672** (0.0286)	-0.0668*** (0.0231)	-0.0636*** (0.0185)	-0.0525*** (0.0154)	-0.0297** (0.0141)	-0.0298* (0.0160)	-0.0285* (0.0168)	-0.0256 (0.0174)	-0.0311* (0.0159)
Physical condition	0.2683*** (0.0281)	0.2637*** (0.0217)	0.2266*** (0.0187)	0.1998*** (0.0146)	0.1758*** (0.0156)	0.1634*** (0.0158)	0.1472*** (0.0181)	0.1373*** (0.0167)	0.1473*** (0.0159)
Quality grade factor	0.4243*** (0.1245)	0.3806*** (0.0792)	0.3937*** (0.0677)	0.3875*** (0.0544)	0.3909*** (0.0488)	0.3472*** (0.0507)	0.364*** (0.0668)	0.4398*** (0.0532)	0.4374*** (0.0657)
Age	-0.0025*** (0.0007)	-0.0025*** (0.0005)	-0.0026*** (0.0005)	-0.0024*** (0.0003)	-0.0025*** (0.0004)	-0.0026*** (0.0004)	-0.0025*** (0.0004)	-0.0021*** (0.0004)	-0.0016*** (0.0003)
Bedrooms	0.0235 (0.0264)	0.0198 (0.0212)	0.0411** (0.0164)	0.0487*** (0.0150)	0.0518*** (0.0126)	0.0463*** (0.0158)	0.0319** (0.0152)	0.0448*** (0.0140)	0.0474*** (0.0133)
Total Bathrooms	0.0059 (0.0320)	0.0258 (0.0192)	0.0372** (0.0153)	0.0572*** (0.0134)	0.034*** (0.0123)	0.028** (0.0142)	0.0279* (0.0145)	0.0152 (0.0149)	0.0152 (0.0178)
AC	0.2074*** (0.0540)	0.2328*** (0.0335)	0.2202*** (0.0309)	0.2217*** (0.0250)	0.2169*** (0.0244)	0.2099*** (0.0259)	0.1711*** (0.0233)	0.1615*** (0.0271)	0.0909** (0.0371)
Fire place	0.1527*** (0.0362)	0.1059*** (0.0220)	0.113*** (0.0191)	0.1052*** (0.0138)	0.0905*** (0.0158)	0.0867*** (0.0150)	0.0799*** (0.0163)	0.0667*** (0.0176)	0.0553*** (0.0153)
Basement garage	0.0573** (0.0263)	0.0169 (0.0203)	0.0298* (0.0168)	0.0159 (0.0140)	0.0113 (0.0144)	0.0142 (0.0144)	0.0085 (0.0185)	0.0032 (0.0172)	-0.0058 (0.0179)
Lot size	-0.0009 (0.0075)	0.0088 (0.0065)	0.0112** (0.0044)	0.0105** (0.0050)	0.0117* (0.0065)	0.0108 (0.0073)	0.0244** (0.0102)	0.0212** (0.0100)	0.0381*** (0.0070)
Sidewalk	-0.0753 (0.0730)	-0.0562 (0.0529)	-0.0216 (0.0462)	-0.035 (0.0325)	-0.0415 (0.0291)	-0.0376 (0.0298)	-0.0559* (0.0315)	-0.0885*** (0.0298)	-0.0933** (0.0410)
Fence	0.1351*** (0.0308)	0.1127*** (0.0249)	0.0967*** (0.0160)	0.0944*** (0.0155)	0.0903*** (0.0130)	0.0912*** (0.0163)	0.0764*** (0.0161)	0.0659*** (0.0156)	0.0434*** (0.0161)
Crime	-0.0004 (0.0010)	-0.0004 (0.0005)	-0.0007 (0.0005)	-0.0005 (0.0005)	-0.0002 (0.0004)	-0.0005 (0.0004)	-0.0008 (0.0005)	-0.0005 (0.0004)	-0.0006 (0.0005)
School quality	0.0014 (0.0014)	0.0001 (0.0011)	-0.0006 (0.0008)	-0.0014** (0.0007)	-0.001 (0.0007)	-0.001 (0.0008)	-0.0009 (0.0010)	-0.0005 (0.0007)	-0.0007 (0.0007)
Distance to highway exit	-0.0046 (0.0116)	-0.007 (0.0085)	-0.0156** (0.0072)	-0.0204*** (0.0061)	-0.0139** (0.0058)	-0.0103* (0.0062)	-0.0154** (0.0064)	-0.0128** (0.0064)	-0.014** (0.0067)
Distance to FSU	-0.0093 (0.0106)	-0.0115 (0.0078)	-0.0072 (0.0060)	0.0005 (0.0054)	-0.0016 (0.0052)	-0.0044 (0.0052)	-0.0024 (0.0056)	0.0015 (0.0061)	0.0055 (0.0067)
ρ	0.2085*** (0.0439)	0.2248*** (0.0341)	0.1709*** (0.0302)	0.1705*** (0.0245)	0.1862*** (0.0248)	0.1841*** (0.0266)	0.1633*** (0.0288)	0.1628*** (0.0267)	0.1694*** (0.0264)
Constant	6.7475*** (0.5188)	6.7145*** (0.4221)	7.569*** (0.3615)	7.7436*** (0.2913)	7.6613*** (0.2727)	7.8642*** (0.3232)	8.3129*** (0.3527)	8.2941*** (0.3355)	8.2796*** (0.3264)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.3D. Spatial Quantile Regression Results for Model (3) – Duration BWNs_year

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Duration BWNs_year	-0.1189*** (0.0294)	-0.0598*** (0.0111)	-0.0432*** (0.0106)	-0.0345*** (0.0064)	-0.0316*** (0.0073)	-0.0204** (0.0098)	-0.0163** (0.0078)	-0.0056 (0.0056)	0.00002 (0.0049)
SQFT	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0321 (0.0374)	-0.0329 (0.0268)	-0.0532** (0.0222)	-0.049*** (0.0169)	-0.0296 (0.0185)	-0.0385* (0.0203)	-0.0101 (0.0258)	0.0124 (0.0219)	-0.0058 (0.0167)
Construction material	-0.0512* (0.0308)	-0.0633*** (0.0235)	-0.0578*** (0.0194)	-0.0564*** (0.0152)	-0.0338** (0.0158)	-0.026 (0.0159)	-0.026* (0.0151)	-0.0235 (0.0189)	-0.0312* (0.0171)
Physical condition	0.2575*** (0.0238)	0.2419*** (0.0245)	0.2177*** (0.0162)	0.1962*** (0.0146)	0.163*** (0.0155)	0.1689*** (0.0133)	0.1478*** (0.0157)	0.1428*** (0.0186)	0.1502*** (0.0196)
Quality grade factor	0.4621*** (0.1186)	0.4054*** (0.0791)	0.422*** (0.0619)	0.3792*** (0.0607)	0.4009*** (0.0452)	0.3436*** (0.0558)	0.3445*** (0.0624)	0.4166*** (0.0630)	0.437*** (0.0641)
Age	-0.0021*** (0.0007)	-0.0025*** (0.0004)	-0.0022*** (0.0005)	-0.0026*** (0.0004)	-0.0027*** (0.0003)	-0.0026*** (0.0004)	-0.0025*** (0.0004)	-0.0021*** (0.0004)	-0.0015*** (0.0003)
Bedrooms	0.0178 (0.0261)	0.0258 (0.0212)	0.0384** (0.0180)	0.0529*** (0.0142)	0.0537*** (0.0109)	0.0511*** (0.0127)	0.0332** (0.0143)	0.0421*** (0.0146)	0.0479*** (0.0148)
Total Bathrooms	0.0063 (0.0342)	0.0264 (0.0212)	0.0438*** (0.0144)	0.0609*** (0.0143)	0.0351*** (0.0128)	0.0272* (0.0141)	0.0266** (0.0127)	0.0165 (0.0166)	0.0144 (0.0161)
AC	0.2058*** (0.0476)	0.225*** (0.0340)	0.2289*** (0.0287)	0.2189*** (0.0238)	0.2244*** (0.0277)	0.2044*** (0.0245)	0.1753*** (0.0292)	0.1564*** (0.0253)	0.0908** (0.0360)
Fire place	0.1733*** (0.0304)	0.1152*** (0.0229)	0.1033*** (0.0202)	0.1048*** (0.0170)	0.0955*** (0.0143)	0.0869*** (0.0169)	0.0826*** (0.0162)	0.0687*** (0.0167)	0.0569*** (0.0166)
Basement garage	0.0512* (0.0277)	0.0255 (0.0197)	0.0273 (0.0195)	0.0157 (0.0161)	0.0188 (0.0143)	0.0074 (0.0150)	0.0089 (0.0152)	0.0027 (0.0161)	-0.0026 (0.0167)
Lot size	-0.0002 (0.0065)	0.0089 (0.0064)	0.0117** (0.0047)	0.0111*** (0.0040)	0.0111* (0.0058)	0.0098 (0.0076)	0.0241*** (0.0090)	0.0207* (0.0109)	0.0379*** (0.0084)
Sidewalk	-0.0863 (0.0839)	-0.069 (0.0446)	-0.0557 (0.0528)	-0.0359 (0.0365)	-0.034 (0.0328)	-0.0363 (0.0291)	-0.0598** (0.0285)	-0.1007*** (0.0366)	-0.0932* (0.0545)
Fence	0.1333*** (0.0360)	0.106*** (0.0225)	0.0976*** (0.0166)	0.0999*** (0.0166)	0.0967*** (0.0136)	0.0908*** (0.0158)	0.0736*** (0.0157)	0.0617*** (0.0158)	0.045*** (0.0150)
Crime	-0.0009 (0.0010)	-0.0009* (0.0005)	-0.0009* (0.0005)	-0.0005 (0.0004)	-0.0004 (0.0004)	-0.0004 (0.0004)	-0.0009** (0.0004)	-0.0006 (0.0004)	-0.0007 (0.0006)
School quality	0.0008 (0.0016)	-0.0003 (0.0011)	-0.0006 (0.0009)	-0.0014** (0.0006)	-0.0009 (0.0006)	-0.0009 (0.0007)	-0.0012 (0.0008)	-0.0005 (0.0008)	-0.001 (0.0008)
Distance to highway exit	-0.0137 (0.0112)	-0.0097 (0.0078)	-0.0148** (0.0066)	-0.0187*** (0.0048)	-0.0111* (0.0059)	-0.0059 (0.0061)	-0.0156*** (0.0060)	-0.0123** (0.0063)	-0.0138* (0.0071)
Distance to FSU	0.0016 (0.0104)	-0.0093 (0.0080)	-0.0059 (0.0055)	-0.0002 (0.0049)	-0.0023 (0.0047)	-0.0034 (0.0053)	-0.0008 (0.0055)	0.002 (0.0066)	0.0053 (0.0066)
ρ	0.1945*** (0.0456)	0.1893*** (0.0415)	0.1567*** (0.0291)	0.1561*** (0.0255)	0.1691*** (0.0272)	0.1788*** (0.0287)	0.1577*** (0.0269)	0.1671*** (0.0237)	0.1756*** (0.0276)
Constant	6.9241*** (0.4896)	7.2404*** (0.4418)	7.7493*** (0.3492)	7.9447*** (0.2963)	7.9237*** (0.2886)	7.8908*** (0.3472)	8.4086*** (0.3052)	8.2293*** (0.2886)	8.2113*** (0.3372)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.4D. Spatial Quantile Regression Results for Model (4) – BWN

