Reports of Water Quality Violations Induce Consumers to Buy Bottled Water

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The 1996 Safe Drinking Water Act Amendments required that water utilities send quality reports to customers. We test whether receiving such reports of health violations increases purchases of bottled water using newly released data and disaggregate changes in demand at the intensive and extensive margins. We find that a water-quality violation makes American households 25 percent more likely to purchase bottled water and, among purchasers, expenditures increase 4–7 percent, both larger responses than found in previous studies. Consumers spend approximately $300 million per year—about 4 percent of annual national spending on bottled water—to avoid health risks associated with violations.

Key Words: demand response to information, environmental quality, water quality violation

The 1974 Safe Drinking Water Act authorized the U.S. Environmental Protection Agency (EPA) to set standards for contaminants in public water systems, and in 1996, a water-quality public right-to-know provision was added via the Safe Drinking Water Act Amendments (SDWAA96). That provision requires that the public be directly informed of drinking water contaminants through annual water quality reports (WQRs). These reports provide the opportunity to estimate economic losses associated with pollution by measuring averting behavior. That is, households may reduce their consumption of tap water and switch to bottled water to limit their exposure to pollution.[1] Fisher and Zeckhauser (1976), for example, described averting behavior in response to pollutants and Courant and Porter (1981) measured benefit values and aversion costs for individuals between the ambient environmental quality and the effectiveness of the averting behavior. Prior studies of aversion behavior associated with poor water quality that analyzed bottled water choices include Smith and Desvousges (1986), which found that nearly 30 percent of the sample reported purchasing bottled water to avoid contamination with hazardous waste and that news of hazardous waste incidents significantly increased purchases of bottled water. In a similar study, Abrahams, Hubbell, and Jordan

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[1] In general, bottled water may not be safer than tap water. The U.S. Food and Drug Administration's regulations for bottled water are less stringent than those of the Safe Drinking Water Act (Government Accountability Office 2009). However, the relevant choice for these consumers is not between typical tap water and typical bottled water; rather, it is whether tap water known to contain pollutants is safer than typical bottled water.

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(2000) found that 23 percent of sampled Georgia residents considered tap water somewhat unsafe and that concerns about the safety and quality of tap water were important determinants when buying bottled water. In contrast to that study, we find that notifications of local tap water problems are not a significant determinant.

The opportunity to measure this effect is valuable from a welfare economics point of view since it allows us to study the value of water quality to the public. It is also relevant to policy. WQRs serve three explicit purposes: support of the principle that Americans have a right to know what is in their drinking water, minimization of public exposure to health risks, and improvement in the drinking quality of tap water by creating a market-driven incentive for water systems to improve performance (EPA 2004). Our results suggest that at least the first two purposes have been served to a significant degree.

The consumer response to water quality violations in our study is about 40 percent larger than the response found in previous studies. Zivin, Neidell, and Schlenker (2011) studied bottled water consumption in the presence of SDWAA96 violations using data on bottled water sales from 200 grocery stores in northern California and Nevada and matching the dates of violations to weekly sales. They found that a water quality violation increased sales of bottled water 17–26 percent. We match data on water quality violations from annual reports to data on purchases from the national Consumer Expenditure Survey (CES), which is conducted by the U.S. Census Bureau for the Bureau of Labor Statistics, and find that U.S. households are 25 percent more likely to purchase bottled water and increase their expenditures on bottled water 4–7 percent after news of a violation, a total change in expenditure of 28–32 percent. Though both studies find large positive effects, our results suggest that Zivin, Neidell, and Schlenker (2011) may have underestimated the extent of pollution-averting behavior. We use individual-level data and are able to disaggregate the extensive margin (likelihood of buying bottled water) from the intensive margin (amount of bottled water purchased) of consumer responses. We find that the extensive margin swamps the intensive margin. This makes intuitive sense because people who already drink bottled water likely drink less tap water and thus have less reason to react to a water quality violation.

Extrapolating from our results, we find that U.S. consumers are willing to pay an additional $300 million dollars per year—4 percent of total annual expenditures on bottled water—to avoid the pollution associated with health violations.

Data

The ideal measure of aversion behavior would be human consumption of tap water but no such data are available. The only data available are for aggregate consumption of residential tap water. Therefore, we follow the literature (e.g., Smith and Desvousges 1986, Larson and Gnedenko 1999, Abrahams, Hubbell, and Jordan 2000, Jakus et al. 2009, Zivin, Neidell, and Schlenker 2011) and use increases in consumption of bottled water as a proxy for decreases in consumption of tap water for drinking. We use two primary data sets: bottled water expenditures from the CES and health-based violations of drinking water standards from EPA's Safe Drinking Water Information System (SDWIS). Table 1 presents means and standard deviations for all of the primary variables broken down by those who purchased bottled water versus those who did not.

