Reports of Water Quality Violations induce Consumers to buy Bottled Water

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Abstract

The 1996 Safe Drinking Water Act Amendments require that water utilities send quality reports to customers. We test whether receiving WQRs of health violations increases purchases of bottled water. With new data, we find a larger response than previous studies, and, unlike previous studies, we disaggregate the intensive and extensive margins of demand changes. We find a water quality violation makes households 25% more likely to purchase bottled water, and, among purchasers, increase expenditures $4-7\%$. Therefore American consumers spend approximately $300 million dollars per year—about 4% of yearly bottled water expenditures—to avoid these health violations.

JEL Codes: Q25, Q53

Keywords: Demand Response to Information, Information about Environmental Quality, Water Quality

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1 Introduction

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). The water quality provision requires that the public be directly informed about drinking water contaminants through annual water quality reports (WQRs). This gives an opportunity to estimate economic losses associated with pollution by measuring averting behavior.[1] Households could reduce tap water consumption and switch to bottled water to reduce exposure to pollution.[2,3]

We find the consumer response to be about 40% larger than previous studies. Zivin et al. (2011) study bottled water consumption in the presence of SDWAA96 violations[4] using bottled water sales data from 200 grocery stores in northern CA and NV, matching date of violations to weekly sales. They find that a water quality violation increases sales of bottled water by $17-26\%$. In contrast, we match annual water report data to national Consumer Expenditure Survey data and find households are 25% more likely to purchase bottled water given news of a violation and increase expenditures between $4-7\%$, which implies a total change in expenditure between $28-32\%$ percent. (See Section 4.) Although both studies find large and positive effects, our results suggest that Zivin et al. underestimate the extent of pollution averting behavior. We use individual-level data and are able to disaggregate the extensive and intensive margins of consumer response: i.e. whether receiving WQRs of health violations in drinking water increases the *likelihood that* and *degree to which* individuals buy bottled water. We find that the extensive margin swamps the intensive margin. This makes intuitive sense, as bottled water purchasers likely already use tap water less for consumption, so have less reason to react to a water quality violation.

Extrapolating from our results, we find that the public is willing to pay $300 million dollars per year on bottled water–4% of total yearly bottled water expenditures—to avoid the pollution associated with health violations.

2 Data

There are two sources of data used in this study: bottled water expenditure from US Bureau of Labor Statistics Consumer Expenditure Survey (CEX) and health-based violations of drinking water standards from the EPA Safe Drinking Water Information System (SDWIS). Table 1 contains

[1] Averting behavior as a response to pollutants was first described in Fisher and Zeckhauser (1976) and been measured in e.g. Courant and Porter (1981).

[2] Note that in general, bottled water may be no safer than tap water; for example, US Food & Drug Administration (FDA) bottled water regulations are less stringent than the Safe Drinking Water Act (US Government Accountablility Office, 2009). However, the relevant choice for these consumers is not between typical : instead for these consumers, the choice they face is whether tap water *with known pollutants* is safer than typical bottled water.

[3] The ideal variable to measure averting behavior would be direct human tap water consumption, but such data are not available. Aggregate residential tap water consumption data exist, but they include tap water used for all household purposes. Therefore, we follow the literature (e.g. Smith and Desvousges (1986), Larson and Gnedenko (1999), Abrahams et al. (2000), Jakus et al. (2009), and Zivin et al. (2011)) and use increase in bottled water consumption as a proxy for a decrease in consumption of tap water.

[4] Other studies of averting behavior to low water quality by choosing bottled water include Smith and Desvousges (1986), who report that nearly 30 percent of their sample report that they purchase bottled water to avoid hazardous waste, and news of hazardous waste significantly increases bottled water purchases. In a similar study, Abrahams et al. (2000) find 23 percent consider tap water somewhat unsafe, and show that concerns about the safety and quality of tap water are important determinants in buying bottled water but, in contrast to our results, they find notification of local tap water problems is not a significant determinant.

the means and standard deviations of all variables, broken down by those who purchased bottled water versus those who did not.

The Consumer Expenditure Survey (CEX). The CEX collects information from the nation's households on buying habits. The 2006 to 2008 CEX includes 9,818 households which we are able to match (see below). The survey consists of a quarterly interview and a purchase diary. Respondents are asked to keep track of all purchases made each day for two consecutive weeks. In this study, we find that households spend an average of \$2.64 on bottled water biweekly. Among households who purchase any bottled water, about 35 percent of households, the average expenditure is \$7.46. On an annual basis, purchasing households spend an average of \$193.96 on bottled water (see Table 1).