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
BWN	-0.5392*** (0.0653)	-0.2971*** (0.0483)	-0.175*** (0.0265)	-0.1017*** (0.0209)	-0.0676*** (0.0171)	-0.0509*** (0.0185)	-0.0449** (-0.0449)	-0.0074 (0.0205)	0.0077 (0.0172)
SQFT	0.0003*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0002*** (0.0000)	0.0003*** (0.0000)	0.0002*** (0.0002)	0.0002*** (0.0000)	0.0002*** (0.0000)
Story height	-0.0357 (0.0372)	-0.0317 (0.0285)	-0.0466** (0.0205)	-0.0374* (0.0197)	-0.0238 (0.0217)	-0.0326* (0.0194)	-0.0065 (-0.0065)	0.0089 (0.0211)	-0.0044 (0.0208)
Construction material	-0.078*** (0.0262)	-0.0762*** (0.0235)	-0.0519** (0.0202)	-0.0567*** (0.0159)	-0.0407*** (0.0152)	-0.0311** (0.0146)	-0.0275* (-0.0275)	-0.0197 (0.0170)	-0.0308** (0.0151)
Physical condition	0.2086*** (0.0238)	0.2265*** (0.0227)	0.2058*** (0.0173)	0.2014*** (0.0173)	0.1733*** (0.0176)	0.1622*** (0.0153)	0.1478*** (0.1478)	0.1407*** (0.0166)	0.1474*** (0.0181)
Quality grade factor	0.5079*** (0.0963)	0.4762*** (0.0734)	0.4752*** (0.0509)	0.4117*** (0.0578)	0.4025*** (0.0609)	0.3566*** (0.0585)	0.3477*** (0.3477)	0.4225*** (0.0632)	0.4505*** (0.0692)
Age	-0.0021*** (0.0006)	-0.0025*** (0.0005)	-0.0024*** (0.0004)	-0.0025*** (0.0005)	-0.0026*** (0.0004)	-0.0026*** (0.0003)	-0.0023*** (-0.0023)	-0.0023*** (0.0004)	-0.0017*** (0.0003)
Bedrooms	0.0165 (0.0161)	0.024 (0.0192)	0.0406** (0.0166)	0.0463*** (0.0165)	0.0447*** (0.0154)	0.0481*** (0.0130)	0.0366** (0.0366)	0.0433*** (0.0128)	0.047*** (0.0141)
Total Bathrooms	-0.0178 (0.0211)	0.021 (0.0223)	0.0406*** (0.0148)	0.0454*** (0.0168)	0.0335*** (0.0118)	0.0273* (0.0141)	0.037*** (0.0370)	0.0148 (0.0172)	0.0143 (0.0153)
AC	0.1847*** (0.0347)	0.2161*** (0.0372)	0.2305*** (0.0272)	0.2244*** (0.0271)	0.2281*** (0.0268)	0.2081*** (0.0295)	0.1684*** (0.1684)	0.1468*** (0.0287)	0.0936*** (0.0334)
Fire place	0.1368*** (0.0260)	0.1306*** (0.0234)	0.1319*** (0.0204)	0.1094*** (0.0159)	0.0972*** (0.0149)	0.0896*** (0.0159)	0.0836*** (0.0836)	0.077*** (0.0165)	0.0604*** (0.0171)
Basement garage	0.0209 (0.0253)	0.0326 (0.0214)	0.0232 (0.0184)	0.017 (0.0179)	0.0153 (0.0151)	0.0081 (0.0153)	-0.0006 (-0.0006)	0.0019 (0.0165)	-0.0104 (0.0181)
Lot size	0.0022 (0.0049)	0.0088 (0.0066)	0.0122** (0.0050)	0.0111** (0.0047)	0.01* (0.0057)	0.0112 (0.0078)	0.022*** (0.0220)	0.0218** (0.0099)	0.0372*** (0.0074)
Sidewalk	-0.0141 (0.0515)	-0.0541 (0.0345)	-0.0527 (0.0443)	-0.0385 (0.0334)	-0.0523 (0.0400)	-0.0374 (0.0312)	-0.0647** (-0.0647)	-0.0876** (0.0357)	-0.0889** (0.0445)
Fence	0.0783*** (0.0277)	0.104*** (0.0226)	0.1003*** (0.0176)	0.0936*** (0.0182)	0.0993*** (0.0156)	0.0938*** (0.0170)	0.0729*** (0.0729)	0.066*** (0.0144)	0.0514*** (0.0155)
Crime	-0.0001 (0.0008)	-0.0009 (0.0007)	-0.0007 (0.0005)	-0.0004 (0.0004)	-0.0001 (0.0005)	-0.0004 (0.0004)	-0.0007* (-0.0007)	-0.0006 (0.0005)	-0.0007 (0.0005)
School quality	0.0018 (0.0012)	0.00002 (0.0011)	-0.0008 (0.0009)	-0.0012 (0.0008)	-0.0005 (0.0007)	-0.0009 (0.0007)	-0.0008 (-0.0008)	-0.0005 (0.0007)	-0.0005 (0.0007)
Distance to highway exit	-0.0158 (0.0104)	-0.0151* (0.0089)	-0.02*** (0.0067)	-0.022*** (0.0065)	-0.0123* (0.0071)	-0.0124** (0.0058)	-0.0146*** (-0.0146)	-0.0163*** (0.0061)	-0.0141* (0.0076)
Distance to FSU	-0.0024 (0.0094)	-0.0072 (0.0079)	-0.0032 (0.0064)	0.0014 (0.0061)	-0.0033 (0.0061)	-0.0006 (0.0048)	-0.0017 (-0.0017)	0.0012 (0.0056)	0.0043 (0.0065)
ρ	0.2047*** (0.0326)	0.1631*** (0.0298)	0.1507*** (0.0284)	0.1497*** (0.0236)	0.1619*** (0.0281)	0.1693*** (0.0274)	0.158*** (0.1580)	0.1442*** (0.0255)	0.1539*** (0.0263)
Constant	7.0339*** (0.3612)	7.5819*** (0.3441)	7.8347*** (0.3136)	7.9704*** (0.2879)	7.9343*** (0.3276)	8.0273*** (0.3113)	8.3479*** (8.3479)	8.5324*** (0.3105)	8.4602*** (0.3152)

Bootstrapped standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 4

Essay 3: The Impact of Access to Raw Water Sources on Residential Water Charges in Rural West Virginia

4.1. Introduction

Public water systems typically obtain their raw water supplies from four main sources: surface water, groundwater, water purchased wholesale from nearby water system, or a combination of two or more of these sources. In addition to these sources, water systems that serve remote, economically depressed, and rural communities sometimes do not have access to reliable raw water sources due to factors such as droughts or pollution. An example is the severe water shortages caused by the 1993 drought that affected multiple public water systems in Randolph County, West Virginia (Natural Resources Conservation Services [NRCS], 2007). In such cases, federal, state, and local governments and organizations work together to develop and maintain alternative raw water sources for these communities. The Natural Resources Conservation Services (NRCS), formerly known as the Soil Conservation Service (SCS), is an agency of the U.S. Department of Agriculture (USDA) and one of the agencies that will assist public water systems in rural communities to obtain raw water supplies by constructing, designing, and/or funding water supply impoundments.

