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BY

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Estimating water demand using price differences of wastewater services

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Many homes in Hawaiʻi use cesspools and other on-site disposal systems (OSDS) instead of the municipal sewer system. Because bills combine water and waste-water services, and homes with OSDS do not pay for sewer service, OSDS residences have lower monthly bills compared to those with sewer-connected systems. We use this price difference in conjunction with selection on observables and matching methods to estimate the price elasticity of residential water demand. Matching methods indicate that OSDS residences have systematically different characteristics than those with sewer-connected systems, suggesting an imperfect natural experiment. We show traditional methods lead to biased elasticity estimates, even though they are robust when selecting on observables using OLS with or without census tract fixed effects, census block fixed effects, and non-parametric controls trained using cross-validation and a lasso. We then estimate demand using a limited sample of OSDS homes that have sewer-connected neighbors, which gives estimates from -0.06 to -0.08. The neighbors have no systematic differences in other characteristics and estimates are robust to further selection on observables, but the sample differs slightly from population means in their physical characteristics. These more defensible demand elasticity estimates, however, are much more inelastic than estimates not based on comparison of neighbors and are generally more inelastic than previous studies. Taken collectively, the results highlight the susceptibility of demand estimates to omitted variable bias. Highly inelastic water demand suggests that considerably higher prices may be needed for sustainable water management, creating some practical challenges under current regulatory guidance. We also use our results to estimate willingness to accept a tax credit for upgrading an OSDS system, a targeted policy that aims to improve water quality. Regardless of whether consumers respond to average or marginal prices, our estimates imply that the tax credit is far too small to induce voluntary participation in the program. Additional consumer welfare topics are also considered.

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1 Introduction

Growing concern about the effects of climate change and other factors impacting water availability make it more critical than ever to gain an improved understanding of water demand and how policies can better manage it. In addition to household characteristics and demographics (Balling, Gober, and Jones 2008; Chang, Parandvash, and Shandas 2010), water consumers have been shown to be sensitive to weather and climate (Balling, Gober, and Jones 2008; Mansur and S. M. Olmstead 2012; Larson et al. 2013; Breyer and Chang 2014; Lott et al. 2014). Climate change is already negatively impacting certain areas of the country like the southwest and California, where water use curtailment policies are needed as a result of shifts in the distributions of temperature and precipitation (Hanemann, Lambe, and Farber 2012). Policies that have proven effective in conserving water include non-price water use curtailment strategies, such as command-and-control measures and campaigns that persuade consumers to voluntarily alter their behavior (Gober and Kirkwood 2010; Mansur and S. M. Olmstead 2012). Other systems face growing scarcity and are ill-prepared for climate change, so a fundamental reworking of the way they are operated will be needed to adapt (Joyce et al. 2011).

Some economists argue that a market-based approach where water use is managed by adjusting prices in accordance with its scarcity would be more efficient than command-and-control policies and water conservation campaigns. A problem with many current pricing regimes is that municipalities typically do not account for the scarcity value of water when determining water price schedules (S. M. Olmstead 2010; Bell and Griffin 2011; Mansur and S. M. Olmstead 2012). Instead, municipalities are typically required under statute to recover tangible costs of delivering water, which may derive from a public source. This is the case in our study area, the Hawaiian island of Oʻahu. S. M. Olmstead, Fisher-Vanden, and Rimsaite (2016) go further to suggest that many managers aim more to maintain affordability for users than trying to recover the full opportunity cost of the resource, which may result in the need for difficult changes in resource use and suggests the need for a better understanding of how the current barriers leading to inefficient pricing can be overcome.

Since accounting for scarcity value would imply an increase in the price charged to consumers, the resulting short-term welfare loss could be difficult to sell politically. However, the price-driven measures would have considerable benefits, including reduced frequency of acute shortages requiring mandatory cutbacks, more sustainable water-conserving investments and development, like drip irrigation and xeriscaping, and better allocative efficiency, such that the highest value uses of water are always served first. There would also be surplus revenue that could be used to serve other public goods and, compared to command-and-control measures, there are reduced costs of monitoring and enforcement (S. Olmstead and R. Stavins n.d.). A price-based conservation policy is essentially costless from an enforcement perspective once it's enacted, relative to non-price programs like temporary bans on lawn irrigation, which are inherently more difficult to police.

Knowledge about the nature and structure of demand helps us to determine efficient pricing, including the prices needed for sustainable use. It also aids evaluation of non-price allocation mechanisms. Previous studies have found residential water demand to be generally inelastic. A literature review by Dalhuisen et al.(Dalhuisen et al. 2003) of 64 studies with 296 elasticity estimates published between 1963 and 2001 found that the mean and median price elasticity of water demand for residential homes is -0.41 and -0.35, respectively, with a standard deviation of 0.86. According to the authors, the variation in the estimates results from the various analysis methods used, different pricing schedules (flat, increasing block, decreasing block) of the utilities, household and consumer characteristics, and using aggregate versus household-level data. This meta-analysis finds elasticities that are slightly more inelastic than an earlier meta-analysis by M. Espey, J. Espey, and Shaw (1997), which finds a mean price elasticity of -0.51 using 124 elasticity estimates from 24 articles published between 1963 and 2001. Meta analyses, however, cannot account for the strength of the study design. Confounding and omitted variables biases are likely pervasive. As an example of how model choice matters, a study by Nieswiadomy and Molina (1989) arrives at an estimate of -0.55. Hewitt and Hanemann (1995), using the same data, use another approach and estimate an elasticity of -1.6. More recent studies that use better quasi-experimental designs have found demand to be less elastic (S. M. Olmstead, Hanemann, and R. N. Stavins 2007; S. Olmstead and R. Stavins n.d.; Lott et al. 2014; Mansur and S. M. Olmstead 2012; Klaiber et al. 2014; Ghavidelfar, Shamseldin, and Melville 2016). However, due to reasons we discuss in the next section, even recent studies may suffer from poor identification and other difficulties.

In this study, we use a unique neighbor matching technique to estimate the price elasticity of water demand for single family homes using household level data from O‘ahu. By matching neighbors who face different pricing structures due to their sewage disposal type, but otherwise have similar characteristics, we estimate demand to be highly inelastic at -0.06 to -0.08. These results are shown to be unbiased and robust, and we compare them to other traditional methods that produce robust, yet biased, estimates. The elasticity estimates are then applied to a consumer surplus scenario specific to Hawai‘i, where the local government is offering a tax credit to homes who upgrade their sewage systems to more expensive alternatives in an attempt to improve water quality in the state. We show the current tax credit is insufficient to cover the net present value of upgrading the systems, considering installation costs and the long-term welfare implications of higher water prices resulting from the upgrades. Also discussed are broader topics of consumer welfare in the context of the water management regime, and related price adjustment scenarios.

The rest of the paper is organized as follows: in section (2) we further discuss the context of our study and describe in more detail the water quality issues in Hawai‘i. Section (3) provides an overview of the data used in our analyses. Section (4) discusses the empirical strategies we implement to estimate residential price elasticity of water demand. The results are provided in section (5), and a discussion of the elasticity measurements and its application to water quality and climate issues, along with consumer welfare, is provided in section (6).

2 Context and Study Design

The methods used to estimate demand in many earlier studies often suffer from one or more shortcomings identified by Nataraj and Hanemann (2011):

1. Most studies obtain variation in price by comparing a cross section of two or more cities, or one city over time. A cross sectional study of many different cities may be omitting unobserved city-specific characteristics. On the other hand, estimating an elasticity using data from one city over time may fail to control for variables that are potentially correlated with price, such as weather effects. There is little focus on truly exogenous, random, or as-if random, changes or differences in water prices.

2. The complexity of block pricing schedules often used to estimate elasticity poses another problem. As mentioned later, there is disagreement in the literature about the importance of price salience and whether consumers respond to average or marginal price, which complicates or confounds elasticity calculations. Customers' elasticities and how they are calculated depend on information availability, along with how the bill is presented to the customer. Some studies choose to use average price (Billings 1990; Hogarty and Mackay 1975), while others use marginal price (Danielson 1979; Lyman 1992). Some include both (Opaluch 1982; Opaluch 1984; Martin and Wilder 1992), or use a combination of the two to create a "perceived price" for their analyses (Shin 1985; Nieswiadomy 1992).

We address these issues by identifying the price elasticity of residential water demand using a new quasi-natural experiment. According to the Environmental Protection Agency, Hawai'i has more cesspools than any other US state.[1] Homes with cesspools comprise about 75% of all homes with on-site sewage disposal systems (OSDS). Other OSDS systems include aerobic and septic systems. While most homes on O'ahu are billed for fresh water by the Honolulu Board of Water Supply, only those connected to the municipal sewer are charged a sewer service fee. Thus, the Honolulu Board of Water Supply has two groups of single-family water customers. One group has an on-site system for sewage disposal, and only pays for clean water delivered to the home. The other group is connected to the municipal sewer system and is buying a joint product: water service and sewer service, where the amount of sewer service received is determined only by the amount of water consumed.