Table 1. Summary Statistics

		Mean (Standard Deviation)		
Variable	**Description**	**Full Sample**	**Purchase Bottled Water**	**Do Not Purchase**
ExpBottle (dollars)	Biweekly expenditure for bottled water	2.64 (5.99)	7.46 (8.09)	0.00 (0.00)
Violation	Population-weighted violations for large areas	0.13 (0.27)	0.12 (0.27)	0.13 (0.28)
Vio · Q2	Second quarter interacted with violation	0.03 (0.16)	0.03 (0.17)	0.03 (0.16)
Vio · Q3	Third quarter interacted with violation	0.03 (0.15)	0.03 (0.14)	0.03 (0.15)
Vio · Q4	Fourth quarter interacted with violation	0.03 (0.14)	0.02 (0.12)	0.03 (0.15)
Q2	Second quarter	0.25 (0.43)	0.27 (0.44)	0.24 (0.43)
Q3	Third quarter	0.25 (0.43)	0.27 (0.44)	0.24 (0.43)
Q4	Fourth quarter	0.25 (0.43)	0.24 (0.42)	0.26 (0.44)
Income ($10,000)	Amount of household income before taxes in past 12 months	7.37 (7.07)	8.50 (7.54)	6.74 (6.72)
Vio · Income	Interaction variable with *Violation* and *Income*	0.95 (2.46)	1.05 (2.59)	0.89 (2.37)
Education	Education of head of household (pseudo-years)	13.36 (1.90)	13.45 (1.87)	13.32 (1.91)
NumAdults	Number of persons 19–63 years of age in household	1.59 (1.02)	1.82 (1.02)	1.46 (0.99)
NumChildren	Number of children younger than 18 in household	0.64 (1.05)	0.83 (1.14)	0.54 (0.99)
Vio·NumChildren	Interaction variable with *Violation* and *NumChildren*	0.09 (0.44)	0.11 (0.51)	0.08 (0.39)
NumElderly	Number of persons 65 or older in household	0.28 (0.58)	0.23 (0.55)	0.31 (0.60)
NonCarbonBevs (dollars)	Biweekly expenditure on noncarbonated beverages	2.22 (6.24)	7.12 (9.48)	0.00 (0.00)
TimeTrend	1 = 2006, 2 = 2007, 3 = 2008	2.00 (0.82)	2.00 (0.82)	2.00 (0.82)
PSU Fixed Effect	Dummies for each PSU			
Number of households		9,818	3,477	6,341

Source: U.S. Bureau of Labor Statistics Consumer Expenditure Survey and EPA Safe Drinking Water Information System.

A single secondary source of data is EPA's state budgets, which were collected as a statistical instrument.

The CES collects information on U.S. households' buying habits through quarterly interviews and purchase diaries. Respondents are asked to keep track of all of the daily purchases they make for a fourteen-day period. Our data set covers three survey years, 2006 through 2008, and includes 9,818 households that could be matched with SDWIS data. We find that households in the data set spent an average of $2.64 on bottled water biweekly. Among the approximately 35 percent of households that purchased some bottled water, the average expenditure during a fourteen-day period was $7.46. Annually, those households spent an average of $193.96 on bottled water (see Table 1).

The SDWIS provides data on water-quality violations from 1,300 water utilities across the country. We use the number of violations of three health-based limits: maximum contaminant level, maximum residual disinfectant level, and treatment technique. These health-based violations are reported in WQRs for drinking water that are made available to consumers annually. We use 2005–2007 SDWIS since the WQRs sent to consumers in 2006, 2007, and 2008 refer to violations that occurred the previous year. We focus on public community water systems—systems that supply water to the same population year-round and serve at least 15 connections or at least 25 people[2]—since they are the only water systems required to provide WQRs to consumers. The SDWAA96 "requires one copy of the report to be mailed to each customer, unless the governor of a state has waived the mailing requirement and the system serves fewer than 10,000 persons" (EPA 1998, p. 7614). These reports must be delivered by July 1 each year. Since we do not know which governors waived this requirement, we focus on systems serving greater than 10,000 persons. There are approximately 52,000 community water systems in the United States and just 8 percent of those systems serve about 80 percent of the U.S. population (EPA 2009).

Geographical Matching

The CES reports data at a household level while the SDWIS data are available at a utility level. Ideally, we would match CES household addresses to their respective utilities. However, addresses are confidential so we instead compute the *expected number of violations for each CES household* given its regional primary sampling unit (PSU) using the 21 largest units (e.g., A102 in the Northeast, which covers the Philadelphia, Wilmington, and Atlantic City area) and county information for each water utility. Tables 2 and 3 provide detailed information about the PSUs used in our study, including the counties covered and the number of households and water utilities in each one. The largest cities in the United States—New York City, Chicago, Dallas / Fort Worth, and Los Angeles—and about one-third of U.S. residents are included in the PSUs.

We first calculate the expected number of violations. Suppose that the water utilities, $u = 1, 2, \ldots, U$, are in PSU_A. Let Pop_u be the population served by utility u and let Vio_u be the number of violations by utility u (these data come from the SDWIS). Then, for all households i in PSU_A, let

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[2] The excluded water systems serve schools, factories, gas stations, and campgrounds.