Raw water sources that are utilized by public water systems play an important role in affecting not only the cost of treatment, but also the residential water. For example, Bae (2007) found that metropolitan public water systems that use groundwater sources have lower residential water charges compared water systems that use surface water or purchased water. Erfanian and Collins (2018) confirm this result for municipal water utilities around the state of West Virginia.

In addition to cost concerns, raw water sources present different risks of contamination. In West Virginia, out of the 446 active community water systems, 51% of them have access to only one raw water source as their water supply (WV Drinking Water Watch, 2019). However, after the Elk River chemical spill in 2014, legislators in West Virginia passed the Source Water Protection Senate Bill 373, also known as the Spill Bill, requiring public water systems that use surface water or groundwater influenced by surface water as supply sources (about 15% of the total community water systems in West Virginia) to complete or update their source water protection plans.¹⁸ One of the main goals of these plans was to assess the ability of public water systems to construct or establish a secondary or backup source that to be used in cases of emergency or contamination of their primary water source. This push toward public water systems to have more than one water supply source may affect the residential water charges, especially in rural areas.

Public water supplies in rural areas in West Virginia are primarily provided by Public Service Districts (PSDs). PSDs are public corporations that were established by county commissions with the approval of the West Virginia Public Service Commission (WV PSC) to develop and maintain water, sewer, and gas systems in rural areas. PSDs can constitute either the whole or any part of one or more counties. Each PSD has a board with the authority to establish rates, fees, and charges for the water service to cover the cost of maintenance, operation, and depreciation. The schedule of water rates, fees, and charges may be based upon one or a combination of the following: (1) the consumption of water on premises connected with the facilities, taking into consideration domestic, commercial, industrial, and public use of water; (2)

¹⁸ For more information, see W.Va. Code §16-1-9C-B9.

the number and kind of fixtures connected with the facilities located on the various premises; (3) the number of persons served by the facilities.¹⁹ The WV PSC approves PSD water rates and fees based only upon cost recovery considerations with no profits being allowed to the PSDs.

Currently, there are 122 PSDs in West Virginia that supply public water to about 200,000 rural households throughout the state (WV PSC, 2017). Many PSDs operate more than one water system and mostly use conventional water supply sources. Some of these PSDs face difficulties in ensuring a reliable raw water supplies for their water systems and have relied upon NRCS's flood control impoundments as the main source for raw water. Without these impoundments, these PSDs are forced to switch to inferior sources in terms of water quality or quantity. One recent example is Preston PSD 1 which has relied on a 50-year old NRCS's dam for their raw water source. Due to replacement work, the PSD has been using another source for their water. However, recent reports show that health and safety concerns have led many residents to stop using tap water due to the low quality associated with the new source (Plum, 2019).

Given the above issues concerning cost and reliability of raw water sources, the objective of this paper is to examine the impact of the access to raw water sources on residential water charges for PSDs in West Virginia. This will help us to determine the relative value for each source compared to the others. Using regression analysis, we compare residential water charges per 4,500 gallons for each PSD that utilize different raw water sources including the surface water, purchased water, or multiple sources. In addition, we examine the difference in water charges between those PSDs that use NRCS's flood control impoundments as a water source compared to those who use other sources. Our results suggest that PSDs that use multiple sources

¹⁹ For more information, see W.Va. Code §16-13A-1.

have higher residential water charges compared to those who utilize a single source. In addition, PSDs that rely on purchased water have higher residential water charges. Finally, we found not statistically difference between water charges of PSDs that use NRCS's impoundments and those who use conventional sources.

The rest of the paper is organized as follows. In section 4.2, we provide a background for water supply sources in West Virginia. In section 4.3, we review the previous literature that examined the different factors affecting residential water prices or charges. In section 4.4, we describe and develop our empirical model. Section 4.5 provide information about the data used in the analysis and their sources. We finally discuss the results in section 4.6 and end with conclusions in section 4.7.

4.2. Water Supply Sources in West Virginia: A Background

4.2.1. Conventional water supply sources

West Virginia is one of the states that has an abundance of water resources. The West Virginia Department of Environmental Protection (WV DEP, 2013) has estimated the available water in the state by developing a seasonal water budget for each of its 32 eight-digit Hydrologic Unite Code Watersheds (HUC-8 WS).²⁰ Based on the water budget results and the estimated consumptive needs of the state, water supply exceeded water demand in all watersheds in West Virginia.²¹ The state receives an average of 44 inches of precipitation annually and based on this average the total annual amount of water available in West Virginia was estimated to be 19.3 trillion gallons (WV DEP, 2013). There are about 10,000 streams with a total of 54,961 stream

²⁰ Water budget is an accounting method that is used to quantify the available water in a hydrologic system, which incorporate both consumptive and non-consumptive water demands.

²¹ According to the U.S. Government Accountability Office (2014), West Virginia is expected to have water availability problems at the local level in the next decade.

miles statewide (WV DEP, 2013; Petty, 2018). Most of these streams in the state are part of one of two major river basins, the Potomac to the east and the Ohio to the west. These streams provide many beneficial uses including being the major water supply source to many public water systems in West Virginia.²² According to WV DEP (2013), public water systems withdraw about 80% of their total use from surface water sources. In particular, 67% of PSDs in West Virginia rely on surface water as the main source for their water supply either directly or indirectly (purchased).

For groundwater sources, based on data from 2003-2005 water use survey, the WV DEP identified two general areas where groundwater resources are both abundant and most commonly used: along the Ohio River and the Eastern Panhandle. Even though public water systems withdraw only 20% of their water use from groundwater sources, they are considered the largest user of groundwater in the state (WV DEP, 2013). About 50% of public water systems use groundwater sources for their supply. Only 23% of PSDs utilize groundwater sources (directly and indirectly) in West Virginia.

4.2.2. NRCS water supply impoundments²³

In 1935, the U.S. Department of Agriculture (USDA) established the Soil Conservation Service (SCS), known currently as the Natural Resource Conservation Services (NRCS), as a permanent agency responsible for enforcing the Soil Conservation Act of 1935 (PL 74-46). One year later, the Flood Control Act of 1936 (PL 74-738) expanded the responsibilities of the agency to study and survey watersheds across the United States for possible improvement works.

²² However, due to pollution caused by human activities, about 60% of these streams are no longer capable of providing such benefits (Petty, 2018).

²³ Most information about the history of the NRCS water resources programs were obtained from Buie (1979), Woodward (2015), and the NRCS website.

Between 1937 and 1943, the agency initiated preliminary studies on 212 watersheds nationwide and detailed surveys on 41 watersheds. Out of the 212 surveys, only 25 recommended the installation of watershed improvements programs. Based on these recommendations, the Flood Control Act of 1944 (PL 78-534) authorized the installation of 11 watershed improvement works.

These 11 authorized watershed projects became the predecessors of the small watershed program that was introduced in the Watershed Protection and Flood Prevention Act of 1954 (PL 83-566). The act authorized the SCS to help local organizations (sponsors) to develop watershed work plans for watersheds less than 250,000 acres and provide financial and technical assistance for installation of improvements. Unlike the previous Flood Control Acts, this act authorized the agency (over several amendments) to provide assistance to purposes other than flood control such as projects for watershed protections, conservation and proper utilization of land, agricultural water management, including irrigation and drainage, public recreation, public fish and wildlife, hydropower, water quality management, groundwater supply, agricultural pollution control, and municipal and industrial water supply.