Table (1) shows the current pricing schedule faced by homes with and without sewer service. All single family residential homes are charged according to an increasing block price structure plus a fixed monthly fee of \$9.26. However, as shown in figure (1), only 18% of households consume

[1] https://www.epa.gov/uic/cesspools-hawaii

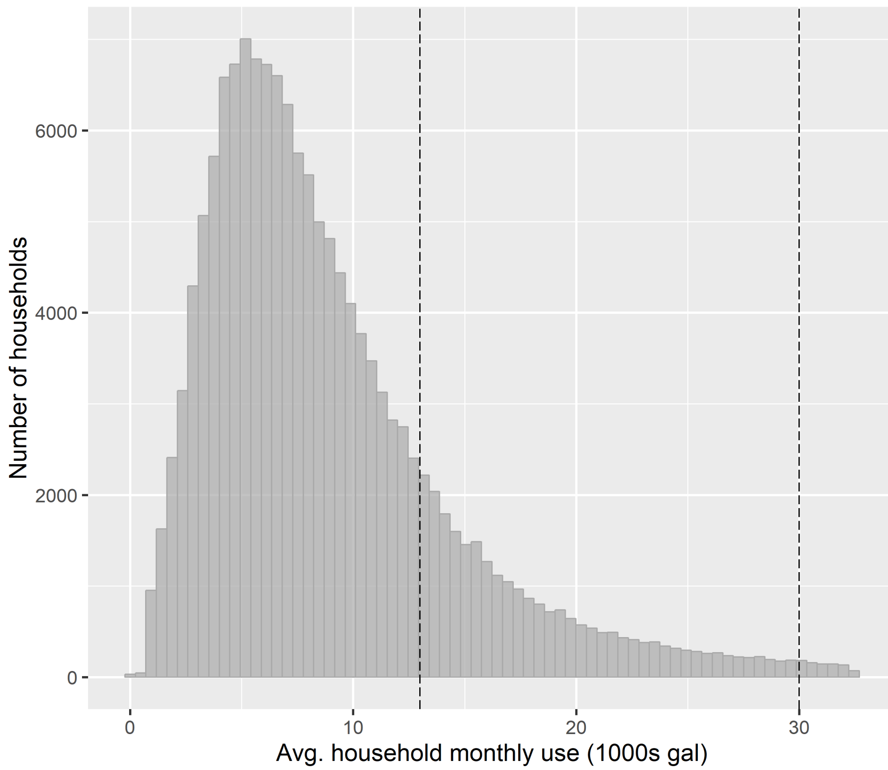


Figure 1: Histogram of household average monthly consumption. The vertical line at 13,000 gallons indicates the first block in the pricing structure. 18% of households have average monthly use at or greater than this cutoff. The third block starts at 30,000 gallons, which is only consistently applied to about 0.5% of homes in the sample period. The median consumption is 7500 gallons per month, and the mean is 8900 gallons per month.

enough water to consistently place them in the second block, and only 0.5% use enough to place them in the third block. The majority of consumers remain within the first block and face a constant volumetric charge of $4.42 per 1000 gallons. A consumer switching from a cesspool to sewer service will experience an increase in fixed cost of $77.55, and a volumetric increase of $4.63 per 1000 gallons. The fixed cost of the sewer service "represents [the] fixed cost associated with operating and maintaining the municipal sewer system," and the volumetric charge "represents [the] variable cost of transporting and treating the wastewater." For homes without a sub-meter that measures water used for irrigation, the volume charged for sewer is reduced by 20%.[2]

Unlike some previous studies, which may rely on relatively small differences in price due to block cutoffs, policy changes, and the like, differences between bills for residences with sewer-connections and those with OSDS systems are substantial. If a household with an OSDS system connects to the sewer, their monthly fixed charge increases by $77.55 and the marginal volumetric charge more than doubles. This situation, where similar consumers face markedly different price schedules,

[2]https://www.boardofwatersupply.com/bws/media/images/about-your-bill-env-2019.jpg

Table 1: Monthly residential water use charges. All water service customers are charged a fixed fee of \$9.26 per month, and a volumetric charge based on the given increasing block price structure. The sewer service fee is in addition to the water service fee for applicable customers.

	Water Service			*Sewer Service*
	Block I	*Block II*	*Block III*	
	$\leq 13,000$ gal/mo	$13,001 - 30,000$ gal/mo	$> 30,000$ gal/mo	
Fixed Cost	\$9.26	—	—	**\$77.55**
Charge per 1000 gal	\$4.42	\$5.33	\$7.94	\$4.63

provides a unique opportunity to study water demand. Not only is the price difference significant between the two groups, but the groups are also contained under one utility in the same small geographic location. Although this comparison does not constitute a perfect natural experiment—OSDS systems are not randomly assigned across residences—we use different methods for finding suitable controls for residences with OSDS systems, some of which are more compelling than others. As we show below, the most compelling natural experiment comes from comparing OSDS homes with immediate neighbors that are connected to the sewer.

We use several methods to estimate the price elasticity of residential water demand to highlight the importance of careful model selection while maintaining interpretability. First, we use OLS to control for observable differences between OSDS and sewer-connected homes, with or without census tract fixed effects, and non-parametric controls trained using cross-validation and a lasso. Using these methods robust results similar to those found in the existing literature are obtained: estimated elasticities range from -0.03 to -0.34 depending on the method used. However, these results could mask the bias due to unobservable differences between OSDS and sewer-connected residences or, in the case of lasso, produce unintuitive results that are difficult to interpret. Even with local fixed effects, we find observable characteristics are unbalanced between the two types of homes. We show this bias persists even after using generalized boosted regression and a propensity score matching technique in an attempt to balance the data. Balance between the two groups is only achieved when we reduce the sample to direct neighbors that vary by sewage disposal type. With this method we estimate robust, unbiased elasticities in the range of -0.06 to -0.08, which is on the lower end of our previous estimates. However, the estimates lose some statistical significance.

In addition to our primary goal of estimating elasticity and its uses in water conservation under climate change, we use the estimates to evaluate a current effort by the local government to phase out cesspools in the state. Following evidence that cesspools contribute significantly to coastal water pollution, Hawai‘i has recently become the last state to outlaw new cesspools[3]. A study by the Hawai‘i Department of Health estimates that existing cesspools release about 53 million gallons

[3] `https://www.civilbeat.org/2016/03/hawaii-bans-new-cesspools/`

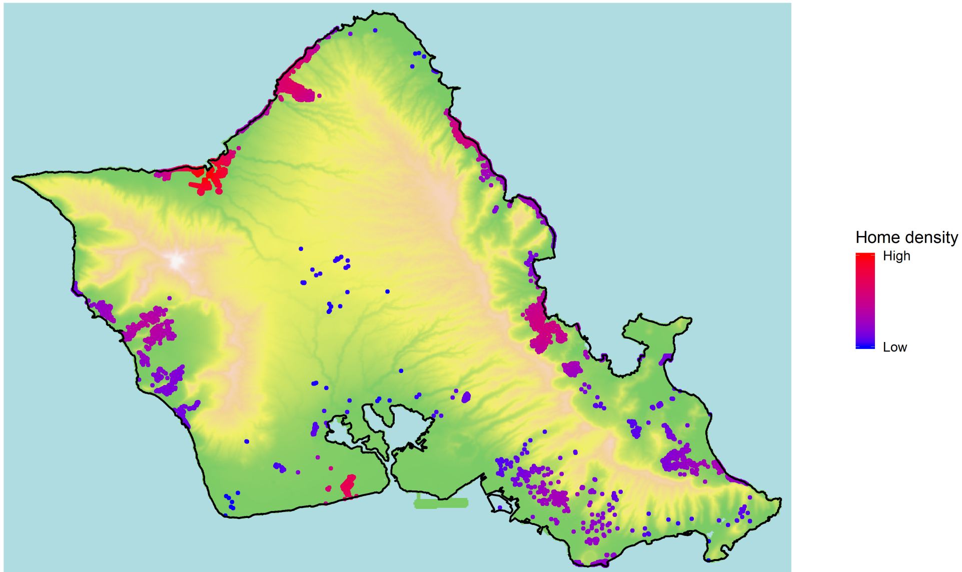


Figure 2: Locations of homes on the Hawaiian island of Oʻahu with other than sewer service. Approximately 75% of these homes have cesspools. Point color indicates density of homes.

of raw sewage into the ground statewide each day[4]. As shown in figure (2), many of these homes are located in coastal areas and the leaking waste is negatively affecting ground and nearshore water quality (Amato et al. 2016; Fackrell et al. 2016).