Table 2. List of PSU Geographic Areas in the Consumer Expenditure Survey

PSU Code ▪ Name ▪ Region

Northeast

A102 Philadelphia – Wilmington – Atlantic City, PA – NJ – DE – MD
New Castle, DE; Cecil, MD; Atlantic City, Burlington, Camden, Cape May, Cumberland, Gloucester, Salem, NJ; Bucks, Chester, Delaware, Montgomery, Philadelphia, PA

A103 Boston – Brockton – Nashua, MA – NH – ME – CT
Windham, CT; Bristol, Essex, Hampden, Hampshire, Middlesex, Norfolk, Plymouth, Suffolk, Worcester, MA; York, ME; Hillsborough, Merrimack, Rockingham, Stratford, NH

A109 New York, NY
Bronx, Kings, New York, Queens, Richmond, NY

A110 New York – Connecticut – Suburbs
Fairfield, Hartford, Litchfield, Middlesex, New Haven, Tolland, CT; Duchess, Nassau, Orange, Putnam, Rockland, Suffolk, Westchester, NY

A111 New Jersey Suburbs
Bergen, Essex, Hudson, Hunterdon, Mercer, Middlesex, Monmouth, Morris, Ocean, Passaic, Somerset, Sussex, Union, Warren, NJ

Midwest

A207 Chicago – Gary – Kenosha, IL – IN – WI
Cook, DeKalb, Du Page, Grundy, Kane, Kankakee, Kendall, Lake, McHenry, Will, IL; Lake, Newton, Porter, IN; Kenosha, WI

A208 Detroit – Ann Arbor – Flint, MI
Genesee, Lapeer, Lenawee, Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw, Wayne, MI

A210 Cleveland – Akron, OH
Ashtabula, Cuyahoga, Geauga, Lake, Lorain, Medina, Portage, Summit, OH

A211 Minneapolis – St. Paul, MN – WI
Anoka, Benton, Carver, Chisago, Dakota, Hennepin, Isanti, Ramsey, Scott, Sherburne, Stearns, Washington, Wright, MN; Pierce, St. Croix, WI

South

A312 Washington, DC – MD – VA – WV
District of Columbia, DC; Calvert, Charles, Frederick, Montgomery, Prince Georges, Washington, MD; Alexandria city, Arlington, Clarke, Fairfax, Fairfax city, Falls Church city, Fauquier, Fredericksburg city, King George, Loudoun, Manassas Park city, Manassas city, Prince William, Rappahannock, Spotsylvania, Stafford, Warren, VA; Berkeley, Jefferson, WV

A313 Baltimore, MD
Anne Arundel, Baltimore, Baltimore city, Carroll, Harford, Howard, Queen Anne's, MD

A316 Dallas – Fort Worth, TX
Collin, Dallas, Delta, Denton, Ellis, Henderson, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, Wise, TX

A318 Houston – Galveston – Brazoria, TX
Austin, Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, San Jacinto, Waller, TX

A319 Atlanta, GA
Cleburne, AL; Barrow, Bartow, Butts, Carroll, Cherokee, Clayton, Cobb, Coweta, Dawson, De Kalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Haralson, Henry, Newton, Paulding, Pickens, Pike, Rockdale, Spalding, Walton, GA

A320 Miami – Fort Lauderdale, FL
Broward, Miami Dade, FL

continued on following page

Table 2 (continued)

PSU Code	**Name**	**Region**
	West	
A419	*Los Angeles – Orange, CA*	Los Angeles, Orange, CA
A420	*Los Angeles Suburbs, CA*	Riverside, San Bernardino, Ventura, CA
A422	*San Francisco – Oakland – San Jose, CA*	Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma, CA
A423	*Seattle – Tacoma – Bremerton, WA*	Island, King, Kitsap, Pierce, Snohomish, Thurston, WA
A424	*San Diego, CA*	San Diego, CA
A429	*Phoenix – Mesa, AZ*	Maricopa, Pinal, AZ

Note: These designations are geographic areas used in the 2000-census-based Consumer Expenditure Survey sample design (since 2005). Source: U.S. Bureau of Labor Statistics Consumer Expenditure Survey.

$$Violation_i = \sum_{u=1}^{U}(Pop_u \cdot Vio_u) \;/\; \sum_{u=1}^{U} Pop_u$$
$$\Longrightarrow Violation_i = \mathrm{E}(\text{number of violations} \mid \text{household } i \text{ lives in } PSU_A).$$

This method may introduce biases. First, the *Violation* variable is an expected violation so there is a bias against finding an impact of violation information on expenditures for bottled water because we observe our independent variable with noise (measurement error). Second, by matching the county of an SDWIS water utility treatment plant to a PSU county, we assume that all of the customers of the water utility live in that PSU. We cannot directly test this assumption, but given that PSUs cover greater metropolitan areas, it seems reasonable. If a significant number of utilities violates this assumption, we observe the expected number of violations with noise. If the likelihood of a utility serving mostly out-of-PSU customers is not correlated with the likelihood of a violation (i.e., if the noise is not correlated with the variable of interest), this is standard measurement error, which biases against finding an effect. A third potential source of bias comes from our exclusion of small community water systems (serving fewer than 10,000 people) that are not required to send WQRs. In principle, these small systems could have sent reports of violations anyway. Thus, we would not observe some consumers who received notice of a violation and reacted, making our baseline probability of buying bottled water larger. Finally, since we use PSUs, our sample is weighted toward urban households and may not accurately describe the responses of rural Americans.