The Safe Drinking Water Information System (SDWIS). The SDWIS reports water-quality violations from 1,300 water utilities across the country. We use the number of reported health-based violations; in particular, Maximum Contaminant Level violations, Maximum Residual Disinfectant Level violations, and Treatment Technique violations. Health-based violations are reported in drinking water quality reports (WQRs) made available to consumers annually. We focus our study on one type of public water system: community water systems (CWS), which supply water to the same population year-round (at least 15 connections or regularly serving at least 25 people, according to the EPA).[5] Only CWSs are required to provide WQRs to consumers. "Each community water system must mail or otherwise directly deliver one copy of the report to each customer for all large water systems, namely CWSs serving more than 10,000 persons," according to SDWAA96. WQRs must be delivered by July 1 each year (US Environmental Protection Agency (1998)). There are approximately 52,000 community water systems. Just 8 percent of those systems serve about 80 percent of the US population (US Environmental Protection Agency (2009)).

Geographical matching. The CEX reports data at the household level, while SDWIS data are available at the utility level. Ideally, we would match CEX household addresses to a particular utility. However, addresses are not available for confidentiality reasons. Instead, we compute *the expected number of violations for each CEX household given their PSU* using the 21 largest Primary Sampling Units and county information for each water utility.[6] See Figure 1 for a US map of the 21 PSUs; note that the largest US cities are covered. About one-third of the US population lives in one of these PSUs.

The expected number of violations is calculated as follows. Suppose utilities $u = 1, \ldots, U$ 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 (which are variables came from SDWIS). Then, for all households i who live in PSU_A, let

$$Violation_i = \frac{\sum_{u=1}^{U} \left(pop_u * vio_u\right)}{\sum_{u=1}^{U} pop_u}$$
$$\implies Violation_i = \mathrm{E}\Big(\text{number of violations} \;\Big|\; \text{household } i \text{ lives in } PSU_A\Big)$$

This method introduces possible biases. First, since the $Violation$ variable is an expected violation, there is a bias against finding an impact of WQRs on bottled water expenditures because we observe our independent variable with noise (measurement error). Second, by matching SDWIS water utility treatment plant county to PSU county, we assume that, if a water utility has a treatment center within a PSU, that all customers of water utility live in that PSU. We cannot

[5] The excluded water systems include those that serve schools, factories, gas stations, and campgrounds.

[6] Appendix A contains details about PSUs, including the listing of PSU counties (Table 4) and the number of households and utilities in each PSU (Table 5.)

directly test this assumption, but, given that PSUs are greater metropolitan areas, this seems to be reasonable. If there are a significant number of utilities for which this fails, then we observe the expected number of violations with noise. If the likelihood of a utility serving mostly out-of-PSU customers is uncorrelated with the likelihood of a violation, (i.e. if the noise is uncorrelated with the variable of interest) then this is standard measurement error, which biases us against finding an effect. Third, we exclude community water systems serving fewer than 10,000 people. In principle, small CWSs may have sent WQRs even though it wasn't required. This introduces another bias against finding an impact of WQRs on bottled water expenditures: namely, if consumers receive WQRs with violations, react to them, and we don't observe those WQRs, we would count that as a larger baseline probability of buying bottled water. Finally, since we use only PSUs, the sample is weighted toward urban households and thus may not accurately describe rural Americans.

Time matching. CEX households in each year (2006, 2007, 2008) are matched to health violations from the previous year (2005, 2006, 2007). The water report that the consumers receive in year t contains violations that occurred in the previous year, year $t-1$.[7]

The summary statistics of the linked data set appear in Table 1.

3 Empirical Analysis

The empirical model is a two-stage procedure: consumers decide whether to buy bottled water (the extensive margin), and then decide how much to spend (the intensive margin). We model our hypothesis between bottled water expenditures and violations as:

$$y_i = X_i^{'}\beta + u_{1i}$$

where y_i is the measure of bottled water expenditures; β a vector of coefficients to be estimated; X_i is a vector of variables explaining expenditures for observation i and a constant term. u_{1i} is error term. The vector of variables, X_i, consists of: the population-weighted violations, the quarter (Q2 through Q4 dummies), the quarter interaction with violations, expenditure on non-carbonated beverages, a number of demographic controls, and PSU fixed effects. The analyses are based on pooled cross-sectional data. CEX does not provide price information so prices are not included.