Current efforts by the local government are underway to reduce the pollution from cesspool leakage. In addition to the ban on new cesspools, a program has been made available to provide a $10,000 tax credit to qualifying households that replace their existing cesspools with modern systems like a septic tank or a sewer connection[5]. Septic tanks, which differ from cesspools in that the wastewater must pass through a leach field that filters the water, may be less expensive than a sewer connection and may therefore be preferred by customers looking to upgrade their systems. This connection is still expensive, however, and the cost must still be paid up front by the customer with the tax credit applying later. It is thus unclear whether the $10,000 tax credit is enough to incentivize customers to voluntarily upgrade their systems. Further, for those who wish to connect to the sewer system (the cleanest, most environmentally-friendly wastewater disposal option), it is quite clear the offered tax credit falls far short of covering the costs associated not only with the initial sewer connection, but also the net present value of an increased water bill as described above. In many cases, connecting to the sewer may otherwise be impossible due to the location of the home

[4] `http://health.hawaii.gov/wastewater/cesspools/`

[5] There are 2064 homes (23% of all homes with cesspools) on O'ahu that potentially qualify for this credit. To qualify, a cesspool has to be within 200 feet of a shoreline, perennial stream, wetland, or within a source water assessment program area such that the duration of time of travel from cesspool to a public drinking water source is less than two years. `http://health.Hawaii.gov/wastewater/home/taxcredit/`

relative to existing sewer lines.

Exactly how much consumer surplus would be lost for a household switching from OSDS to sewer depends on the elasticity of demand. Additionally the rationality of the consumers is likely bounded, whether from indifference, ignorance, or poor information communication by the utility. While economic theory tells us rational consumers will make consumption decisions based on marginal price, it is unclear in many cases whether consumers actually respond to marginal or average price. Previous studies have found different results on this topic. Several studies suggest consumers tend to base consumption decisions on average price (Shin 1985; Worthington, Higgs, and Hoffmann 2009; Ito 2014; Wichman 2014). If this is true in the case of water consumption on O'ahu, it may have significant consumer welfare implications given the steep fixed price incurred by sewer service customers. If they were to base decisions on average price, this large fixed cost may cause them to consume a lesser quantity of water than the utility-maximizing amount. The current distribution of household water use on the island seems to suggest this may be the case, since a response to marginal price would be evident by consumption bunching at the pricing blocks. Figure (1) shows this bunching does not exist, suggesting consumers are instead responding to average price. However, there is a literature with results suggesting some customers may react only to marginal price (Howe and Linaweaver Jr 1967; Nataraj and Hanemann 2011). Those that do respond to marginal price in this study tended to be large users with higher incomes. This makes sense, since high-income consumers using large amounts of water are more likely to have larger discretionary uses, as mentioned above. In light of these contradictory findings we consider both cases for our welfare analysis and, by comparing the consumption behavior of the two groups, it is possible to determine how much sewer customers are under-consuming if we assume they are responding to average price. Overall, our results indicate there is little difference in welfare loss between the two cases. The loss in consumer surplus from switching from cesspool to sewer service remains much more significant.

3 Data

Billing data for 140,646 single family homes on O'ahu were obtained from the Honolulu Board of Water Supply. It contains monthly data between June 2011 and March 2016. Characteristics of these homes, such as year built, effective year built[6], assessed value, and square footage, are provided for each home by the Honolulu Real Property Assessment Division, and information regarding the sewer, cesspool, and septic tank connections of these homes is from the Department of Health. A small neighborhood with a separate sewer service provider, American Hawaii Water, is charged according to a different pricing structure and were thus removed from the analysis.

[6]Many older homes have been renovated, effectively decreasing the age of the home. To account for this, the "effective" year built is provided by the Honolulu Real Property Assessment Division.

Table 2: Summary of home characteristics by wastewater disposal type. In the data, there are 131,519 homes with sewer service, and 9127 with OSDS. Of the homes with OSDS, 7044 have cesspools. The t-tests suggest the difference between means of the characteristics for the two groups is significantly different from 0, and using Kolmogorov–Smirnov tests suggest the distributions are not similar.

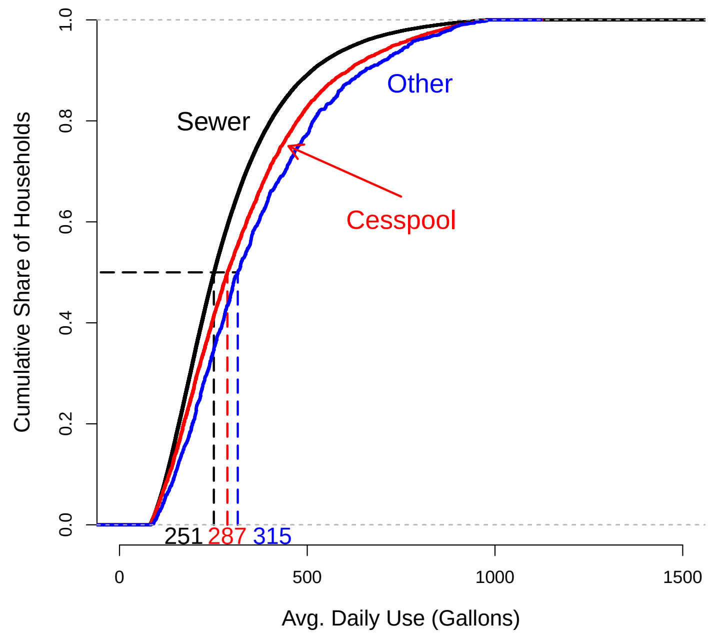
Characteristic	Median		Mean		t-statistic	D-statistic
	Sewer	OSDS	Sewer	OSDS		
Year built	1970	1970	1973	1968	19.9***	0.14***
Effective year built	1975	1972	1977	1974	11.7***	0.10***
Home size (sq. ft.)	1656	1484	1837	1735	7.3***	0.14***
Home value ($1000s)	667	614	751	808	−6.5***	0.14***
Yard size (sq. ft.)	4517	6180	5486	9938	−19.5***	0.25***
Num. bedrooms	4.0	3.0	3.8	3.5	26.6***	0.09***
Num. bathrooms	2.0	2.0	2.2	2.0	13.4***	0.14***

*p<0.1; **p<0.05; ***p<0.01

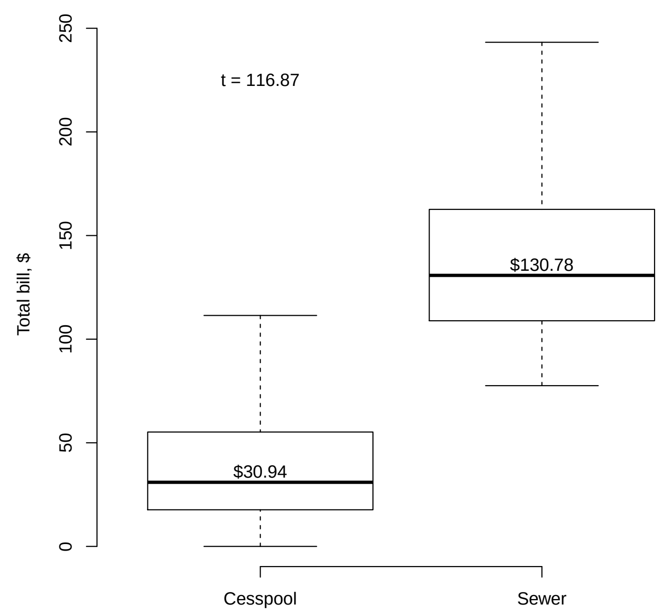
Table (2) summarizes select physical characteristics of the homes. Of the homes 9127, or about 6.5%, are characterized as having other than a municipal sewer connection. Approximately 75% of these are cesspools. For each characteristic, t-tests were performed to determine whether the means of the characteristics differed between the two groups. These tests suggest the means are significantly different between the two groups. Kolmogorov-Smirnov tests were also performed to test whether the distributions of the characteristics differed between homes with OSDS and homes with sewer connections. The reported D-statistic simply measures the maximum distance between the two groups' empirical cumulative distribution functions in absolute terms, so larger numbers indicate distributions that are less similar. For each characteristic, the tests suggest the distributions are significantly different from one another. This means homes with OSDS are not entirely similar to homes with sewer connections; in experimental terms, the treatment and control groups are not randomly assigned. We discuss the significance this difference in distributions has in more detail in the empirical strategy section below.