Time Matching

We matched CES households to reports of health violations for 2006, 2007, and 2008. The WQR that consumers receive in year t provides information about violations that occurred in the preceding year, $t - 1$, and can be delivered at any time between January 1 and July 1. Since we do not know when each WQR is

Table 3. Percent of Households Sampled by PSU

PSU Code	Number (Percent) of Households Sampled	Number of Community Water Systems Serving 10,000+	Population 1: Served by Water Systems	Population 2: Served by Water Systems with Violations
1102	581 (5.92)	85	5,745,896	317,251
1103	582 (5.93)	162	8,447,005	351,798
1109	643 (6.55)	3[a]	8,070,718	5,368,479
1110	680 (6.93)	92	6,116,332	850,200
1111	583 (5.94)	113	6,270,762	409,193
1207	982 (10.00)	171	8,212,501	486,398
1208	513 (5.23)	89	4,366,684	48,010
1210	250 (2.55)	31	2,787,723	100,000
1211	284 (2.89)	62	2,649,979	145,325
1312	455 (4.63)	31	4,590,334	402,500
1313	269 (2.74)	14	2,442,626	105,385
1316	429 (4.37)	73	5,657,220	122,000
1318	364 (3.71)	59	4,244,811	71,277
1319	387 (3.94)	45	4,535,247	125,991
1320	317 (3.23)	28	1,771,896	16,090
1419	903 (9.20)	64	4,443,397	34,518
1420	306 (3.12)	48	3,157,317	70,074
1422	499 (5.08)	32	4,207,028	131,563
1423	305 (3.11)	63	3,392,230	134,763
1424	221 (2.25)	20	4,515,463	—[b]
1429	265 (2.70)	31	3,863,602	299,245
Total	9,818 (100.00)	1,316	99,488,771	9,590,058

[a] There are only three water supply systems in New York: Croton, Catskill, and Delaware.

[b] No violations reported.

Notes: Population 1 is the number of people who are served by a community water system supporting at least 10,000 households in each PSU. Population 2 is the average number of people served by a community water system that supports at least 10,000 households and for which violations occurred for one or more of those systems in 2005–2007. The data are from the U.S. Bureau of Labor Statistics Consumer Expenditure Survey and the EPA Safe Drinking Water Information System.

delivered, we cannot use that information in matching and attempt to control for this with quarterly dummy variables.

The argument could be made that, instead of $Violation_t$, we should use $Violation_t - Violation_{t-1}$, the change in the number of violations. However, as shown in Table 3, the vast majority of people in the sample ($Pop1 - Pop2$) experienced no reports of violations, implying that there is very little difference empirically between $Violation_t$ and $Violation_t - Violation_{t-1}$.

Instrument: State EPA Budgets

To address possible omitted variables, we investigated a statistical instrument: state-level environmental budgets for water and water quality. We searched online for state budgets that were itemized by topic and summed the dollars spent in those budgets on water-related items. The full results of the search are too lengthy to include here (but are available upon request) so we instead provide an example. In Indiana, the Department of Environmental Management is the state EPA agency. Indiana's State Budget Agency maintains past budgets for fiscal year 2005–2007 and fiscal year 2007–2009, and from those budgets we selected three water-related line items from Section III-1, Conservation and Environment: water division general fund, water management permitting, and the Safe Drinking Water Program.

See Table 4 for final data for all relevant states. No line item budgets could be found for Delaware or for the District of Columbia for fiscal years 2005 and 2006 so those values were imputed from budgets of neighboring states.

Once we identified each state's budget amounts, we imputed a water-protection budget for each PSU using 2010 census figures. When a PSU was contained within a single state, we multiplied the state-level budget by the ratio of the PSU's population (constructed from county-level data) to the state's population. When a PSU spanned multiple states, each state's budget was multiplied by the ratio of the PSU's population in that state (again, from the