The independent variable, bottled water expenditure, is zero for about 66% of the sample. Since many of the independent variable values are zero, this may appear to be a candidate for Heckman selection correction (Heckman, 1979). However, these zeros are not due to selection bias, and therefore this is not the appropriate technique. To understand why, consider the canonical Heckman selection bias problem: a data set in which the independent variable is wage, where a fraction of the sample is unemployed. The unemployed fraction of the sample has an observed value of zero, but *would have had a positive value* if the individuals were employed and their wages were observed. By contrast, in our problem, individuals choose how much water to purchase, and they choose zero. This zero does *not* represent a 'true' positive value of water purchased that was not observed: it truly represents zero desired water. Therefore, since selection bias is not an issue, one can avoid Heckman selection correction and take a simpler route of a Probit to determine the

[7] An argument can be made that, instead of $violations_t$, we should use $(violations_t - violations_{t-1})$; that is, change in the number of violations. We do not pursue this, for two reasons. As can be seen in Table 5, the vast majority of people $(pop1 - pop2)$ experience no violations; this implies that empirically, there is very little difference between $violations_t$ and $(violations_t - violations_{t-1})$.

extensive margin and simple OLS to determine the intensive margin on the restricted sample of those individuals with a positive expenditure.[8]

In some Probit regressions, interaction variables are used; to get the correct magnitude of the interaction effects, we follow Ai and Norton (2003) and Norton et al. (2004), who compute the cross derivative of the expected value of the dependent variable.

4 Results

We present the Probit results (the choice to purchase; the extensive margin) in Table 2 and the OLS results (the amount purchased; the intensive margin) in Table 3. Table 1 contains definitions and summary statistics for the variables used in these regressions. Both sets of results test the same four sets of variables: Models 1 and 2 are the base cases, and we add the interaction terms with $Violation$ variables in Models 3 and 4.

Extensive margin (Table 2).[9] Models 1 through 4 show a strong positive effect of violations on the propensity to buy bottled water: they show an increase in the probability of purchasing bottled water of about 8 percentage points upon news of a violation.[10] Since the base probability of purchasing water is 34%, this implies a 25% increase in the probability of purchasing bottled water upon news of a violation.[11] Equivalently, this implies a 25% increase in the number of households purchasing bottled water upon news of a violation.

The results in Model 4 show that a violation increases the propensity of purchasing bottled water in quarter two. Water systems are legally required to deliver their WQRs by the end of quarter two. Therefore, the higher propensity to purchase bottled water in quarter two following a violation could result from consumers' fairly quick response to the WQR. This provides evidence that at least some of the effect on bottled water purchases is via WQRs *per se*, and not violations through some other mechanism.

Intensive margin (Table 3). Models 1 and 2 show that news of a violation increases biweekly expenditures by around 45 cents, or about 6%.[12] Models 3 and 4 imply between 30 cents and 54 cents, or increases between 4 and 7%.[13]

Interpretation. The percent increase in total bottled water expenditure in the face of a violation, $\%\Delta TExp$, is between $28-32\%$ percent, the bulk of which is attributable to new purchasers

[8]One can argue that these zeros represent a 'true' desired negative amount of good purchased. From this point of view, a Tobit is an appropriate alternative empirical strategy, because the zeros represent a truncation or 'bottom-coding.' This would result in an analysis which extrapolate into changes of desired negative bottles of water purchased. That is not of interest here. Moreover, the Tobit approach combines the extensive and intensive margin into one empirical test, while we wish to analyze these two margins separately. For both of these reasons, we did not choose Tobit.

[9]The Probit coefficients in Table 2 have been transformed into marginal effects so they can be interpreted directly. Raw coefficient estimates are available upon request.

[10]For Models 3 and 4, interaction effects, evaluated at average levels, must also be included. For example, the effect for Model 3 is: $[0.073 + 0.109(= 0.073 + 0.036) + 0.056(= 0.073 - 0.017) + 0.085(= 0.073 + 0.012)] \cdot \frac{1}{4} = .080$, assuming that one quarter of all households in CEX appear in each quarter, which is approximately true. A similar exercise with Model 4 reveals an average effect of .085.

[11]$.25 \approx \frac{.08}{.34}$

[12]The average expenditure among bottled water purchasers is \$7.50.