For water use, we aggregate consumption across all billing periods for each home. From this we find the average daily consumption of each home, and examine the basic water use patterns among homes with different wastewater disposal types. Figure (3(a)) shows the empirical CDF of average daily water use for homes with and without sewer connections. A basic calculation using only the raw billing data shows that homes with cesspools consume about 14% more water than homes with sewer connections. Performing a Kolmogorov-Smirnov test between the distributions of water use for homes with sewer connections and homes with OSDS (cesspools and "other" combined) yields a D-statistic of 0.15 that is significant at the 99% level, suggesting the distributions of water use between the two groups is significantly different. Using the billing data and the Board of Water Supply price schedule in table (1), we can also calculate the amount charged to each customer in a billing period. As expected, figure (3(b)) shows that the monthly bills of consumers with sewer service are typically much larger than homes with cesspools due to the increased fixed and variable costs.

One characteristic of the distribution of homes on O‘ahu is that many areas have homes with cesspools interspersed among homes with sewer service. For example, consider the Black Point and Tantalus neighborhoods in figure (4). In panels (a) and (c), the color of the home indicates the type of wastewater disposal. In many cases, homes with cesspools are located closely to homes with sewer service in the same neighborhood. Panels (b) and (d) show us that households with cesspools tend to consume more water than homes with sewer service. One method we attempt to use in order to estimate consumer sensitivity to price is matching homes that are close to one another but differ by wastewater disposal type. However, this method may not be suitable since the type of wastewater disposal system a home has is not entirely randomly assigned. This is evidenced by the lack of balance between the two groups shown in table (2). The t-tests suggest the means of the characteristics of the homes are significantly different between the two groups, and the D-statistics show the distributions themselves are not the same. We also see from the figure that homes with OSDS in both neighborhoods tend to have more land, as evidenced by the large areas surrounding the points. In Black Point, all homes on the coast, which we expect to have a higher value, exclusively have OSDS. We discuss in the next section how several empirical approaches typically used to estimate elasticity may produce biased results if factors such as these are not accounted for.

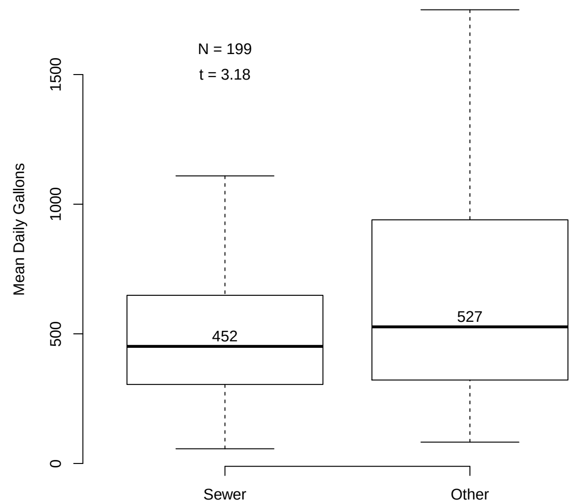


(a) Empirical cumulative distribution functions of water use by wastewater disposal type. Households with sewers typically consume the least water, with a median of 251 gallons per day. Those with cesspools consume more, with a median of 287 gallons per day. Households classified as "other", which contains aerobic and anaerobic septic tanks, among others, consume the most with a median of 315 gallons per day.



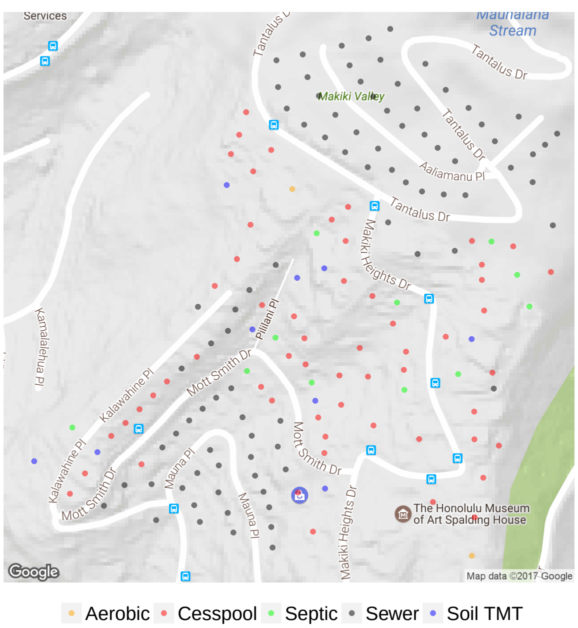
(b) Monthly water bills by wastewater disposal type. Due to the large increase in both the fixed and variable costs of sewer service, households with sewer service pay a median of \$130.78 per month on their total water bill, compared to a median of \$30.94 for households with cesspools. Water bills were calculated manually using the BWS pricing schedule.

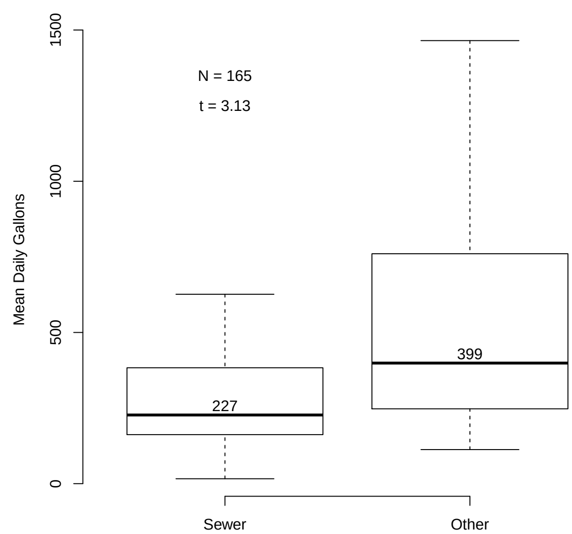
Figure 3: Simple comparison of wastewater disposal groups.



(a) Locations of Black Point homes of various sewage types. Many of these homes, particularly those along the coast, are very large (median 2761 sq. ft., compared to the Oʻahu median of 1638 sq. ft.) and have other characteristics not typical of a home on Oʻahu, such as being on the coast. Note that all the coastal homes have OSDS.

(b) Average daily water use of Black Point homes in gallons. Of the 199 homes on Black Point, those with sewer connections consume a median 452 gallons per day, and those with cesspools 527 gallons per day.





(c) Locations of Tantalus homes of various sewage types. These homes are also quite large (median 2756 sq. ft.), and we see homes with OSDS tend to have more surrounding property than those with sewer connections.

(d) Average daily water use of Tantalus homes in gallons. Of the 165 homes, those with sewer connections consume a median 227 gallons per day, and those with cesspools 399 gallons per day.

Figure 4: Examples of neighborhoods with mixed sewage disposal types.

4 Empirical strategy

Often, we face a tradeoff between models that are easy to interpret and those that produce robust, unbiased results. For example, a simple linear OLS model is very easy to interpret, but may not accurately reflect relationships in the data. Alternately, more advanced methods like modern machine learning techniques tend to produce unbiased and robust results, but are complex and lack interpretability. For our study, in order to estimate an unbiased price elasticity of residential water demand, we must account for the imbalance between the characteristics of homes with sewer connections and homes with on-site sewage disposal systems. Our goal is to do this in a way that retains the intuitive nature of linear regression while having the robustness of more advanced techniques. We first demonstrate the methods that produce robust, sensible results, but hide the bias or are difficult to interpret. These methods include simple OLS, lasso regression, and propensity score-boosted regression models. Then, we show that accounting for the differences between the two groups of homes, using an application of the nearest neighbor matching technique, produces a robust elasticity estimate that produces an unbiased result while also being intuitive and easy and interpret.

The first method we attempt to use to estimate elasticity is traditional OLS. The model takes the form

$$\log(w_i) = \alpha_0 + \alpha_1 S_i + \boldsymbol{\beta} \boldsymbol{X}_i + \varepsilon_i, \tag{1}$$

where w_i is the average monthly water use of household i, S is the sewage type dummy variable, and X is a vector of household characteristics. These characteristics include the physical characteristics from table (2) above, along with other controls for climate and household demographics. To control for other unobserved demographic characteristics of the households, a model with census block and census tract dummy variables was also tested. In this log-linear model the coefficient of interest, α_1, then tells us the relative water use between homes with sewer and homes with OSDS. We can then take the characteristics of a median home to calculate $\widehat{\log w_i}$ for homes with and without OSDS. Using the pricing schedule in table (1) and these estimated quantities, we can finally arrive at an estimate for price elasticity of demand[7].