Table 4. State Environmental Protection Agency Budgets Dedicated to Water

	Million Dollars per Fiscal Year			
State	**2005**	**2006**	**2007**	**2008**
Arizona	6.99	11.53	13.11	14.78
California	728.56	769.78	1,011.62	777.38
Connecticut	36.54	34.14	40.45	40.75
Delaware	—	—	—	—
District of Columbia	—	—	7.92	14.03
Florida	499.09	829.55	652.27	451.44
Georgia	31.10	57.30	37.60	40.60
Illinois	57.51	55.57	57.37	54.73
Indiana	19.56	25.30	26.25	22.87
Maine	13.44	9.06	8.45	9.44
Maryland	106.90	120.70	127.90	168.20
Massachusetts	87.47	86.47	92.15	60.04
Michigan	43.73	48.06	45.11	47.34
Minnesota	130.74	156.08	190.49	199.59
New Hampshire	92.59	98.70	92.90	100.50
New Jersey	25.32	26.10	26.60	30.78
New York	112.23	131.13	134.89	128.03
Ohio	45.10	44.60	49.00	47.90
Pennsylvania	14.96	16.31	16.38	13.69
Texas	45.34	49.24	48.66	56.90
Virginia	44.95	45.43	49.68	49.17
Washington	72.19	89.59	89.59	115.81
West Virginia	118.60	151.97	159.05	145.48
Wisconsin	103.98	113.71	121.23	126.37

Note: The figures are the authors' compilation from state budget websites (available upon request).

county-level population) to that state's population and the resulting budgets were summed.

Empirical Analysis

Our empirical analysis involves a two-stage model. Consumers first decide whether to buy bottled water (the extensive margin) and then decide how much to spend on it (the intensive margin). We model our hypothesis of the relationship between bottled water expenditures and water quality violations as $y_i = \mathbf{X}_i'\boldsymbol{\beta} + u_{1i}$ where y_i is the measure of bottled water expenditure, $\boldsymbol{\beta}$ is a vector of coefficients to be estimated, $\mathbf{X}_i$ is a vector of variables that explain expenditures for observation *i* and a constant term, and u_{1i} is the error term. The vector of variables, $\mathbf{X}_i$, consists of population-weighted violations, the quarter dummy variables (*Q2*, *Q3*, and *Q4*), interactions between those quarter dummy variables and violations, expenditures on noncarbonated beverages, several demographic controls, and fixed effects of PSUs. The analysis is based on pooled cross-sectional data. CES does not provide price information so prices are not included.

The value of the dependent variable y_i, bottled water expenditure, is zero for about 66 percent of the sample. Consequently, the variable appears to be a candidate for Heckman selection correction (Heckman 1979). However, the zero values do not come from selection bias. To understand why, consider the classic Heckman selection bias problem: a data set in which the dependent variable is wages and a fraction of the sample is unemployed. The unemployed fraction of the sample has an observed value of zero but *would have a positive value* if all individuals were employed and their wages were observed. In our problem, individuals choose how much water to purchase and some choose zero. Therefore, this zero does not represent a true positive value for unobserved purchases of water: it represents zero desired water.

Since selection bias is not an issue, we can avoid Heckman selection correction and take the simpler route of using a probit model to determine the extensive margin and simple ordinary least squares (OLS) to determine the intensive margin for the restricted sample of individuals who had positive expenditures.[3] In probit regressions in some prior studies, interaction variables were used. To obtain correct magnitudes for the interaction effects, we follow Ai and Norton (2003) and Norton, Wang, and Ai (2004), which computed the cross-derivative of the expected value of the dependent variable.

Results

Table 1 provides definitions and summary statistics for the variables used in the regressions. For both the probit (Tables 5 and 6) and the OLS (Table 7) regression, model 1 is the base case and we then add the interaction terms with violation variables in models 2 and 3. The standard errors shown in the tables are adjusted for clustering on PSU codes. Clustering allows for intragroup correlation.

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[3] The zeros arguably represent a "true" negative desired amount of good purchased. From this point of view, a Tobit model is an appropriate alternative empirical strategy because the zeros represent a truncation or bottom-coding. This analysis would extrapolate onto changes of negative desired bottles of water purchased, which is difficult to interpret. We completed a Tobit analysis and found that the results were not significantly different from the results presented here.

In terms of the results for the extensive margin (choice to purchase), Table 5 presents the marginal effects, which can be interpreted directly, and Table 6 reports the probit coefficients. Models 1, 2, and 3 show a strong positive effect of violations on the propensity to buy bottled water of about 8 percentage points.[4] Since the base probability of purchasing water is 34 percent, this result translates to a 25 percent increase in the probability of purchasing bottled water (0.08 / 0.34 ≈ 0.25), the equivalent of a 25 percent increase in the number of households purchasing water.

The results from model 3 show that a violation increases the propensity to purchase bottled water in the second quarter. Since the WQRs must be delivered by the end of the second quarter, this result may reflect a fairly rapid response from consumers, providing evidence that at least some of the increase in bottled water purchases results from violations reported in the WQRs and not from violations discovered through some other mechanism.

On the intensive margin (amount purchased), model 1 shows that news of a violation increases biweekly expenditures by around 45 cents (about 6 percent). Models 2 and 3 produce increases of 30–54 cents (4–7 percent).[5] The average expenditure among bottled water purchasers is $7.50.