[13]For Models 3 and 4, interaction effects, evaluated at average levels, must also be included. For example, the effect for Model 3 is: $[1.051 + 0.794(= 1.051 - 0.257) - 0.191(= 1.051 - 1.242) - 0.426(1.051 - 1.477)] \cdot \frac{1}{4} = 0.307$, assuming that one quarter of all households in CEX appear in each quarter, which is approximately true. A similar exercise with Model 4 including vioIncome times average income reveals an effect of .54.

of bottled water.[14]

For a household experiencing a violation, we would expect yearly average expenditure on bottled water to increase by \$20.52. This also implies an increase of approximately 300 million dollars in total expenditures on bottled water per year,[15] which is an increase of 4% of the total bottle water expenditures.[16]

These results are comparable to, but stronger than, Zivin et al. (2011), which found bottled water expenditures increase between 17 to 26 percent, using a similar source of violations data but a different source of bottled water consumption data (discussed below). It must be stressed that these results both show a strong and positive response in bottled water expenditure due to news of health violations. The discussion that follows details three plausible reasons why Zivin et al. show a smaller effect than we do.

First, Zivin et al. may have underestimated a national scale response because they are not representative of south, midwest, or northeast regions. Zivin et al. use data from a grocery store chain in Northern CA and Nevada. The closest we can match their geographical area in our data are PSUs A422 (San Francisco and environs) and A429 (Pheonix and environs). (See Table 4 in the appendix.) The coefficients of the fixed effects associated with these PSUs are consistently large and positive.[17] If households in this region have a higher base propensity of purchasing bottled water, then there are fewer households who might switch to purchasing bottled water upon news of a violation, and therefore a smaller effect measured by Zivin et al.

Second, Zivin et al. include rural households while our data largely include only urban households. Rural households are much more likely to get drinking water from sources other than a community water system, e.g. a well on ones' own property. Rural households that are not served by a community water system would obviously not receive news from their community water system about violations, and therefore not react to such news. This would tend to dampen the effect measured by Zivin et al.

Third, Zivin et al. assume that consumers react to the public announcement of water quality violations, which are required by the SDWAA96 to notify customers within 24 hours (for immediate threats) or within 30 days. Our analysis accounts for reactions under a longer time span, under the assumption that consumers respond mainly to the annual WQRs, so our results may capture reactions to *both* annual WQRs and immediate notifications. The cumulative effect would also lead to our results exceeding Zivin et al.

[14] The total expenditure equals the number of purchasers times the average expenditure. Therefore:

$$\begin{aligned} TExp &= N \cdot avgExp \\ \implies \Delta TExp &= avgExp \cdot \Delta N + N \cdot \Delta avgExp \\ \implies \Delta TExp/TExp &= \Delta N/N + \Delta avgExp/avgExp \\ \implies \%\Delta TExp &= \%\Delta N + \%\Delta avgExp \end{aligned}$$

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

[15] CEX data reveal an average of \$2.64 spent on bottled water per household each two weeks, times 26 two-week periods per year, times a 30% increase in expenditures due to a violation, times 0.13 violations on average experienced by each household, times approximately 115 million households in the U.S. (Source: U.S. Census).

[16] $30\% \cdot .13 \approx 4\%$

[17] Fixed effect estimates available upon request.

5 Conclusion

We use bottled water expenditures as a measure of consumer avoidance of tap water in the presence of SDWAA96 violations using the Consumer Expenditure Survey from 2006 to 2008. We match 9,818 households to 1,300 water utilities and measure the impact of health-based water violations on bottled water expenditure. Thus, this paper offers a direct test using micro-level data on actions that households took to avoid low-quality tap water. The main purpose of this paper is to test whether receiving WQRs of health violations in drinking water increases the *likelihood that* and *degree to which* individuals buy bottled water.

We find total expenditures on bottled water increase by about 30 percent in response to a water quality violation. This impact consists of two parts, the extensive margin–additional purchasers–and the intensive margin–more purchases by those already buying. The extensive margin outweighs the intensive margin about $4-$to-1, which is intuitive: non-bottled water purchasers are those most affected by tap water quality and therefore are the most likely to react to news of poor quality. We find an effect which is larger than the most similar study, Zivin et al. (2011), which finds only a 17 to 26 percent increase in expenditure following water quality violations. We are also, unlike Zivin et al., able to distinguish the extensive and intensive margins.