Over the years, the NRCS assisted local organizations to develop watershed plans and provided financial and technical assistance for 1,458 projects (about 12% of total projects constructed by the NRCS) that were designed for the purpose of providing water supply for public water systems across the United States (National Inventory of Dams [NID], 2018).²⁴ In West Virginia, the NRCS has designed and installed 170 watershed dams with 14 of them are

²⁴ In the entire U.S., the NRCS has constructed about 11,400 dams on some 2,000 watershed projects with the main objective in most projects being flood control.

currently being used for water supply by 15 municipalities and 12 public service districts (NRCS, 2019).

The first multipurpose dam, for water supply and flood control features, that was constructed under the Watershed Protection and Flood Prevention Act in West Virginia was the Upper Grave Dam No. 1 in 1959. This dam was built to help the City of Cameron to cope with its water problems including floods, droughts, and to replace the old water system that had been in operation for over 100 years (Sharpe, 1964). Currently, this dam is the primary water source for the city and provide water for its 950 residents. Another NRCS's project of interest is the Elkwater Fork Dam in the Upper Tygart Valley River Watershed. This dam is the only dam in West Virginia that was constructed with the main purpose being water supply instead of flood control. It provides raw water for seven water systems that estimated to serve about 27,800 people in four municipalities and three public service districts. Table 4.1 shows the 12 public service districts and information about their water supply sources. Half of them have access to more than one water supply source; however, in most PSDs, only one source is usually active. The last column shows whether NRCS's impoundment is one of the active sources that the PSD is using or not. Except for three PSDs, most use NRCS impoundments as the primary source, which shows how important these impoundments to the communities served by these PSDs.

4.3. Literature Review

We divide this section into two subsections. The first is concerned about defining the economic value of water and the methods that economists have developed to measure this value. Since we are interested on the impact water supply sources on water charges, we review the studies that examined the determinants of water charges and prices in the second section to develop a broader understanding of the factors that affect these charges.

4.3.1. Value of water: Definition and measures

The economic value of water is defined as the amount that a rational user of a water resource is willing to pay for it. Thus, it is dependent on both the user and the use of water. In most marketed commodities, prices are good indicator for value. However, in the case of water resources, water prices usually reflect an amount set by the political and social system to achieve specific goals such as equity and sustainability, and therefore water prices are a poor guide to economic value (Roger et al., 2002; Hanemann, 2006).

Since water is not priced as an economic good, economists have developed multiple methods to estimate the value of water to provide signals of the relative scarcity that are otherwise not available due to the absence of markets. Figure 4.1 shows the different types of economic water valuation methods based on the categories provided by Young and Loomis (2014). They divide valuation methods into deductive or inductive techniques based on the mathematical procedures and type of data employed in the valuation process. In general, the goal of these methods is to estimate the value of marginal product (VMP) in the case of producers, and the willingness to pay or accept (WTP or WTA) in the case of consumers. It should be noted that we are interested in relative value of raw water sources and not absolute value. The former can be defined as the value of one object relative to another object, whereas the absolute value is the value of one object compared to some absolute standard (Brown, 1984). That is, what one raw water source is worth relative to another source. One valuation method that we are interested in is the estimation of producer's cost function using regression analysis, which we discuss in detail in the empirical model section.

4.3.2. The determinants of water charges and prices

Before we start examining previous studies, it is important to distinguish between the different pricing terms used in the literature. Various pricing terms are used including water

price, water rate, water charge, water fee, and water tariffs. According to Griffin (2016, p. 303) water price is a volumetric price placed on metered water and often means the same thing as water rate. However, water rates, expressed plurally, can refer to the entire package of charges applied by a water supplier including both volumetric charges (i.e. per unit charge) and flat charges (e.g. new connection fee). Also, outside the U.S. and in some academic literature, water rates may be called water tariffs. In the U.S., water charges are used to express the total amount paid (for volumetric plus flat) to acquire a certain quantity of water and is used as one way to standardize the acquisition of water across the different pricing structures available between water suppliers (Erfanian & Collins, 2018).

Many researchers have been interested in what factors affecting water price or charges. We categorize these studies into three main groups: (1) studies that explored the impact of multiple economic and non-economic factors on water charges, (2) studies that focused on the impact of water system ownership on water price, and (3) studies that examined the impact of specific factors, such as water quality, on water price.

In the first group, three older studies analyzed the factors affecting water prices and charges. Afifi (1969) examined the various factors affecting residential (5,000 gallons per month), commercial (10,000 gallons per month), and industrial (750,000 gallons per month) water charges using regression analysis in Illinois. Among the numerous variables that he examined, ten were found to be the most important determinants of water supply charges including total population served, type of ownership, source of raw water, quantity of water produced, long-term debts, type of treatment applied to water, percentage of customers metered accounts, per capita income, average cost of water produced, and time elapsed since the last water rate change.

Similarly, Hollman and Boyet (1975) examined the determinants of residential and commercial water charges using data for 86 small water systems in Mississippi and simple OLS estimation methods. They examined multiple factors and only six of them had statistically significant impacts on water charges. They found that the number of customers served, whether there is any change in water source in last ten years, and government subsidies are associated with lower water charges. On the other hand, production and distribution costs, installation charges, and whether the water system is FHA-financed (proxy for debt) are associated with higher water prices.

A more comprehensive study by Mann (1972) examined the relationship between multiple measures of water prices (five measures of water rates for specific consumption levels, four measures of average price, and three measures of water rate structure) and internal utility (operation and financial), demographic, and municipal finance variables for utilities across the United States. He found that primary determinants of water prices include operation expenses, taxes, and debt service costs. Secondary determinants of water price which are cost-related include reliance on surface sources, system scale, and the extent of waste and free service.

More recently, studies such as Bae (2007), Thorsten et al. (2009), and Erfanian and Collins (2018) have used similar approach to the previous studies, but with different datasets and estimation methods. For example, Bae (2007) grouped the factor affecting water prices into four major categories: (a) institutional arrangements and characteristics, (b) government regulations, (c) supply factors and characteristics, and (c) natural environment and local characteristics and used data for 259 water systems across the United States. In terms of methods, Thorsten et al. (2009) and Erfanian and Collins (2018) employed spatial econometrics techniques to examine whether water charges in a system are affected by water charges in nearby systems. In general,

these studies found that several factors are associated with lower water charges such as water source and governmental regulations. Using a dataset for 308 cities in 102 countries, Zetland and Gasson (2012) examined the factors affecting water prices globally. They found that higher water prices are correlated with lower per capita consumption, smaller local populations, lower water availability, higher demand, and a lower risk of shortage.

The second group of studies are mainly concerned about whether privatization of water systems increase water prices (Chong et al. 2006; Zaki & Amin 2009; Martínez-Espíñeira et al. 2009; Ruester & Zschille 2010; García-Valiñas et al. 2013; Barbosa & Brusca 2015; Romano et al. 2015; Procher 2017). Most of these studies were conducted outside the United States and use various measures for the dependent variable such as yearly charges and average price for different rates. Overall, these studies found that privatization result in higher water prices for residential consumers.

Finally, the studies in the third group examined the impact of specific factors on water prices. Piper (2003) examined the impact of water quality (measured as the difference between total hardness in raw and treated water) and found that poor water quality result in higher treatment costs and higher water rates. Klien (2015) studied the effect of both political determinants and yardstick competition on water prices in Austria. He found that water prices are lower when political competition is strong and before elections. Also, using spatial econometrics models he examined the existence of strategic interaction between municipalities and found that the magnitude of the political budget cycle depends on neighboring jurisdictions, which affect water prices indirectly. Similarly, Chica-Olmo et al. (2013) investigated spillover effects in setting water prices in Southern Spain and found that local governments follow neighboring municipalities when revising water rates.

4.4. Empirical Model

As mentioned in the previous section, economists have developed multiple methods to estimate the value of water. The main goal of these methods is to estimate the value of marginal product for producers and the willingness to pay (or accept) for consumers. Since we are working with PSDs that produce drinking water, we focus on the methods used to estimate the producer's value of water. From Figure 4.1, there are two main types of methods. First, deductive methods, such as mathematical programming, that derive an accounting price or financial value from constructed models of individual economic decisions made by producers. Second, inductive methods that estimate producer's value of water using regression techniques. For example, estimation of production, cost, or hedonic property functions.

Based on data availability, we use the cost function approach to estimate the relative value of raw water from different water sources used by PSDs. The basic idea is that raw water is an input in the production of drinking water. The cost of supplying drinking water is impacted by the source of raw water used. These cost impacts will be transmitted to residential users through water charges for the delivered water. Supposing that raw water supplied by a specific source has a lower the cost of production for the PSD than other raw water sources, then the relative value of this water can be measured by the reduction in these water charges. This economic logic make sense given the regulatory mandate of the WV PSC to ensure that PSDs base their water charges only on costs of production and delivery – not on the value to the residential customers. Many studies have followed this approach to estimate the value of raw water. For studies that examine the costs of water supply systems specifically, examples include Abildtrup et al. (2013), Fiquepron et al. (2013), Vincent et al. (2016), and Faria Lopes et al. (2018).