The percent increase in total bottled water expenditures in the face of a violation, $\%\Delta TExp$, is 28–32 percent, the bulk of which is attributable to new purchasers of bottled water.[6] We would thus expect the annual average expenditure on bottled water by a household that receives notice of a violation to increase by $20.52. This implies a nationwide increase of approximately $300 million (4 percent)[7] in total expenditures on bottled water per year.

Note that these results show a strong and positive response in bottled water expenditures after news of water quality violations. Our analysis generates estimates that are comparable to but larger than those of Zivin, Neidell, and Schlenker (2011), in which bottled water expenditures increased 17–26 percent in an analysis that used a similar source of violation data but a different source of data on consumption of bottled water. There are several potential

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[4] For models 2 and 3, interaction effects evaluated at average levels must be included. For example, the effect for model 2 is [0.073 + 0.109(= 0.073 + 0.036) + 0.056(= 0.073 – 0.017) + 0.085(= 0.073 + 0.012)] × 0.25 = 0.080 when assuming that one-quarter of all households in the CES data appear in each quarter, which is approximately true. A similar exercise with model 3 reveals an average effect of 0.085.

[5] For models 2 and 3, interaction effects evaluated at average levels must be included. For example, the effect for model 2 is [1.051 + 0.794(= 1.051 – 0.257) – 0.191(= 1.051 – 1.242) – 0.426(1.051 – 1.477)] × 0.25 = 0.307 when assuming that one-quarter of all households in the CES data appear in each quarter, which is approximately true. A similar exercise with model 3, which includes $Vio \cdot Income$ times average income, reveals an effect of 0.54.

[6] The total expenditure equals the number of purchasers times the average expenditure. Therefore,

$$TExp = N \cdot avgExp$$

$$\Rightarrow \Delta TExp = avgExp \cdot \Delta N + N \cdot \Delta avgExp$$

$$\Rightarrow \Delta TExp \;/\; TExp = \Delta N \;/\; N + \Delta avgExp \;/\; avgExp$$

$$\Rightarrow \% \Delta TExp = \% \Delta N + \% \Delta avgExp$$

where $\%\Delta N$ can be derived from the probit (extensive margin) results and $\%\Delta avgExp$ from the OLS (intensive margin) results.

[7] $30\% \cdot 0.13 \approx 4.0\%$. Total expenditure is calculated as [average of $2.64 spent on bottled water per household each two weeks (CES data)] × [26 two-week periods per year] × [a 30 percent increase in expenditures due to a violation] × [0.13 violations on average experienced by each household] × [approximately 115 million households (census data)].

Table 5. Decision to Buy Bottled Water: Probit Marginal Effects

	Marginal Effect (Standard Error)		
	Model 1	**Model 2**	**Model 3**
Violation	0.081	0.073	0.078
	(0.011) ***	(0.018) ***	(0.024) ***
Vio · Q2	—	0.036	0.035
		(0.023)	(0.019) *
Vio · Q3	—	–0.017	–0.017
		(0.023)	(0.019)
Vio · Q4	—	0.012	0.011
		(0.023)	(0.018)
Q2	0.041	0.036	0.036
	(0.020) **	(0.021) *	(0.021) *
Q3	0.038	0.040	0.040
	(0.017) **	(0.019) **	(0.019) **
Q4	–0.009	–0.011	–0.011
	(0.014)	(0.016)	(0.016)
Income ($10,000)	0.003	0.003	0.003
	(0.001) ***	(0.001) ***	(0.001) ***
Vio · Income	—	—	–0.000
			(0.002)
NumChildren	0.032	0.032	0.032
	(0.004) ***	(0.004) ***	(0.004) ***
Vio · NumChildren	—	—	–0.005
			(0.005)
NumAdults	0.059	0.059	0.059
	(0.006) ***	(0.006) ***	(0.006) ***
NumElderly	0.021	0.021	0.021
	(0.011) *	(0.011) *	(0.011) *
NonCarbonBevs (dollars)	0.016	0.016	0.016
	(0.001) ***	(0.001) ***	(0.001) ***
Education	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)
TimeTrend	0.014	0.014	0.014
	(0.005) ***	(0.005) ***	(0.005) ***
Constant[a]	—	—	—
Number of observations	9,818	9,818	9,818

[a] The constant term disappears when taking a partial derivative to get marginal effects.

Notes: The marginal effects are calculated at the means of the regressors. The marginal effects of all dummy variables are calculated as the discrete change as the variable changes from 0 to 1. The standard errors are adjusted for clustering on PSU codes. * indicates statistical significance at $p < 0.10$, ** at $p < 0.05$, and *** at $p < 0.01$.