WQRs serve three explicit purposes: First, to support the principle that Americans have the right to know what is in their drinking water and whether it poses any risk to their health. Second, to minimize public exposure to health risks. Third, to improve drinking tap water quality and to create a market-driven (i.e. demand-driven) incentive for water systems to improve performance instead of relying traditional command and control methods. The results from this paper suggest the reports have significantly served at least the first two purposes. Additionally, the estimated $300 million in increased bottled water expenditures due to water quality violations per year imply that the information the EPA has collected and disseminated under this program is valuable to the American public. These results also weigh heavily on the side of evidence for averting behavior in the face of negative environmental news.

Figure 1: Map of the 21 PSUs

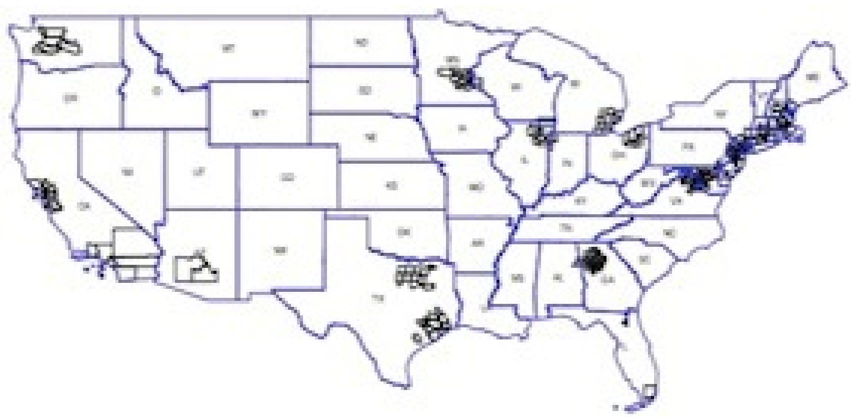

Table 1: Summary Statistics

Variable	Description	Full Sample	Purchase	Not Purchase
		Mean (Standard Deviation)		
ExpBottle($)	Biweekly expenditure for bottled water.	2.64 (5.99)	7.46 (8.09)	0.00 (0.00)
Violation	Population weighted violations for large areas.	0.13 (0.27)	0.12 (0.27)	0.13 (0.28)
Vio·Q2	Second quarter interacted with Violation.	0.03 (0.16)	0.03 (0.17)	0.03 (0.16)
Vio·Q3	Third quarter interacted with Violation.	0.03 (0.15)	0.03 (0.14)	0.03 (0.15)
Vio·Q4	Fourth quarter interacted with Violation.	0.03 (0.14)	0.02 (0.12)	0.03 (0.15)
Income (10000s$)	Amount of household Income before taxes in past 12 months.	7.37 (7.07)	8.50 (7.54)	6.74 (6.72)
Education	Education of head of household. (Pseudoyears.)	13.36(1.90)	13.45(1.87)	13.32(1.91)
Num Adults	Number of persons between 19 and 63 in household.	1.59 (1.02)	1.82 (1.02)	1.46 (0.99)
Num Children	Number of children less than 18 in household.	0.64 (.1.05)	0.83 (1.14)	0.54 (0.99)
Num Elderly	Number of persons over 64 in household.	0.28 (0.58)	0.23 (0.55)	0.31 (0.60)
NonCarbonBevs($)	Biweekly expenditure on noncarbonated beverages.	2.22 (6.24)	7.12 (9.48)	0.00 (0.00)
	Number of Households	9,818	3,477	6,341

†Source 1 : US Bureau of Labor Statistics Consumer Expenditure Survey.
‡Source 2: EPA Safe Drinking Water Information System.

Table 2: Decision to Buy Bottled Water: Probit Marginal Effects †

	(1) ME(se)	(2) ME(se)	(3) ME(se)	(4) ME(se)
Violation	.084	.081	.073	.078
	(.011)***	(.011)***	(.018)***	(.024)***
Vio·Q2			.036	.035
			(.023)	(.019)*
Vio·Q3			−.017	−.017
			(.023)	(.019)
Vio·Q4			.012	.011
			(.023)	(.018)
Q2		.041	.036	.036
		(.020)**	(.021)*	(.021)*
Q3		.038	.040	.040
		(.017)**	(.019)**	(.019)**
Q4		−.009	−.011	−.011
		(.014)	(.016)	(.016)
Income(10000s$)	.003	.003	.003	.003
	(.001)***	(.001)***	(.001)***	(.001)***
Vio·Income				−.000
				(.002)
Num Children	.032	.032	.032	.032
	(.004)***	(.004)***	(.004)***	(.004)***
Vio·NumChildren				−.005
				(.005)
Num Adults	.059	.059	.059	.059
	(.006)***	(.006)***	(.006)***	(.006)***
Num Elderly	.021	.021	.021	.021
	(.011)*	(.011)*	(.011)*	(.011)*
NonCarbonBevs.($)	.016	.016	.016	.016
	(.001)***	(.001)***	(.001)***	(.001)***
Education	.006	.006	.006	.006
	(.004)	(.004)	(.004)	(.004)
TimeTrend	.014	.014	.014	.014
	(.005)***	(.005)***	(.005)***	(.005)***
PSU Fixed Effect	Yes	Yes	Yes	Yes
Number of obs	9,818	9,818	9,818	9,818

†Marginal effects (ME) computed at their mean values.