Since water charges are related to the cost of producing and delivering water, it is reasonable to use water charges as proxy for cost of supplying it under the assumption that water

charges cover the operation, maintenance, and repair costs of water systems in the PSD (Piper, 2003). Following previous literature, a general form of a model that explains the factors affecting water charges to customers from the PSDs can be written as:

$$WC = f(Q, S, X, \varepsilon) \quad (1)$$

where WC is the water charges for 4,500 gallons of water which represent the residential water charges in West Virginia; Q is the quantity of water sold by the PSD; S a vector reflects the PSD's source of raw water source; X is a vector of relevant exogenous variables that affect costs of producing and delivering water which potentially contribute to differences in water charges between PSDs, and ε is an error term.

For X , as we shown in section 4.2, there are many factors that can affect water charges. However, internal operating and financial variables have always been found to be important determinants of water prices. Thus, we control for such variables including long-term debts, water treatment expenses and ownership, water main lines length, volume of water loss in production cycle, number of Safe Drinking Water Act violations, number of water main breaks and leaks, whether the PSDs provides sewer service or not, and number of customers and population density. We also control for the type of rates (i.e. increasing, decreasing, or constant rates) .We realize that there are other factors that have been found to affect water prices in previous studies such as Bae (2007), but since our focus is only on PSDs in West Virginia, there is little heterogeneity between our observations in terms of factors such as government regulations and geography. Therefore, our model does not control for these variables.

For functional form, we evaluate the data using linear and log-linear specifications. Using Box-Cox specification test, the results in Table 4.2 indicate that linear specification provides the

best fit for our data. Thus, based on (1) and the variables described above, an empirical equation for water charges is written as:

$$WC = \beta_0 + \beta Z + \varepsilon \quad (2)$$

Where Z represents a vector of factors that drive the cost of service in the PSD including raw water source variables.

4.5. Data

In this paper, we rely on two main data sources. The first is the annual reports provided by PSDs available on WV PSC.²⁵ The Second is historical watershed work plans/agreements reports between the NRCS and local conservation agencies in West Virginia. There are currently 122 PSDs in West Virginia (WV PSC, 2017). Due to missing data, we had to drop some observations and the final number of observations is 110 PSDs.

The WV PSC's reports provide information about the PSDs financial and scale of operation status including number of customers, length of water main lines, gross revenue, total debt among many others. We follow the literature and use the information available in these reports to control for important variables that have been documented to affect residential water charges. In addition, we use West Virginia Drinking Water Watch to obtain detailed information about the raw water source used by each PSDs.²⁶

For our variable of interest, we mainly use historical watershed work plans/agreements reports between the NRCS and local conservation agencies to identify those dams that were constructed with the objective to supply raw water for public water systems. These reports are

²⁵ All our data comes from 2018 reports, except for eight PSDs with the latest report being in 2017.

²⁶ Available on <http://129.71.204.189:1977/DWWpublic/index.jsp>

provided by The University of Pennsylvania (The Online Books Page) and the USDA's National Agricultural Library. Additional information about the dams were also obtained from the National Inventory of Dams (NID). The main objective of most NRCS's dams is flood control, however, some of them have multiple objectives such as recreation and water supply.²⁷ We focus on the latter and use it to construct our main binary variable, whether the PSDs is using raw water from these dams or not.

Table 4.3 provides summary statistics and descriptions for all variables that we considered in the analysis. The dependent variable, water charges per 4,500 gallons, ranges from \$20.60 to \$92.79 reflecting an over fourfold difference between PSDs in terms of water production costs. Explanatory variables are grouped into three categories. First, the focus variables related to PSD's raw water sources. About 11% of the PSDs in the dataset utilize raw water from NRCS dams as one of their raw water sources. Most of the PSDs (54%) purchase their water from other systems (municipal water utilities) or use multiple sources (15%).²⁸ A second group of variables includes those related to financial and operational status of PSD water systems. There are large differences in most of these variables across the PSDs. For rate type, most of the PSDs (86%) have decreasing block rates and the rest have constant rates. Sold water per capita (1,000 gallons) ranges from 18.52 to 586.08.²⁹ One interesting observation is that some PSDs lose up to 67% of their water production due to leaks in the network. This reflect poor water infrastructure in such areas.

²⁷ Table 1A provides information about all dams that were constructed to provide water supply for public water systems in West Virginia.

²⁸ Table 4.4 shows the PSDs and the number of sources available for them.

²⁹ This variable measures the total water sales from the PSD. Therefore, it includes all types of sales to, for example, residential, commercial, and industrial customers. Also, it includes sales to public authorities and fire protection.

Finally, the third group includes one variable: population density where the PSD is located. Since the exact boundaries for PSD service areas are not available, we use rural population density in the county where the PSD is located. We calculate this variable by subtracting county's municipal population and land area from county's total population and land area. This measure will let us obtain a more accurate measure for population density than the total population density since PSDs mainly serve rural areas.

In terms of expectations, we expect that PSDs who utilize a NRCS flood control dam will be able to obtain raw water supplies at a lower cost than other systems, and therefore, residential water charges will be lower. Based on the results found in previous studies (e.g. Erfanian & Collins, 2018), we expect that PSDs that rely on groundwater sources will have lower water charges compared to the other sources since groundwater require less treatment than surface water. Due to considerations of economies of scale, we expect sold water to have a negative impact on water charges (Tsagarakis, 2013). We also expect population density to have a negative impact on water charges due to economies of density (Guerrini et al., 2013). The expected effect of sewer service on water charges is ambiguous. Based on the perspective of economies of scope, the provision of sewer service along with water service may lead to lower water charges since PSDs can share production inputs (e.g. personnel, machines, buildings, and equipment) and transfer some of the water supply costs to sewer service. However, if PSDs are able to transfer sewer service costs to water service instead, then it will result in higher water charges. Percentage of water loss, number of violations, number of breaks, and number of leaks represent the overall inefficiency in the maintenance and operation of the PSD's water systems. We expect that if these factors increase, then water charges will increase as well (Bae, 2007). For treatment variables, we expect that PSDs that own treatment facilities will incur more operational

expenses and as a result water charges will increase. Finally, PSDs with more debts will be more likely to have higher water charges to repay them.

4.6. Results

Table 4.5 shows the results from the different models that were estimated using water charges as the dependent variable. The difference between these models is that some variables were dropped that convey similar information or have missing values (e.g. inefficiency and treatment variables). Overall, these models show similar results in terms of estimated coefficients and adjusted R-squared.

For raw water sources, in all specifications, the NRCS variable had a statistically insignificant coefficient, so that flood control dams supplying raw water to a PSD does not impact residential water charges. Our results do show, however, that other raw water sources do have important impacts on residential water charges. Specifically, using multiple raw water sources resulted in a \$15 higher residential water charge per 4,500 gallons compared to a PSD with a single source of raw water. This is about 29% of the average residential water charge among PSDs in West Virginia. This result is expected since a PSD will need to invest in more infrastructure to be able to utilize more than one raw water source. Also, from the results, we observe that as PSDs acquire more raw water sources, residential water charges per 4,500 gallons are lowered (Table 4.5). In addition, there is statistical evidence that PSDs which utilize purchased water as a raw water source have substantially higher residential water charges than those who use their own water sources. Specifically, the use of purchased water results in higher water charges per 4,500 gallons by \$8.5 compared to PSDs that obtained their own raw water. This result confirms findings by Bae (2007).

For the financial and operational variables, only three variables that show consistent and statistically significant impacts on residential water charges: long-term debt, network length, and sewer service. Long-term debt per customer is positive and statistically significant at 1% level as expected, where a \$1,000 debt increase results in about \$1.8 increase in residential water charges per 4,500 gallons. This result is also in line with the results found in other studies such as Bae (2007) and Thorsten et al. (2009). Network length per customer is positive and statistically significant with a large impact on water charges. An 0.1 of a mile increase in the average number of miles per customer in the network results in \$13.8 higher residential water charges per 4,500 gallons. Given the low population density of rural areas that are served by PSDs, this result is not surprising. PSDs that provide sewer service in addition to water service have lower residential water charges per 4,500 gallons by \$5.11, which supports the existence of economies of scope among PSDs in West Virginia.

Finally, sold water per customer is negative and statically significant at 10% level in model (4). This provides a weak evidence of the existence of economies of scale in PSDs in West Virginia. The result indicates that a 1,000-gallon increase in water sales would decrease water charges by \$0.03. Therefore, economies of scale that may be achieved by merging PSDs with municipalities or other PSDs may benefit residential consumers by enhancing financial performance and lowering water charges. One example of these economies of scale can be observed with the consolidation of Haymond PSD with Taylor PSD in 2011. This consolidation doubled the number of customers for Taylor PSD and decreased the residential water charges per

4,500 gallons by \$2.52 after the merge for customers that were previously served by Haymond PSD.³⁰

4.7. Conclusions

Due to the continuous increase in the number of contamination events of public water systems supply sources, policymakers in West Virginia are attempting to push public water systems to have more than one water supply source to be used in cases of emergency. Previous research has shown that the type of raw water source used by utilities is an important determinant of residential water charges (Bae, 2007; Erfanian & Collins, 2018). Thus, utilizing multiple raw water sources will not only impact public water systems but also the charges paid by their residential customers.