Table 6. Decision to Buy Bottled Water: Probit Coefficients

	Coefficient (Standard Error)		
	Model 1	**Model 2**	**Model 3**
Violation	0.220 (0.030) ***	0.198 (0.050) ***	0.213 (0.065) ***
Vio · Q2	—	0.093 (0.100)	0.091 (0.098)
Vio · Q3	—	−0.056 (0.065)	−0.056 (0.065)
Vio · Q4	—	0.035 (0.097)	0.033 (0.098)
Q2	0.110 (0.053) **	0.097 (0.057) *	0.098 (0.057) *
Q3	0.101 (0.045) **	0.108 (0.051) **	0.108 (0.051) **
Q4	−0.025 (0.039)	−0.030 (0.043)	−0.030 (0.043)
Income ($10,000)	0.009 (0.003) ***	0.009 (0.003) ***	0.009 (0.003) ***
Vio · Income	—	—	−0.001 (0.006)
NumChildren	0.087 (0.012) ***	0.087 (0.011) ***	0.089 (0.013) ***
Vio · NumChildren	—	—	−0.012 (0.014)
NumAdults	0.160 (0.016) ***	0.160 (0.016) ***	0.160 (0.016) ***
NumElderly	0.058 (0.030) *	0.058 (0.030) *	0.058 (0.030) **
NonCarbonBevs (dollars)	0.044 (0.004) ***	0.044 (0.004) ***	0.044 (0.004) ***
Education	0.017 (0.011)	0.017 (0.011)	0.017 (0.011)
TimeTrend	0.038 (0.015) ***	0.038 (0.015) ***	0.038 (0.015) ***
Constant	−1.560 (0.155) ***	−1.515 (0.150) ***	−1.558 (0.155) ***
Number of observations	9,818	9,818	9,818
Log pseudo-likelihood	−1.795e+08	−1.795e+08	−1.795e+08

Notes: The dependent variables take one of two values, 0 or 1, and the raw coefficients have no particular interpretation. The standard errors are adjusted for clustering on PSU codes. * indicates statistical significance at $p < 0.10$, ** at $p < 0.05$, and *** at $p < 0.01$.

Table 7. Bottled Water Expenditures: Ordinary Least Squares

	Coefficient (Standard Error)		
	Model 1	**Model 2**	**Model 3**
Violation	0.446 (1.194)	1.051 (0.362) ***	1.723 (0.857) *
Vio · Q2	—	–0.258 (1.850)	–0.310 (1.802)
Vio · Q3	—	–1.243 (0.763)	–1.215 (0.734)
Vio · Q4	—	–1.477 (1.472)	–1.620 (1.372)
Q2	0.223 (0.438)	0.249 (0.334)	0.246 (0.336)
Q3	–0.220 (0.354)	–0.070 (0.346)	–0.086 (0.341)
Q4	–0.003 (0.444)	0.173 (0.440)	0.178 (0.440)
Income ($10,000)	0.067 (0.024) **	0.066 (0.024) **	0.071 (0.029) **
Vio · Income	—	—	–0.046 (0.073)
NumChildren	0.014 (0.130)	0.013 (0.131)	0.079 (0.144)
Vio · NumChildren	—	—	–0.377 (0.235)
NumAdults	1.034 (0.207) ***	1.029 (0.203) ***	1.027 (0.204) ***
NumElderly	0.626 (0.375)	0.627 (0.375)	0.628 (0.374)
NonCarbonBevs (dollars)	0.034 (0.018) *	0.034 (0.018) *	0.033 (0.018) *
Education	0.107 (0.088)	0.109 (0.087)	0.110 (0.087)
TimeTrend	0.576 (0.122) ***	0.576 (0.122) ***	0.576 (0.123) ***
Constant	2.617 (1.178) **	2.534 (1.227) *	2.439 (1.219) *
Number of observations	3,477	3,477	3,477
R-square	0.062	0.062	0.063

Notes: The standard errors are adjusted for clustering on PSU codes. * indicates statistical significance at $p < 0.10$, ** at $p < 0.05$, and *** at $p < 0.01$.

explanations for this difference. The authors may have underestimated the nationwide response because their consumption data, which came from a grocery store chain in northern California and Nevada, were not representative of southern, midwestern, and northeastern regions of the country. Our closest matches to their data in terms of geographical area are PSU A422 (San Francisco and environs) and PSU A429 (Phoenix and environs), and the coefficients of the fixed effects associated with these PSUs in our regression are consistently large and positive.[8] If households in those regions have a larger base propensity to purchase bottled water, there would be fewer households that could switch to bottled water upon news of a violation, resulting in a smaller effect being measured by Zivin, Neidell, and Schlenker (2011). In addition, the data in their study included rural households while our data set includes mostly urban households. Rural households are much more likely to get drinking water from sources other than a community water system (such as a well). As a result, many households in rural areas would not receive reports of violations to which they would react, which would decrease the measured effect of such reports. Lastly, the authors assumed that consumers reacted to public announcements of water quality violations that were given within 24 hours of an immediate threat or within 30 days (per SDWAA96). Our analysis accounts for reactions over a longer time span via annual WQRs so our results may capture reactions to both annual WQRs and immediate notifications. This cumulative effect would make our estimates larger than theirs.