We then try nonlinear regression using splines as a more robust method to estimate price elasticity controlling for household location and characteristics. With the log of water use as the dependent variable, B-splines were created for each continuous control variable. With these splines, each pos-

[7]The elasticity is calculated using predicted water use for a median home. As was found with most homes in the data, these predicted values remain within the first block of the rate schedule in table (1), simplifying the elasticity calculation.

sible combination of interactions between them were also created, resulting in approximately 60 splines tested in our model. Additional home characteristics that were included as linear terms were the number of bedrooms and the number of bathrooms in the home. The explanatory variable of interest, whether or not the home has a sewer connection or an OSDS, is included in the regression as a dummy variable. The model takes the general form

$$\log(w_i) = \alpha_0 + \alpha_1 S_i + \boldsymbol{\beta} \begin{bmatrix} b(X_1) \\ \vdots \\ b(X_n) \end{bmatrix} + \varepsilon_i, \tag{2}$$

where the vector $[b(X_1) \cdots b(X_n)]^{\mathrm{T}}$ contains B-splines of home characteristics (and their interactions) X which were chosen through a LASSO cross validation process.

The model with the best out-of-sample predictions is selected using lasso with cross-validation at the ahupuaʻa level. Ahupuaʻa are traditional Hawaiian subdivisions of land that typically run from the coast to the mountains. Figure 5 shows a map of ahupuaʻa within the major districts of Oʻahu. There are 64 ahupuaʻa on the island with single family homes. Given the geography and development patterns of the island, these land divisions span a wide range of microclimates and home characteristics and vintages (figure (6)). Adding ahupuaʻa fixed effects to our models allows us to control for unobserved characteristics unique to these neighborhood-like divisions. Using the results from this model, we find the median predicted water use for homes with and without an OSDS. Again, the price charged to the homes can be calculated using the water and sewer rates from BWS. These quantity and price values are combined to estimate the price elasticity of residential water demand.

The final traditional technique we show is propensity score matching with generalized boosted regression. Whether or not the household has an OSDS is used as treatment. Generalized boosted regression, a machine learning technique, is used for model selection and estimating the propensity scores. Covariates are the same used in the regression models. The resulting treatment effect is used to estimate a price elasticity in a similar manner to the regression techniques.

The results of the regression and propensity score techniques are then compared to those of a one-to-one nearest neighbor matching method. The difficulty encountered with the previous techniques is that the two groups of homes are not balanced; even the propensity score matching method used was unable to effectively account for the differences in characteristics between homes with OSDS and those with sewer connections. As already noted before, homes with OSDS are often grouped with one another, and have no suitable matches to homes with sewer connections. However, in

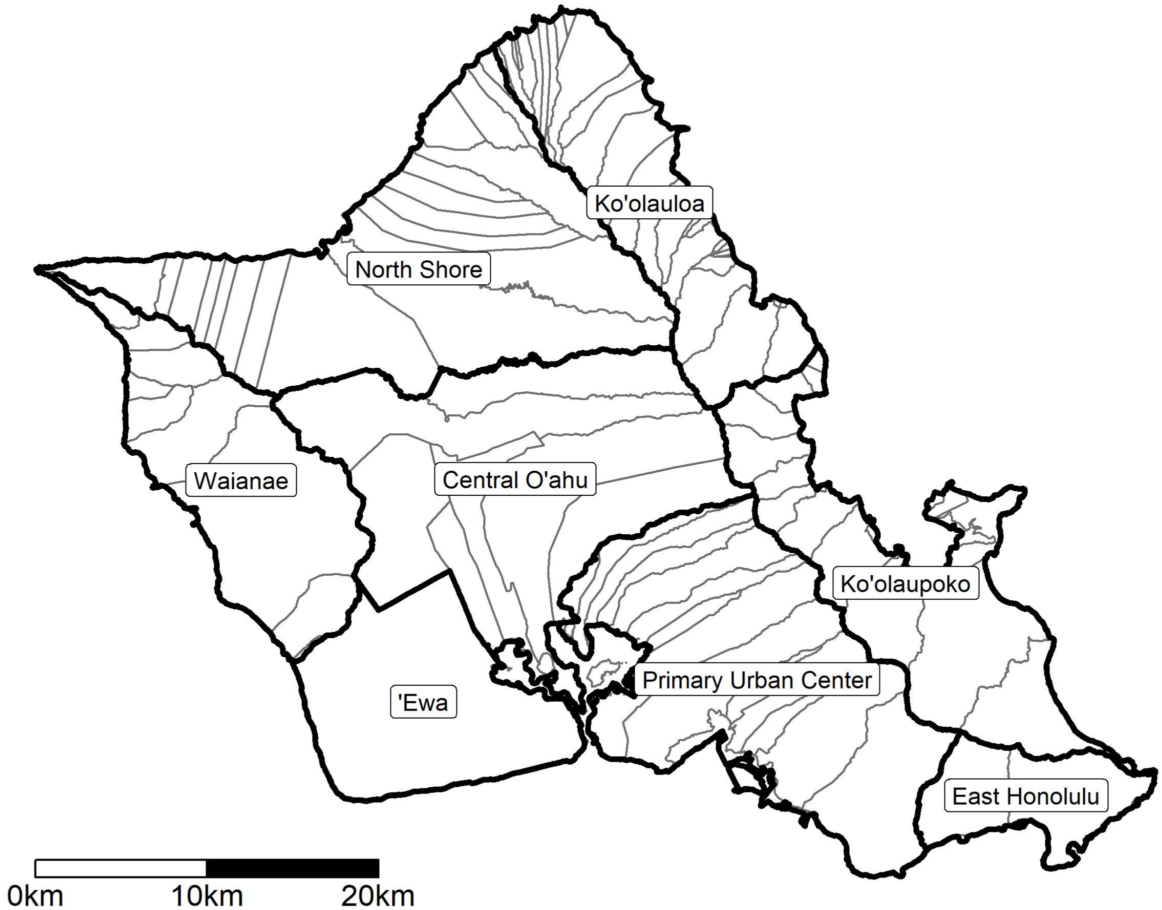
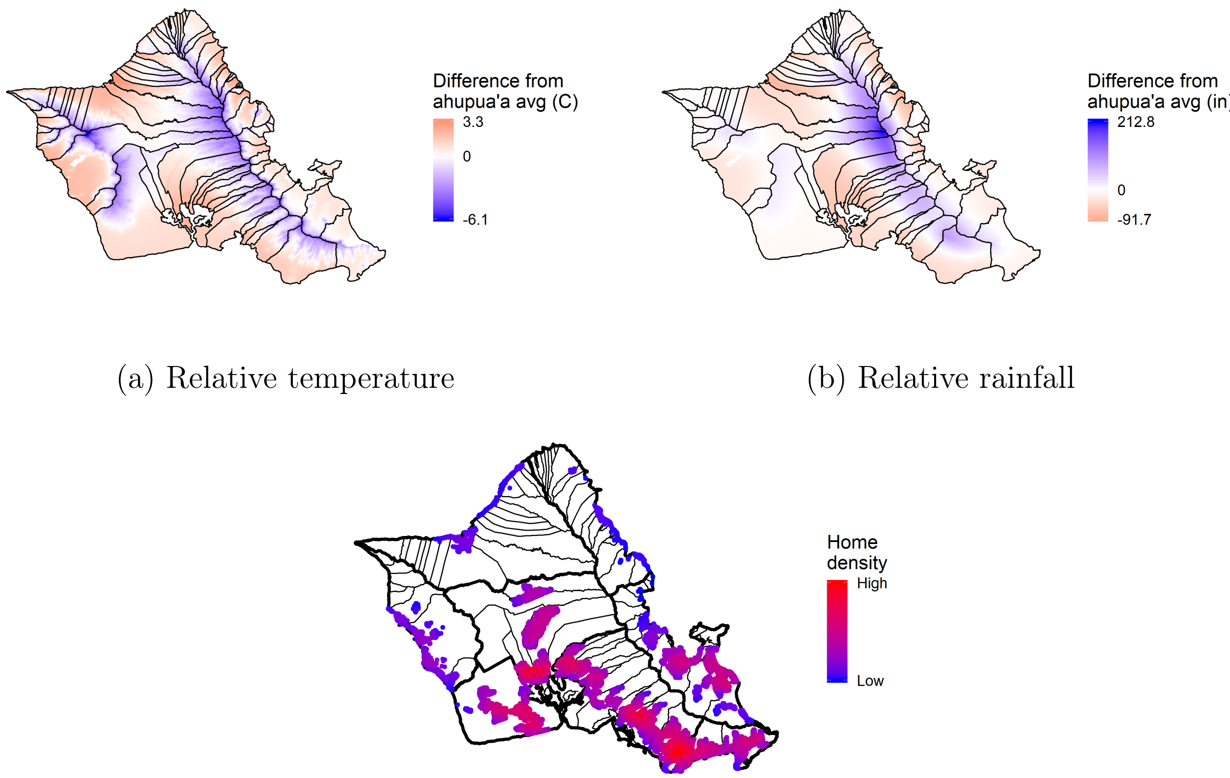


Figure 5: A map of ahupuaʻa within Oʻahu's major districts.