In this paper, we examine the impact of access to the different raw water sources on public service districts (PSDs) residential water charges per 4,500 gallons in West Virginia. PSDs typically obtain their raw water supply from four main (conventional) sources: surface water, groundwater, water purchased wholesale from nearby water system, or a combination of two or more of these sources. However, due to drought or pollution, alternative sources sometimes are used such as flood control impoundments constructed by the NRCS.

Using data from 110 PSDs and controlling for important financial and operational factors that drive water production cost, our results indicate that when a PSD uses multiple raw water sources, its residential water charges are \$15 higher for 4,500 gallons compared to a PSD that relies on a single raw water source. This is about 29% of the average PSDs residential water

³⁰ Here, we examine the difference between water charges when Haymond PSD was active (\$41.72) and Taylor PSD after the consolidation (\$39.20). Also, the number of customers for Taylor PSD increased from 500 to 1,000 after the consolidation.

charges in West Virginia. Therefore, policies, such as SB373, that encourage public water systems to have multiple raw water sources may result in an unintended consequence of higher production costs and therefore, higher residential water charges. Also, our results indicate that PSDs which have their own raw water sources have lower residential water charges than PSDs which purchase water. Finally, we could not find any statistically significant impact of NRCS's flood control impoundments on residential water charges. One possible explanation of why we do not find a statistically significant impact for the NRCS variable is that water in West Virginia is a relatively plentiful resource. Thus, having access to raw water from NRCS dams does not impact the cost structure of a PSD any more than other raw water sources such as groundwater, rivers, or streams.

In terms of policy implications, based on our results, if policymakers make it mandatory for public water systems to have more than one water supply, then the resulting increases in residential water charges may lead to affordability problems across the state. Mack and Wrase (2017) examine the impact of continuous increase in water rates and affordability across the United States. They found that West Virginia has the highest percentage of tracts (47%) that are considered at-risk category. Meaning that if water rates continue to increase, people living in these census tracts will not be able to afford their water bills in the next five years based on their current income levels.

Limitations relate primarily to the small sample size used in the analysis. Future endeavors can expand this research by examining the impact of water supply sources on municipalities' water charges across the United States. Alternatively, since West Virginia is a water rich state, focusing on areas with scarce water resources, such as areas in western U.S., may yield different results.

4.8. References

- Abildtrup, J., Garcia, S., & Stenger, A. (2013). The effect of forest land use on the cost of drinking water supply: A spatial econometric analysis. *Ecological Economics*, 92, 126–136. <http://doi.org/10.1016/j.ecolecon.2013.01.004>
- Afifi, H. H. H. (1969). Economic evaluation of water supply pricing in Illinois. *Journal of American Water Works Association*, 61(1), 41–48.
- Bae, S. (2007). Explaining geographical differences in water prices: Do institutional factors really matter? *The Review of Regional Studies*, 37(2), 207–250.
- Barbosa, A., & Brusca, I. (2015). Governance structures and their impact on tariff levels of Brazilian water and sanitation corporations. *Utilities Policy*, 34, 94–105. <http://doi.org/10.1016/j.jup.2015.02.002>
- Bel, G., González-Gómez, F., & Picazo-Tadeo, A. J. (2015). Does market concentration affect prices in the urban water industry? *Environment and Planning C: Government and Policy*, 33(6), 1546–1565. <http://doi.org/10.1177/0263774X15614144>
- Buie, E. (1979). *A history of water resource activities of the United States Department of Agriculture*. Soil Conservation Service, USDA. Retrieved from https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_021271.pdf
- Brown, T. C. (1984). The concept of value in resource allocation. *Land Economics*, 60(3), 231–246. <http://doi.org/10.2307/3146184>
- Chica-Olmo, J., González-Gómez, F., & Guardiola, J. (2013). Do neighbouring municipalities matter in water pricing? *Urban Water Journal*, 10(1), 1–9. <http://doi.org/10.1080/1573062X.2012.690436>
- Chong, E., Huet, F., Saussier, S., & Steiner, F. (2006). Public-private partnerships and prices: Evidence from water distribution in France. *Review of Industrial Organization*, 29(1–2), 149–169. <http://doi.org/10.1007/s11151-006-9106-8>
- Erfanian, E., & Collins, A. R. (2018). Charges for water and access: What explains the differences among West Virginian municipalities? *Water Economics and Policy*, 04(04), 1850017. <http://doi.org/10.1142/s2382624x18500170>
- Faria Lopes, A., Macdonald, J. L., Quinteiro, P., Arroja, L., Carvalho- Santos, C., Cunha-e-Sá, M. A., & Dias, A. C. (2018). Surface vs. groundwater: The effect of forest cover on the costs of drinking water. *Water Resources and Economics*. <http://doi.org/10.1016/j.wre.2018.06.002>
- Fiquepron, J., Garcia, S., & Stenger, A. (2013). Land use impact on water quality: Valuing forest services in terms of the water supply sector. *Journal of Environmental Management*, 126, 113–121. <http://doi.org/10.1016/j.jenvman.2013.04.002>

- García-Valiñas, M. de los ángeles, González-Gómez, F., & Picazo-Tadeo, A. J. (2013). Is the price of water for residential use related to provider ownership? Empirical evidence from Spain. *Utilities Policy*, 24, 59–69. <http://doi.org/10.1016/j.jup.2012.07.009>
- Griffin, R. C. (2016). *Water resource economics: The analysis of scarcity, policies, and projects* (2nd edition). Cambridge, MA: MIT Press.
- Guerrini, A., Romano, G., & Campedelli, B. (2013). Economies of scale, scope, and density in the Italian water sector: A two-stage data envelopment analysis approach. *Water Resources Management*, 27, 4559–4578. <http://doi.org/10.1007/s11269-013-0426-9>
- Hanemann, W. M. (2006). The economic conception of water. In P. P. Rogers, M. R. Llamas, & L. Martinez-Cortina (Eds.), *Water crisis: Myth or reality?* (pp. 61–91). London, UK: Taylor & Francis.
- Hollman, K. W., & Boyet, W. E. (1975). An empirical analysis of water-price determinants in small municipalities. *Journal of American Water Works Association*, 67(5), 274–277. <http://doi.org/10.1002/j.1551-8833.1975.tb02215.x>
- Klien, M. (2015). The political side of public utilities: How opportunistic behaviour and yardstick competition shape water prices in Austria. *Papers in Regional Science*, 94(4), 869–890. <http://doi.org/10.1111/pirs.12101>
- Mack, E. A., & Wrase, S. (2017). A burgeoning crisis? A nationwide assessment of the geography of water affordability in the United States. *PLoS ONE*, 12(1), 1–19. <http://doi.org/10.1371/journal.pone.0169488>
- Mann, P. C. (1972). *Water service prices: A principal component and regression analysis of determinants*. Regional Research Institute. Morgantown, WV.
- Martínez-Espiñeira, R., García-Valiñas, M. A., & González-Gómez, F. (2009). Does private management of water supply services really increase prices? An empirical analysis in Spain. *Urban Studies*, 46(4), 923–945. <http://doi.org/10.1177/0042098009102135>
- Natural Resources Conservation Service. (2019). West Virginia watershed operations. Retrieved from <https://www.nrcs.usda.gov/wps/portal/nrcs/main/wv/programs/planning/wo/>
- Petty, T. (2018). Streams. Retrieved from <https://www.wvencyclopedia.org/articles/610>
- Piper, S. (2003). Impact of water quality on municipal water price and residential water demand and implications for water supply benefits. *Water Resources Research*, 39(5). <http://doi.org/10.1029/2002WR001592>
- Plum, K. (2019). Water woes in Preston County: Utility will explain its case amid complaints. Retrieved from <https://www.dominionpostlive.com/2019/04/29/water-woes-in-preston-county-utility-will-explain-its-case-amid-complaints/>