As a robustness test, we use a statistical instrument for violations. While reverse causality is not a concern, omitted variables might be. We use line items in state-level environmental protection budgets that address water and water purity. When controlling for other effects, increases in state-level budgets for water quality should have an exogenous impact on the likelihood that a given water quality violation is found by inspectors. We use this instrument to test the probit (extensive margin) and OLS (intensive margin) models in two stages. First, following the standard method, we use the budgets and all of the other variables to predict the number of violations. We then use those predicted violations and all of the other variables to predict the dependent variable of interest, bottled water expenditures.

We find moderate support for our main findings, as shown in Table 8. While the two-stage probit yields no significant results, the two-stage OLS estimates of the effect of predicted violations on bottled water expenditure are positive and significant and have the same sign as the original estimates.[9] Insignificant two-stage probit results are not presented here but are available upon request. The first stage shows that the instrument is a fairly weak predictor of the number of violations; however, it appears to be strong enough that the predicted number of violations remains as a significant determinant of bottled water expenditure. The first stage does not have sufficient degrees of freedom to conduct a joint *F*-test of whether all of the coefficients are zero, which identifies weak instruments (Stock and Yogo 2005). This lack of sufficient degrees of freedom indicates that the instrument is weak. Moreover, *F*-tests on subsets of the coefficients that have sufficient degrees of freedom yield results

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[8] The fixed-effect estimates are available from the authors.

[9] The original estimates and estimates with the statistical instrument differ greatly in magnitude. In particular, the estimate of the primary coefficient of interest increases from 0.446 to 8.438, likely due to bias introduced by the weakness of the instrument. (Our thanks to an anonymous referee for this observation.)

Table 8. Expenditures in the Instrumental Variable Regression

	Stage 1			**Stage 2**	
	Coefficient (Standard Error)			**Coefficient (Standard Error)**	
Budget	−0.0012	(0.0009)	$\widehat{Violation}$	8.438	(4.314) *
Q2	0.0076	(0.0082)		0.158	(0.468)
Q3	−0.0042	(0.0046)		−0.184	(0.331)
Q4	−0.0019	(0.0051)		0.016	(0.409)
Income	0.0003	(0.0003)		0.064	(0.024) ***
NumChildren	−0.0025	(0.0021)		−0.008	(0.134)
NumAdults	−0.0011	(0.0019)		1.048	(0.210) ***
NumElderly	0.0026	(0.0022)		0.603	(0.356) *
NonCarbonBevs	−0.0001	(0.0001)		0.035	(0.018) *
Education	−0.0024	(0.0022)		0.128	(0.098)
TimeTrend	−0.0424	(0.0384)		0.906	(0.363) **
Constant	0.2134	(0.1093) *		1.079	(1.933)
Number of observations	3,477			3,477	
R-square	0.725			0.028	
Wald Chi-square				1,012.05	
Probability > Chi-square				0.0000	

Joint *F*-test: Stage 1 lacks the necessary degrees of freedom for this test, which implies that it is a weak instrument.

Note: * indicates statistical significance at $p < 0.10$, ** at $p < 0.05$, and *** at $p < 0.01$.

that do not exceed the Stock-Yogo cut-off value. Therefore, these results should be interpreted with caution.

Conclusion

We use bottled water expenditures as a measure of consumers' avoidance of tap water in response to reports of SDWAA96 violations using CES data for 2006–2008. We match 9,818 households to 1,300 water utilities and measure the impact of health-based water violations on expenditures for bottled water. We thus offer a direct test of consumer responses using micro-level data on actions that households took to avoid low-quality tap water. Our primary goal was to determine whether receiving reports of health-related violations of drinking water standards increases *the likelihood that individuals will purchase bottled water* (avoid tap water) and *how much individuals will spend on bottled water*.

We find that a household's total annual expenditure on bottled water increases about 30 percent in response to a water quality violation. This impact is composed of two parts, the extensive margin (additional purchasers) and the intensive margin (greater expenditures by those already buying). The impact on the extensive margin outweighs the impact on the intensive margin about four to one. This swamping of the intensive margin is intuitive: individuals who do not normally buy bottled water are most affected by the quality of their tap water and consequently are most likely to react to news of water quality violations. The effect found in our models is larger than the effect found in the study most similar to ours, Zivin, Neidell, and Schlenker (2011), of a 17–26 percent increase. Our study allows us to distinguish impacts on the extensive and intensive margins.

WQRs serve three explicit purposes. First, they support the principle that Americans have a right to know what is in their drinking water and whether that water poses any risk to their health. Second, WQRs minimize the public's exposure to health risks by allowing them to avoid using water known to be contaminated. Third, the reports can foster improvements in the quality of the tap water provided and create a market-driven (i.e., demand-driven) incentive for water systems to improve their performance rather than relying on traditional command and control methods. Our results suggest that the first two purposes have been served to a significant degree. In addition, the estimated $300 million annual increase in bottled water expenditures nationwide in response to water quality violations suggests that the information that EPA collects and disseminates under the program is valuable to Americans. The results weigh heavily in support of the idea that consumers use averting behavior in the face of negative environmental news.

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