(a) Relative temperature

(b) Relative rainfall

(c) SFD locations

Figure 6: Ahupuaʻa characteristics. Maps show the relative temperature and rainfall within ahupuaʻa, and the locations and density of single family homes. Generally, higher elevation areas are relatively cool and wet. Homes can be seen to span across a wide variety of these microclimates, even within a small geographic area.

some cases, there are homes with OSDS that have direct neighbors with sewer connections. This was clearly seen in figure (4), where homes were largely grouped by sewage disposal type, but there are several cases where direct neighbors had different sewage disposal systems. We thus restrict our matching method only to homes that are direct neighbors, but differ by the type of sewage disposal system. Ties (cases where a home with OSDS has more than one neighbor with a sewer connection) are broken by matching to the home with the closest yard size, which was chosen since it created the best balance between matches among the covariates tested. The robustness of the choice of this tie-breaking characteristic is tested in the appendix on page (35). This is important to check, since over half of all homes with OSDS neighboring a home with a sewer connection, neighbors more than one home with a sewer connection. That is, more than half of all homes on OSDS who have a neighbor with a sewer connection have two or more neighbors with a sewer connection. In our analysis, we only perform one-to-one matching so must break many ties.

We show the balance of home characteristics between these neighbors is much improved under the matching method. Also worth noting in support of using a nearest neighbor matching method is that unobserved characteristics, such as demographics and location relative to the urban center of Honolulu, are likely to have significant effects on water use. Households in relatively wealthy neighborhoods, like the Black Point neighborhood previous discussed, may have very different uses for water than those in the more rural areas of the island. Normal OLS does not account for these differences, but a nearest neighbor method is able to address them by making better comparisons and yield less biased results. Using OLS with dummies to control for the matched home pairs, we obtain a robust, unbiased estimate for elasticity that is much less elastic than what was found using the regression and propensity score techniques.

5 Results

Table (3) summarizes the results of all models described in the last section. Columns (1) through (3) correspond to equation (1) using all homes in the dataset. Column (1) is a simple comparison of the two groups, where the only variable on the righthand side is a dummy indicating if the homes has an on-site system. Column (2) adds the home's physical characteristics and local climate as controls, and column (3) includes physical characteristics and census tract dummies that aim to control for unobserved demographic characteristics of the households. The full regression tables for these results can be found in table (A1) in the appendix on page (34). These regressions produce statistically significant results for the OSDS coefficient, indicating homes with on-site systems consume between 7% and 23% more water than homes with sewer connections. If we use the median characteristics of a home[8], we calculate elasticities between -0.031 and -0.31 for these models using the BWS water rate table. However we know that these estimates are biased, since in table (2) we saw there is an imbalance between the characteristics of homes with OSDS and those with sewer connections.

Next, we use lasso regression with cross validation at the ahupuaʻa level which is not shown in the summary table. As discussed in the empirical strategy section, splines were developed for each continuous variable and their interactions. This resulted in 63 splines. The method allows the individual coefficients to reduce to 0, resulting in a large sparse matrix that is impractical to display. However, the coefficient on OSDS was estimated to be 0.1518, meaning homes with OSDS use, on average, about 15% more water than their counterparts with sewer service. An elasticity estimate can be derived from this result using the same strategy used with OLS: we take the median characteristics for a home and use the results to estimate water use for a home with and without OSDS. With robust errors clustered at the ahupuaʻa level, the elasticity is estimated to be -0.28, with a 95% confidence interval of $(-0.20, -0.37)$. This is robust to both choice of cross validation grouping and error clustering: no significant difference was observed when 2010 census tracts were used instead of ahupuaʻa. Again, however, these results are based on imbalanced data, which we attempt to fix using propensity score matching and neighbor matchign techniques.

Columns (4) and (5) in table (3) show the results of the propensity-score weighted GLM models. No controls are used in model (4), but model (5) includes home characteristic and climate covariates. In both cases the statistical significance of the coefficient estimates drop considerably, with corresponding elasticity estimates of -0.028 and -0.058. Imbalance between the characteristics of the homes with cesspools and the homes with sewer connections remained even after using boosted regression. Table (4) compares the balance of characteristics of the entire dataset with the balance resulting from the boosted regression. Overall, the t-statistics improved after matching. However, statistically significant differences between the two groups still remain. Note also that the D-statistics from the Kolmogorov-Smirnov tests are omitted since this method weights individual observations, and thus a empirical CDF of the characteristics which is needed to calculate the statistic is not informative.

[8]This hypothetical median home has 1648 square feet, a 4555 square foot yard, is 44 years old, has an annual household income of \$83,472, has an average annual temperature of 23.4°C, and experiences an average annual rainfall of 34.7 inches.

Table 3: Summary of regression models. Elasticity calculated using daily gallons consumed by a median home with a sewer connection ($\hat{y} \mid$ median characteristics and $OSDS = 0$) and using the OSDS coefficient to estimate the water use if it had OSDS. Associated prices used in the elasticity estimate were calculated using the BWS rates. For the models, columns (1) through (3) use standard OLS using all data. Columns (4) and (5) use the propensity score-weighted boosted GLM model, and columns (7) and (8) use OLS on the matched neighbors dataset. Robust errors clustered by census tract except for model (8), which uses only robust standard errors since the matched data are already neighbors and thus spatially clustered. Only complete cases were used across all like models. *p<0.1; **p<0.05; ***p<0.01

	Dependent variable:							
	Log mean daily water use (gallons)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSDS coefficient	0.214***	0.230***	0.071**	0.021	0.045	0.041	0.059	0.040
(SE)	(0.010)	(0.025)	(0.029)	(0.036)	(0.045)	(0.060)	(0.051)	(0.074)
Data	All	All	All	All	All	Neighbors	Neighbors	Neighbors
Model	OLS	OLS	OLS	PS wtd. GLM	PS wtd. GLM	OLS	OLS	OLS
Home characteristic controls	No	**Yes**	**Yes**	No	**Yes**	No	**Yes**	**Yes**
Climate controls	No	**Yes**	No	No	**Yes**	No	**Yes**	No
Census tract dummy	No	No	**Yes**	No	No	No	No	No
Neighbor pair dummy	No	No	No	No	No	No	No	**Yes**
Observations	109,875	109,875	109,875	109,875	109,875	559	559	559
R^2	0.005	0.214	0.274	0.000	0.237	0.001	0.373	0.812
Adjusted R^2	0.005	0.214	0.270	0.000	0.237	−0.001	0.362	0.414
Elasticity estimate	−0.31	−0.34	−0.031	−0.028	−0.058	−0.059	−0.083	−0.057
(95% CI)	(−0.18, −0.46)	(−0.26, −0.41)	(−0.027, −0.036)	(0.063, −0.122)	(0.056, −0.179)	(0.105, −0.236)	(0.058, −0.233)	(0.269, −0.326)

Table 4: Summary of home characteristics by wastewater disposal type before and after boosted regression propensity score matching. Since the boosted regression weights the observations according to how well they match under the propensity score matching method, weighted means and t-statistics are reported for the matched pairs. The t-tests suggest the difference between means of the characteristics for the two groups are significantly different from 0, even after boosted regression propensity score matching. D-statistics from the Kolmogorov-Smirnov tests are not reported since observations are weighted by the model.

Home characteristic	Mean (all data)		Wtd mean (matched pairs)		t-statistic	
	Sewer	OSDS	Sewer	OSDS	All data	Matched pairs
Year built	1973	1968	1974	1968	19.9***	12.5***
Effective year built	1977	1974	1975	1974	11.7***	5.2***
Home size (sq. ft.)	1837	1735	1855	1739	7.3***	8.0***
Home value ($1000s)	751	808	948	873	-6.5^{***}	6.1***
Yard size (sq. ft.)	5486	9938	13,802	9759	-19.5^{***}	12.3***
Num. bedrooms	3.8	3.5	3.7	3.6	26.6***	8.4***
Num. bathrooms	2.2	2.0	2.2	2.0	13.4***	9.7***

*p<0.1; **p<0.05; ***p<0.01

The neighbor matching method, whose results are shown in columns (6) through (8) of table (3), resulted in matches that were much more similar in terms of home characteristics, as is shown in table (5). The results with this method are much more stable across specifications, and the two groups of homes are much more balanced. The differences in the characteristics were mostly reduced to statistically insignificant values, except for yard size and the number of bedrooms. However, the balance between even these characteristics were improved compared to the previous method. This suggests the estimated effect of sewage disposal type on household water use will be much less biased than the results from the previous methods. Applying results from this method to all homes in the dataset must be done with caution though since, as shown in table (6), the homes used in this method may not be representative of the homes in the full dataset. There are statistically significant differences in many of the characteristics of these homes, both with and without OSDS. For homes with sewer, homes in the matched neighbors dataset are typically older, larger, more valuable homes with larger yards compared to the population. On the other hand, homes with OSDS in the matched neighbors dataset are slightly newer, larger, and more valuable, but have smaller yards.