- Porcher, S. (2017). The ‘hidden costs’ of water provision: New evidence from the relationship between contracting-out and price in French water public services. *Utilities Policy*, 48, 166–175. <http://doi.org/10.1016/j.jup.2017.08.002>
- Public Service Commission of West Virginia. (2017). *Annual statistical report*. Retrieved from <http://www.psc.state.wv.us/AnnualStatRpts/anstatrpt2017.pdf>
- Rogers, P., Silva, R. De, & Bhatia, R. (2002). Water is an economic good: How to use prices to promote equity, efficiency, and sustainability. *Water Policy*, 4, 1–17.
- Romano, G., Masserini, L., & Guerrini, A. (2015). Does water utilities’ ownership matter in water pricing policy? An analysis of endogenous and environmental determinants of water tariffs in Italy. *Water Policy*, 17(5), 918–931. <http://doi.org/10.2166/wp.2015.016>
- Ruester, S., & Zschille, M. (2010). The impact of governance structure on firm performance: An application to the German water distribution sector. *Utilities Policy*, 18(3), 154–162. <http://doi.org/10.1016/j.jup.2010.03.003>
- Sharpe, G. (1964). Making flood waters behave – the story of Cameron, West Virginia. *Extension Service Review*, 35(4), 56–57.
- Thorsten, R. E., Eskaf, S., & Hughes, J. (2009). Cost plus: Estimating real determinants of water and sewer bills. *Public Works Management & Policy*, 13(3), 224–238. <http://doi.org/10.1177/1087724x08324302>
- Tsagarakis, K. P. (2013). Does size matter? Operating cost coverage for water utilities. *Water Resources Management*, 27, 1551–1562. <http://doi.org/10.1007/s11269-012-0256-1>
- U.S. Army Corps of Engineers. (2019). National inventory of dams. Retrieved from [https://nid.sec.usace.army.mil/ords/f?p=105:1:1:::1:::](https://nid.sec.usace.army.mil/ords/f?p=105:1:1:::)
- Vincent, J. R., Ahmad, I., Adnan, N., Burwell, W. B., Subhrendu, I. I. I., & Thomas, J. T. K. (2016). Valuing water purification by forests: An analysis of Malaysian panel data. *Environmental and Resource Economics*, 64(1), 59–80. <http://doi.org/10.1007/s10640-015-9934-9>
- West Virginia Department of Environmental Protection. (2013). *West Virginia water resources management plan*. Charleston, WV. Retrieved from http://www.dep.wv.gov/WWE/wateruse/WVWaterPlan/Documents/WV_WRMP.pdf
- West Virginia Drinking Water Watch. (2019). Water system details. Retrieved from <http://129.71.204.189:1977/DWWpublic/index.jsp>
- Woodward, D. E. (2015). A look back at the Water Protection and Flood Prevention Act of 1954 (PI-566). In G. E. Moglen (Ed.), (pp. 160–168). Reston, VA. <http://doi.org/https://doi.org/10.1061/9780784479322.015>

- Young, R. A., & Loomis, J. B. (2014). *Determining the economic value of water: Concepts and methods* (2nd edition). New York, NY: RFF Press.
- Zaki, S., & Amin, A. T. M. N. (2009). Does basic services privatisation benefit the urban poor? Some evidence from water supply privatisation in Thailand. *Urban Studies*, 46(11), 2301–2327. <http://doi.org/10.1177/0042098009342902>
- Zetland, D., & Gasson, C. (2012). A global survey of urban water tariffs: Are they sustainable, efficient and fair? *International Journal of Water Resources Development*, 29(3), 327–342. <http://doi.org/10.1080/07900627.2012.721672>

4.9. Tables and Figures

Figure 4.1. Methods used to estimate the economic value of water

Table 4.1. PSDs and their reliance on NRCS water supply impoundments (directly or indirectly)

PSD	Total number of water supply sources available	Number of active water supply sources	NRCS's impoundment is the primary source?
Bluewell PSD	4	1	Yes
Clover PSD	2	2	Unknown*
Downs PSD	2	1	No
Green Valley-Gleenwood PSD	6	2	Yes
Hardy County PSD (Baker)	1	1	Yes
Huttonsville PSD	3	1	Yes
Leadsville PSD	1	1	Yes
Mannington PSD	1	1	No
Midland PSD	1	1	Yes
Preston County PSD No. 1	2	1	No
Southern Jackson County PSD	1	1	Yes
Walton PSD	1	1	Yes

Note: If the PSD has more than one system and they sell water to each other or obtain water from the same source, then this source was not counted in the total number.

* Clover PSD buys water from a municipality that utilize two water supply sources: NRCS dam and non-NRCS dam. It is unknown if the municipality sells water from one or both sources.

Source: WV Drinking Water Watch

Table 4.2. Box-Cox specification test results

			Number of obs = 105
			LR chi2 (18) = 59.010
Log likelihood = -382.338			Prob > χ^2 = 0.000
Cost	Coefficient	Std. Err.	P-value
theta	0.594	0.291	0.041
Test H0:	Restricted log likelihood	LR statistic χ^2	P-value
theta = -1	-398.078	31.480	0.000
theta = 0	-384.467	4.260	0.039
theta = 1	-383.294	1.910	0.167

Table 4.3. Summary statistics and variable descriptions

Variable	Description	Unit	Mean	Std. Dev.	Min	Max	Expected Sign
<i>Dependent variable</i>							
Cost	Water charge per 4,500 gallons to residential customers	\$	51.38	12.50	20.60	92.79	
<i>Independent variables</i>							
Raw water source variables							
NRCS	1 = if the PSD use NRCS's dam as a source of raw water, 0 = otherwise	0/1	0.11	0.31	0	1	-
Surface water	1 = if the PSD use surface water as the main source, 0 = otherwise	0/1	0.18	0.39	0	1	+
Groundwater	1 = if the PSD use groundwater as the main source, 0 = otherwise	0/1	0.13	0.33	0	1	-
Purchased	1 = if the PSD use purchased water as the main source, 0 = otherwise	0/1	0.54	0.5	0	1	+
Multiple	1 = if the PSD use multiple sources of raw water, 0 = otherwise	0/1	0.15	0.36	0	1	+
Number of sources	Numb of raw water sources available to the PSDs	Number	1.73	2.82	1	27	+
Financial and operation variables							
Rate type	1 = if the PSDs has constant rate, 0 = decreasing block rates	0/1	0.14	0.35	0	1	+
Sold water	Sold water per customer	1,000 Gallons	61.10	68.40	18.52	586.08	-
Debt	Debt per customer	\$	2,507.63	2,235.60	0	16,308.25	+
Treatment plant ownership	1 = if the PSD own treatment plant, 0 = otherwise	0/1	0.44	0.50	0	1	+
Treatment expenses	Water treatment expenses per customer	\$	42.21	61.88	0	250.73	+
Sewer service	1 = if the PSD provides sewer service, 0 = otherwise	0/1	0.34	0.48	0	1	+/-
Network length	Main line length per customer	Miles	0.06	0.03	0.01	0.17	+
Water loss	Percentage of unaccounted water loss	%	22.78	15.38	0	67.13	+
Violations	Total number of SDWA violations	Number	3.65	6.51	0	40	+
Breaks	Number of water main breaks	Number	13.79	18.68	0	106	+
Leaks	Number of leaks	Number	23.75	29.19	0	186	+
Demographic variables							
Population density	County's population density	Population/mi2	72.83	68.24	7.58	381.76	-

Observations = 111, for Rate type = 110, Breaks = 108, and Leaks = 105

Table 4.4. PSDs that use multiple raw water sources

PSD	Number of water sources
Berkeley County PSD	27
Bluewell PSD	4
Central Barbour PSD	2
Central Hampshire PSD	5
Clay Roane PSD	2
Flatwoods-Canoe Run PSD	2
Frankfort PSD	3
Hammond PSD	2
Hardy County PSD	4
Logan County PSD	4
Mason County PSD	8
McDowell County PSD	8
Nettie-Leivasy PSD	5
Oakland PSD	6
Pendleton County PSD	6
Pocahontas County PSD	3
Red Sulphur PSD	7

Table 4.5. OLS regression results: dependent variable is water charge per 4,500 gallons to residential customers