Table 3: Bottled Water Expenditures: OLS

	(1) Coef.(se)	(2) Coef.(se)	(3) Coef.(se)	(4) Coef.(se)[a]
Violation	.483	.446	1.051	1.723
	(1.201)	(1.194)	(.362)***	(.857)*
Vio·Q2			–.258	–.310
			(1.850)	(1.802)
Vio·Q3			–1.243	–1.215
			(.763)	(.734)
Vio·Q4			–1.477	–1.620
			(1.472)	(1.372)
Q2		.223	.249	.246
		(.438)	(.334)	(.336)
Q3		–.220	–.070	–.086
		(.354)	(.346)	(.341)
Q4		–.003	.173	.178
		(.444)	(.440)	(.440)
Income(10000s$)	.067	.067	.066	.071
	(.024)**	(.024)**	(.024)**	(.029)**
Vio·Income				–.046
				(.073)
Num Children	.011	.014	.013	.079
	(.131)	(.130)	(.131)	(.144)
Vio·NumChildren				–.377
				(.235)
Num Adults	1.033	1.034	1.029	1.027
	(.208)***	(.207)***	(.203)***	(.204)***
Num Elderly	.621	.626	.627	.628
	(.376)	(.375)	(.375)	(.374)
NonCbevge($)	.034	.034	.034	.033
	(.018)*	(.018)*	(.018)*	(.018)*
Education	.109	.107	.109	.110
	(.087)	(.088)	(.087)	(.087)
TimeTrend	.581	.576	.576	.576
	(.122)***	(.122)***	(.122)***	(.123)***
Constant	2.587	2.617	2.534	2.439
	(1.231)**	(1.178)**	(1.227)*	(1.219)*
PSU Fixed Effect	Yes	Yes	Yes	Yes
Number of Obs.	3,477	3,477	3,477	3,477

[a]The standard errors are adjusted for clustering on PSUs codes. * indicates statistical significance at $p < 0.10$, ** at $p < 0.05$, and *** at $p < 0.01$

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Appendices

A Details about Primary Sampling Units (PSUs)

Table 4: List of PSU's Geographic Areas in the CE Survey.

PSU Code	PSU Name	Region/Definition†‡ (County, State)
	NORTHEAST	
A102	Philadelphia - Wilmington - Atlantic - City, PA - NJ - DE - MD	New Castle, DE; Cecil, MD; Atlantic, 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, Strafford, 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; Dutchess, 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	

Continued on next page

PSU Code	PSU Name	Region/Definition†‡ (County, State)
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, 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	Broward, Miami Dade, FL
	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	Island, King, Kitsap, Pierce, Snohomish, Thurston, WA
A424	San Diego, CA	San Diego, CA
A429	Phoenix - Mesa, AZ	Maricopa, Pinal, AZ

†Geographic Areas in the CE Survey's 2000 Census-Based Sample Design (since 2005).

‡Source: US Bureau of Labor Statistics Consumer Expenditure Survey.

Table 5: Percent of Household Sampled by PSUs

PSU Code	Number of Households Sampled (%) †	Number of CWS ‡[c]	*pop*1 ‡[a]	*pop*2 ‡[b]
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[d]	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	-[e]
1429	265 (2.70)	31	3,863,602	299,245
Total	9,818(100.00)	1,316	99,488,771	9,590,058

†Source 1: US Bureau of Labor Statistics Consumer Expenditure Survey.
‡Source 2: EPA Safe Drinking Water Information System.

[a] *pop*1: Population which 10,000 or more population served by CWSs in a given PSU.

[b] *pop*2: Average population which 10,000 or more population served by CWSs with violations over three years, 2005-2007.

[c] CWSs which serve $\geq 10,000$ persons in a given PSU.

[d] There are only three water supply systems in New York, NY: the Croton system, the Catskill system, and the Delaware system.

[e] No violations reported.