Table 5: Summary of home characteristics by wastewater disposal type before and after neighbor matching. The t-tests suggest the difference between means of the characteristics for the two groups overall are significantly different from 0, and Kolmogorov–Smirnov tests suggest the distributions are not similar. However, after matching using the neighbor method, these differences become insignificant except for yard size and the number of bedrooms.

Home characteristic	Mean (all data)		Mean (matched pairs)		t-statistic (matched pairs)		D-statistic (matched pairs)	
	Sewer	OSDS	Sewer	OSDS	All data	Matched pairs	All data	Matched pairs
Year built	1973	1968	1969	1970	19.9***	−0.69	0.14***	0.11*
Effective year built	1977	1974	1974	1976	11.7***	−1.05	0.10***	0.09
Home size (sq. ft.)	1837	1735	2058	1952	7.3***	0.43	0.14***	0.05
Home value ($1000s)	751	808	967	993	−6.5***	−0.33	0.14***	0.06
Yard size (sq. ft.)	5486	9938	6832	6177	−19.5***	2.02**	0.25***	0.18***
Num. bedrooms	3.8	3.5	4.0	3.7	26.6***	2.18**	0.09***	0.11*
Num. bathrooms	2.2	2.0	2.4	2.3	13.4***	0.33*	0.14***	0.01

*p<0.1; **p<0.05; ***p<0.01

Table 6: Mean values of each characteristic for all homes in the data and those used in the match. In general, homes used in the matching method do not share similar characteristics with the rest of the population, as there are statistically significant differences between the neighbors group and all homes in the data.

Home characteristic	Sewer				OSDS			
	Neighbors	All	t-statistic	D-statistic	Neighbors	All	t-statistic	D-statistic
Year built	1969	1973	-3.52^{***}	0.16^{***}	1970	1968	1.51	0.17^{***}
Effective year built	1974	1977	-2.55^{**}	0.14^{***}	1976	1974	1.30	0.14^{***}
Home size (sq. ft.)	1994	1837	2.37^{**}	0.10^{***}	1952	1735	3.04^{***}	0.10
Home value ($1000s)	967	751	4.04^{***}	0.15^{***}	993	808	3.12^{***}	0.17^{***}
Yard size (sq. ft.)	6832	5486	5.96^{***}	0.22^{***}	6177	7405	-4.87^{***}	0.17^{***}
Num. bedrooms	3.96	3.84	1.68^{**}	0.07^{**}	3.72	3.50	2.66^{***}	0.06
Num. bathrooms	2.32	2.19	2.04^{**}	0.09^{***}	2.29	2.03	3.58^{***}	0.10^{**}

* $p< 0.1$; $^{**}p< 0.05$; $^{***}p< 0.01$

The lasso regression was also attempted using only the matched neighbors subset of the observations but the OSDS dummy variable was thrown out during the cross validation process, indicating demand would be estimated to be perfectly inelastic. Overall, both OLS and LASSO produce statistically significant, but biased, results when all observations are used. The propensity score matching reduced, but did not eliminate, bias in the data and produced a much smaller elasticity. The OLS model with the least amount of bias, where the observations are limited to those chosen in the neighbor matching method, produced similarly small elasticities. Although the results with the unbiased data are not statistically significant at the 10% level, they allow us to provide an estimate of the bounds of the elasticity. That is, for OLS, we estimate residential water demand to be no more elastic than -0.33 when we include the neighbor pair dummy variable. This is slightly more inelastic than many current estimates for water demand in the literature.

6 Discussion

Having an accurate estimate of the price elasticity of water demand is becoming increasingly critical as governments and utilities explore options for conserving water under a changing climate. This is especially true in Hawai‘i, where currently the only viable source for fresh water is the island's aquifers which are replenished by rainfall. With less precipitation and warmer temperatures expected (Izuka and Keener 2013), a decrease in water supply and increase in demand will require a more careful water management strategy until other sources like desalination become more viable. Regulating prices to influence water use is one way this can be accomplished, but relies heavily on consumers' sensitivity to these prices. Without accurate estimates of price sensitivity, it will be impossible to reach water sustainability goals with these measures. Since, in most cases, prices would have to be raised in order to conserve water, this leads to the potential for a loss in consumer surplus with no benefit to the water resource. Due to the variety of methods used, data availability, pricing structures, and consumer characteristics, there is an extensive range of estimates of price elasticity of water demand. Indeed, as we have seen in previous studies and this study, the estimate can vary widely when different models are used with the same underlying data.

Our inelastic demand estimates suggest it may be worthwhile to explore alternative conservation strategies, at least under the current pricing. Although a price increase may be justified since the scarcity value of the water isn't taken into account in the current pricing scheme (i.e. the price of water is entirely based on the costs incurred by the utility), our results suggest that the extremely inelastic demand makes price adjustment as a tool for water conservation much less feasible. However, it may be that demand becomes more elastic at higher prices. For example, the demand for water by single family homes may actually be convex, and we only observe the inelastic portion at lower prices in our study. More work in this area would need to be done to determine the shape of demand at all prices. Knowing this information would be invaluable for analyzing the welfare impacts of a price increase and how it would relate to the currently-ignored scarcity value of water. If demand is inelastic at all prices, then increasing the price to account for the scarcity value may result in an unreasonable loss in consumer welfare. On the other hand, if demand is convex, the loss in welfare would be less when the price is increased to match the scarcity value. In this case, increasing the price to a level closer to that which accounts for the scarcity value of water may be more feasible.

For analyses on a longer time horizon, studying the impact of conservation, the evolution of groundwater extraction over time, increasing reliance on alternative sources of water, and the impact on consumer welfare will be critical. Given the continually-falling cost of renewable energy (Branker, Pathak, and Pearce 2011; Trancik 2015) and energy storage (Ralon et al. 2017; Gardner et al. 2016), alternative water management solutions may become more viable. In particular, desalination may become an increasingly affordable alternative to groundwater extraction as energy costs decrease. Therefore, in the long run, if we abstract from other concerns like ecological and cultural impacts, issues regarding consumer welfare may become more critical than the specific source of the fresh water. Even without alternatives like desalination, the optimal use of a renewable resource like water will typically reach a state where the growth of the stock is equal to the extraction rate. In the case of the aquifers of O‘ahu, water may continue to be drawn until it reaches its sustainable yield, defined by parameters such as acceptable salinity measures. In theory the head level will be reduced to the limit (plus some safety margin for water salinity standards, etc.), since any stock not extracted may be lost to groundwater discharge to the ocean. The path taken from our current status to the backstop, where we reach minimum head level and desalination becomes more affordable than extraction, that also maximizes consumer welfare is another question altogether (J. A. Roumasset and Wada 2010). That is, not only is the problem of maximum sustainable yield important, but the optimal extraction and investment in conservation from now until we reach that level can have significant impacts on consumer welfare. Additionally, the timing of the transition, and how quickly it is done, from pure groundwater extraction to a hybrid of extraction and desalination can have significant effects on consumer welfare as well (J. Roumasset and Wada 2014).

In the meantime, other studies examining the efficacy of non-price strategies show these programs are promising alternatives to price controls. Persuasive means of reducing water use have been shown to be effective at developing positive attitudes toward compliance, and these attitudes can be used as predictors of water use (Landon, Kyle, and Kaiser 2016; Landon, Woodward, et al. 2018). That is, water conservation campaigns can be used as an effective means to persuade customers to reduce their water use. In one study (Otaki, Ueda, and Sakura 2017), showing the customer's usage with emoticons indicating the level of use, and their use relative to other customers, was found to be an effective way to reduce consumption. Another study (Woltemade and Fuellhart 2013) found similar results for outdoor water use, where customers are shown estimates of how much water they should need for irrigating their lawns, and the water use of their neighbors. This effect was shown to grow stronger over time through repetition.

By significantly simplifying the consumer surplus problem at hand and ignoring potential relationships with optimal pricing and groundwater extraction, our results can help estimate the economic impact of the statewide ban on cesspools. Hawai'i has banned the construction of new cesspools on all islands, and is providing tax incentives to customers to upgrade their systems to either a septic tank or sewer connection. Using back-of-the-envelope calculations, we can show that the offered tax credit of $10,000 is not enough to cover the installation of either upgraded system, let alone the net present value of increased monthly charges incurred by those who upgrade to sewer.

In December 2018, SB2567[9] went into effect, requiring owners to upgrade any cesspools on the property within 180 days of the sale of the home. In many cases, homes will more likely upgrade to a septic tank than connect to the sewer system. This is because, with a septic tank, there is no additional monthly cost the customer must pay, like there is if they upgrade to sewer service. The bill states that the average owner pays $20,000 to upgrade the system, but this may vary drastically depending on the system being installed, location relative to existing sewer lines, and geography. In certain cases, it may be impossible to upgrade to a sewer connection due to the lack of existing sewer lines in the area, or the location of the home relative to the sewer line.