	(1)	(2)	(3)	(4)
NRCS	-0.6264 (2.6147)	0.0811 (2.6094)	0.3542 (2.6281)	0.7206 (2.4225)
Surface water	4.7138 (3.5049)	4.6895 (3.2438)	5.2789* (2.9869)	4.2617 (2.8829)
Purchased water	10.2371** (4.7908)	6.8656* (4.1277)	5.0764* (3.0241)	8.5523** (3.5077)
Multiple sources	14.8837*** (4.6454)	12.9710*** (4.2020)	14.1575*** (4.1454)	15.1023*** (4.3238)
Number of sources	-0.5951** (0.2820)	-0.6727** (0.3181)	-0.6768** (0.3118)	-0.7635** (0.2999)
Rate type	-2.9759 (3.0195)	-3.5639 (3.1576)	-2.9155 (3.0442)	-2.9710 (3.1153)
Sold water	-0.0254 (0.0158)	-0.0242 (0.0153)	-0.0236 (0.0148)	-0.0276* (0.0151)
Debt	0.0017*** (0.0004)	0.0017*** (0.0004)	0.0017*** (0.0004)	0.0018*** (0.0004)
Treatment plant ownership	3.3947 (4.0171)	1.8389 (3.5815)		1.8943 (3.2871)
Treatment expenses	-0.0206 (0.0268)	-0.0254 (0.0243)	-0.0269 (0.0228)	
Sewer service	-4.1377** (2.0087)	-4.5581** (1.9278)	-4.9768** (1.9163)	-5.1048*** (1.9142)
Network	142.3721*** (37.1783)	141.9174*** (36.5798)	139.3766*** (36.7070)	138.3515*** (34.0134)
Water loss	0.0190 (0.0897)	0.0685 (0.0819)	0.1035 (0.0737)	0.0882 (0.0746)
Violations	0.2536 (0.1998)	0.2356 (0.1859)		
Breaks	0.0352 (0.0577)			
Leaks	0.0021 (0.0309)			
Population density	-0.0093 (0.0167)	-0.0058 (0.0166)	-0.0070 (0.0160)	
Constant	33.3587*** (6.0067)	35.6017*** (5.6281)	37.4481*** (5.1140)	33.7163*** (4.9858)
Observations	104	110	110	110
R-squared	0.4584	0.4329	0.4204	0.4136
Adj R-squared	0.3513	0.3425	0.3411	0.3411

Robust standard errors in parentheses *** p<0.01, ** p<0.05,

* p<0.1

4.10. Appendix

Table 4.1A. NRCS water supply dams and water suppliers in West Virginia

Dam	Common Dam Name	County	City	Water Supplier	Notes
Brush Creek No. 19A	Kee Reservoir	Mercer	Edison	Bluefield Valley Waterworks (Operated by WVAWC)	
Brush Creek No. 14	Glenwood Park Lake or North Fork	Mercer	Glenwood Park	Green Valley-Glenwood PSD	This System Sells Raw Water To: (1) Bluewell PSD
Brush Creek No. 15	North Fork	Mercer	Princeton	Green Valley-Glenwood PSD	
Brush Creek No. 9	James P. Bailey Dam	Mercer	Stoney Gap	Green Valley-Glenwood PSD	
Charles Fork	Spencer Water Supply/Spring Creek No. 17	Roane	Spencer	City of Spencer Waterworks	This System Sells Raw Water To: (1) Clover PSD (2) Town of Reedy Waterworks
Elkwater Fork WS Dam		Randolph	Huttonsville	Elkins Municipal Water Department Beverly Water Department Mill Creek Municipal Water Department Huttonsville PSD	Mill Creek sells raw water to Huttonsville Water Dept Elkins Mun Water Dept sells raw water to: (1) Leadsville PSD (2) Midland PSD
Lost River No. 10 Dam		Hardy	Needmore	Hardy County PSD (Baker)	
Mill Creek No. 13	Tug Fork & O'Brien Lake	Jackson	Ripley	Ripley Municipal Water Department	This system sells raw water to: (1) Southern Jackson County PSD
New Creek No. 14 Dam	Keyser Water Supply Dam	Grant	Laurel Dale	City of Keyser Water Department	
North Fork Hughes River Site 21C Dam	North Fork of The Hughes	Ritchie	Cornwallis	Town of Harriville City of Pennsboro City of Ellenboro Town of Cairo	Hughes River Water Board is the wholesaler to these systems
Pocatalico No. 14	Silcott Fork Lake	Roane	Walton	Walton PSD	
Upper Buffalo No. 2	Huey Run Dam	Marion	Deep Valley	Mannington Municipal Water Department	This system sells water to: (1) Mannington PSD (2) Downs PSD
Upper Deckers No. 1		Preston	Arthurdale	Preston County PSD No. 1	
Upper Grave No. 1		Marshall	Cameron	City of Cameron	

Sources:

- (1) National Inventory of Dams (NID)
- (2) NRCS's Watershed Plans and Environmental Assessment Reports
- (3) NRCS's Dam Rehabilitation Reports
- (4) NRCS's Watershed Progress Report (1977)
- (5) Regional Planning and Development Council (RPDC) Water Source Protection Plans
- (6) WV Department of Health and Human Resources (DHHR) Source Water Assessment Reports
- (7) WV Drinking Water Watch

CHAPTER 5

Summary and Conclusions

This dissertation examines how changes in water quality and/or reliability affect health care expenditures, residential property values, and residential water charges.

5.1. Summary Results and Policy Implications

In the first essay, the impacts of drinking water quality violations on state level per capita health care expenditures are estimated using a proxy variable of the percentage of population served by public water systems that experienced violations of Safe Drinking Water Act (SDWA) health-based standards. A positive and statistically significant relationship is found between drinking water quality violations and state level per capita health care expenditures. Using spatial econometrics, there exists a large difference between the direct (in-state) and indirect (regional) effects of violations on health care expenditures. One possible explanation for this difference is that drinking water violations are indicative of broader water source contamination problems that cross state lines, such as extreme weather events. Such an explanation warrants a more coordinated regional approach across states when addressing water quality problems related to drinking water quality violations as is practiced by entities such as river basin commissions.

In the second essay, the impact of water supply unreliability is examined for single-family, residential property sales in Marion County, WV using spatial and non-spatial hedonic property price models. To measure the impact of water supply unreliability, four variables are defined based on issuance of boil water notices (BWNs) one year prior to the sale and link them to house sale transactions. There are statistically significant, negative impacts on house prices from prior issuances of BWNs. Depending upon the model and how unreliability is measured, BWNs can depreciate housing prices at the margin from 0.57% to 18%. Furthermore, by using a quantile regression approach, water supply unreliability is shown to have a larger impact on low-

price houses compared to high-price houses. These estimates indicate that some households in Marion County have a positive MWTP for a greater reliability in their water supply. Based on these estimates, the aggregate MWTP for a one-day reduction of the annual BWN in Marion County is calculated to be approximately \$4.60 million. This value may help to guide water systems in their decisions regarding water pricing and investments in the water distribution network. In addition, since an unreliable water supply has a negative impact on property valuation and therefore property tax revenues collected by the county. Thus, these estimates can help inform water infrastructure investments at the local government level.

In the third essay, the impact of the different water supply sources is examined on public service districts (PSDs) residential water charges per 4,500 gallons in West Virginia. PSDs typically obtain their raw water supply from four main (conventional) sources: surface water, groundwater, water purchased wholesale from nearby water system, or a combination of two or more of these sources. However, due to drought or pollution, alternative sources sometimes are used such as flood control impoundments constructed by the NRCS. The results indicate that when a PSD uses multiple raw water supply sources, its residential water charges is about 20% higher of the average PSDs residential water charges in West Virginia. Also, similar to previous research, groundwater is the least expensive raw water supply source that PSDs can use. Finally, no statistically significant impact of NRCS's flood control impoundments is found on residential water charges per 4,500 gallons. Based on these results, if policymakers make it mandatory for public water systems to have more than one water supply, then the resulting increases in residential water charges may lead to affordability problems across the state.

5.2. Limitations and Future Research

Limitations in the first essay relate primarily to the data that are used. First, using an aggregated data at the state level may average out the effects at the local level where drinking water quality violations are occurring, therefore resulting in biased estimates. Second, sometimes people get exposed to contaminants in drinking water multiple times a year. However, our analysis does not account for this. Therefore, including some kind of an intensity treatment in the analysis may result in different conclusions. Third, our data only covers public water systems, thereby excluding about 45 million people who use private wells for their drinking water and thus are not regulated under the SDWA. Considering this population in future research would expand results to consider the implications of drinking water violations to more rural areas.

Fourth, the proxy variable that we used to reflect exposure to drinking water contamination also has its flaws. These data include multiple types of contaminants that affect human health differently (i.e. short- and long-run health impacts). However, we did not include a lag system for population exposure to drinking water violations in our model to account for a range of temporal health impacts from contaminant exposures.

Finally, water systems have financial incentives not to comply with all the U.S. EPA regulations due to the higher costs that it will impose on these systems. Therefore, there is a higher probability that false or missing data are being reported. For example, the agency estimated that states were not reporting 40% of all health-based violations. Employing these changes in the drinking water quality variable may yield different results from our current models.

For the second essay, the area of study is a relatively small geographical area. Also, due to missing data we had to drop a relatively large number of BWNs (90) from our analysis. In addition, when allocating BWNs to house sale observations, most BWNs affect one or multiple

streets in addition to surrounding areas. Due to limited knowledge, I was unable to include those surrounding areas in our analysis. Therefore, not all of the house sale transactions affected by BWN were included in this analysis so that the monetary estimates of BWN impacts should be regarded as conservative.

Finally, limitations in the third essay relate primarily to the small sample size used in the analysis. Future endeavors can expand this research by examining the impact of water supply sources on municipalities' water charges across the United States. Alternatively, since West Virginia is a water rich state, focusing on areas with scarce water resources, such as areas in western U.S., may yield different results.