In any case, the cost of installing the new system alone exceeds the existing tax credit which provides little incentive for owners to voluntarily upgrade, especially since the owners will initially have to front the cost and receive the tax credit at a later time. If we consider the net present value of future monthly sewer service payments, the difference becomes even larger. Figure (7) shows the effect upgrading from cesspool to sewer connection will have on the surplus of the consumer. As noted earlier, there is disagreement about whether consumers respond to average or marginal price, but we show here that the difference would be minimal if consumers were acting completely rationally. Despite discussions of conservation and reducing water use, this figure suggests an increase in welfare may be observed if consumption is *increased*, since the evidence suggests residences are currently responding to average price.

Using back-of-the-envelope calculations with a discount rate of 3% and an infinite horizon, the

[9] `https://www.capitol.hawaii.gov/session2018/bills/SB2567_.HTM`

net present value of sewer costs (not including the initial installation costs) would be

$$(\$77.55 + \$40.47 + \$1.77) \times 12/0.03 = \$47,916,$$

where the monthly \$40.77 comes from the welfare loss associated with the conversion in figure (7). Even without the initial installation costs, this amount far exceeds the tax credit currently offered. This would be in addition to the installation cost of the sewer connection, bringing the total net present value to about \$67,916. An important note is that the actual amount that would need to be offered as a credit would likely be less than this, since there are costs associated with maintaining an OSDS which includes emptying, repairing, and replacing the system. However, these costs vary widely depending on system age, system type, location, and other idiosyncratic factors that make an exact calculation difficult to perform. If we extend this value to all single family homes on O'ahu with cesspools (7044 homes), the island-wide net present value of the upgrades totals over \$337 million. Again, this would be an upper limit to the value since the costs associated with the maintenance of on-site systems is ignored due to their complexity. However, this also excludes the idiosyncratic initial upgrade costs.

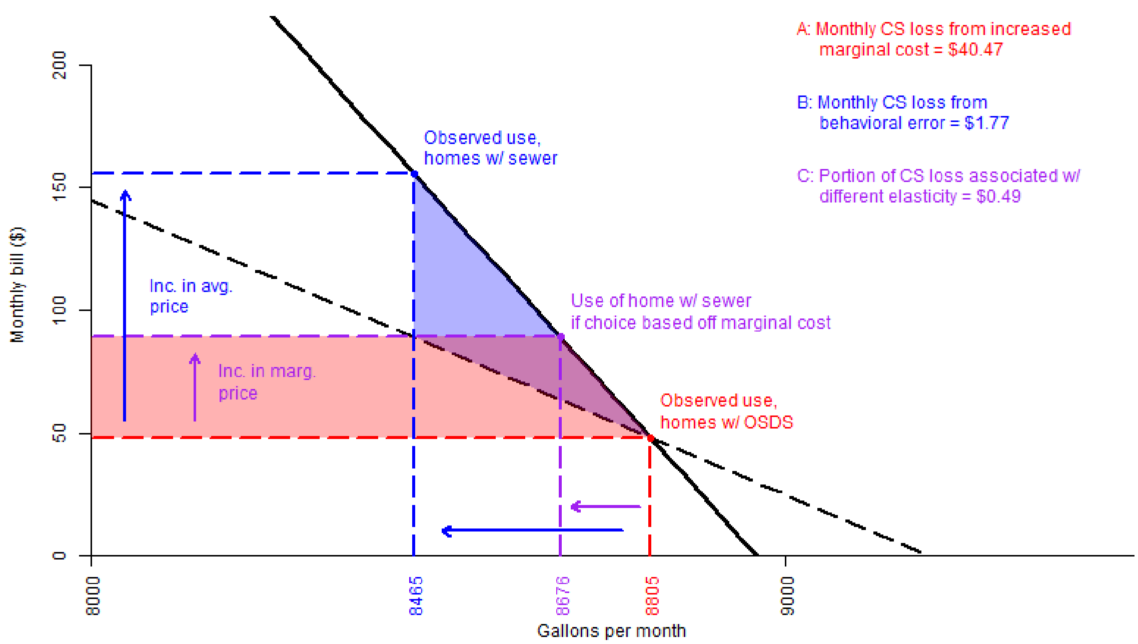


Figure 7: Loss in consumer surplus when switching from OSDS to a sewer connection. The solid line is the estimated demand curve, assuming consumers respond to average price *as if* it were marginal price. The dashed demand curve shows what the response to marginal cost would look like with the assumption customers actually respond to average price.

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A Appendix

A.1 Full regression tables

Table (A1) shows the full regression results summarized in table (3). The coefficient estimates, for the most part, have the expected signs. Perhaps most surprising is the lack of effect of yard size, which is thought to be one of the larger sources of discretionary water use.

Table A1: Full results of regression summary shown in table (3).

	Dependent variable:							
	Log mean daily water use (gal)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OSDS	0.214***	0.230***	0.071**	0.021	0.045	0.041	0.059	0.040
	(0.046)	(0.025)	(0.029)	(0.036)	(0.045)	(0.060)	(0.051)	(0.074)
Net val ($100,000)		0.019***	0.023***		0.021***		0.018***	0.046***
		(0.001)	(0.002)		(0.002)		(0.005)	(0.013)
Home size (1000s sq ft)		0.101***	0.101***		0.079***		0.098**	−0.018
		(0.007)	(0.006)		(0.018)		(0.042)	(0.108)
Yard size (1000s sq ft)		0.001	0.0003		0.001		0.030***	−0.010
		(0.0005)	(0.0003)		(0.001)		(0.007)	(0.022)
Eff. home age (decades)		−0.015***	0.013***		−0.008		0.019	0.057*
		(0.004)	(0.003)		(0.005)		(0.016)	(0.035)
Median HH income ($10,000)		0.001			−0.001		−0.007	
		(0.003)			(0.003)		(0.011)	
Avg. ann temp (C)		0.066***			0.210***		0.250***	
		(0.018)			(0.058)		(0.082)	
Avg ann rain (in)		−0.008***			−0.005**		−0.008***	
		(0.001)			(0.002)		(0.002)	
Num beds		0.064***	0.056***		0.059**		0.024	0.036
		(0.005)	(0.003)		(0.026)		(0.022)	(0.054)
Num baths		0.052***	0.062***		0.030		0.085**	0.111
		(0.005)	(0.004)		(0.029)		(0.040)	(0.095)
Data	All	All	All	All	All	Neighbors	Neighbors	Neighbors
Model	OLS	OLS	OLS	PS wtd. GLM	PS wtd. GLM	OLS	OLS	OLS
Census tract dummy	No	No	**Yes**	No	No	No	No	No
Neighbor pair dummy	No	No	No	No	No	No	No	**Yes**
Observations	109,875	109,875	109,875	109,875	109,875	559	559	559
R^2	0.005	0.214	0.274	0.000	0.237	0.001	0.373	0.812
Adjusted R^2	0.005	0.214	0.270	0.000	0.237	−0.001	0.362	0.414

Note: *p<0.1; **p<0.05; ***p<0.01
Robust standard errors clustered by census tract except model (8)
Observations limited to complete cases

Table A2: Robustness of OSDS coefficient estimates with different characteristics used for neighbor tie-breaking. The best matching variable, yard size, was chosen based on its ability to create the most balanced matches. Rows ordered according to matching effectiveness (best at the top). Matching effectiveness based on mean t-statistics of differences between matched pairs. Mean D-statistics are also reported. None of the coefficient estimates are significant at the 10% level.

Neighbor tie-breaker variable	Model OSDS coefficient estimate			Mean t-statistic	Mean D-statistic
	(6)	(7)	(8)		
Yard size (table (3))	0.041	0.059	0.040	−0.33	0.059
Home size	0.028	0.046	0.039	−0.42	0.048
Effective home age	−0.011	0.042	0.013	−0.51	0.067
Net value	0.010	0.007	−0.051	−0.80	0.047

A.2 Neighbor matching robustness to tie-breaking characteristic

In the neighbor matching method, the yard size was used to break ties whenever a home with a cesspool had more than one neighbor with a sewer connection. We test the robustness of the resulting OSDS coefficient estimates to those derived by tie-breaking with other characteristics. This is shown in table (A2). The columns marked (6) through (8) correspond to the regression models from table (3). Only the coefficient estimates for OSDS are shown. The best characteristic to break ties was determined using t-statistics of the resulting pairs' characteristic matches. Overall, the characteristic that yielded the lowest mean t-statistic was used to break ties. Note that, while the sign and magnitude vary slightly from model to model, the estimates remain insignificant at the 10% level. All R^2 and adjusted R^2 values remained largely unchanged compared to those presented in table (3).