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## A Meta-analysis to Uncover the Effects of Drinking Water Pollution on Home Values

Dennis Guignet
*Appalachian State University*

Anna Silva
*Appalachian State University*

Department of Economics
Appalachian State University
Boone, NC 28608
Phone: (828) 262-2148
Fax: (828) 262-6105
www.business.appstate.edu/economics

# A Meta-analysis to Uncover the Effects of Drinking Water Pollution on Home Values

Dennis Guignet[1] and Anna Silva[2]

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**Abstract:**
We conduct a meta-analysis of hedonic studies examining the effects of potable water contamination on home values. We assess the robustness of the results to alternative weights, test for publication bias, and estimate meta-regressions to assess price effect heterogeneity. We find that the adverse effects on home values are similar across public versus private water sources, and that declines in home values persist for more than 10 years, on average. When contamination is detected the average decrease in home values is about 4-5%; and this effect increases to a 12-13% depreciation when contamination levels exceed regulatory or health-based standards.

**JEL Classification:** Q51 (Valuation of Environmental Effects); Q53 (Air Pollution; Water Pollution; Noise; Hazardous Waste; Solid Waste; Recycling)

**Keywords:** benefit transfer, drinking water, groundwater, hedonic, housing value, property value, meta-analysis

1. Corresponding Author: Department of Economics, Appalachian State University, 416 Howard Street, ASU Box 32051, Boone, NC, 28608-2051. Ph: 828-363-2117. guignetdb@appstate.edu.

2. Walker College of Business, Appalachian State University.

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## I. INTRODUCTION

Access to clean potable water is essential for a healthy life. Approximately 15% of people in the United States rely on private groundwater wells as their primary water source, and yet there is no required monitoring of these water sources (US EPA 2025). Testing and treating private wells can be expensive, and residents relying on a private well are often unaware of the need for routine testing. Harmful contaminants can go undetected and be consumed by unaware residents. In contrast, public water systems are regulated by the Safe Drinking Water Act, which requires monitoring to ensure the provision of safe potable water. Such provisions are not guaranteed, however, as illustrated by recent high-profile incidents, including lead pollution in Flint, MI, and per- and polyfluoroalkyl substances (PFAS) or "forever chemicals" contamination in Wilmington, NC. Estimating the social cost of contaminated potable water is important for informing policies and programs to protect human health. Hedonic property value methods are an ideal revealed preference approach to monetize the impacts in this context because potable water services are a key part of a housing bundle. Little research exists on how ground and drinking water quality affect home values, primarily due to a general lack of data on potable water quality, particularly in the context of private groundwater wells (Boyle et al. 2010; Case et al. 2006; Guignet et al. 2016; McCormick 1997).

To help fill this gap and better inform policymakers, we conduct a meta-analysis of the hedonic property value literature on the association between potable water quality and home values in the United States. We set out to provide benefit estimates for subsequent unit value and function transfers to inform policy, and to answer three primary research questions: (i) To what extent does contamination in ground and drinking water affect home values? (ii) Are there differential impacts across homes on private groundwater wells versus public water systems? (iii) Does the literature suggest that any negative effects on home values diminish or persist over time?

We construct a comprehensive meta-dataset of hedonic property value studies that explicitly estimate the association between potable water quality and home values in the United States. Using all pairwise combinations from a set of keywords, we systematically searched the economic literature and identified 42 candidate studies for potential inclusion in our meta-dataset. We established a list of criteria to determine which studies should be included, and identified 15 relevant studies. The 15 included studies cover several drinking water issues, including industrial pollution (e.g., PFAS and volatile organic compounds (or VOCs)), leaking underground storage tanks, agricultural runoff, and lead service lines. Eight of these studies focus on private potable wells and groundwater, and the other seven examine public water systems. The publication dates range from 1990 to 2026, and the study areas span from FL to ME, and as far west as CA. The studies utilize a variety of econometric methods, including two-sample t-tests, hedonic price regressions, matching, spatial econometrics, and difference-in-differences techniques. The final meta-dataset of 15 studies includes n=338 meta-observations, with each study contributing anywhere from one to 64 unique estimates of how potable water contamination affects home values.

We employ a series of meta-analytic techniques to empirically synthesize this literature, estimating mean unit values and meta-regression models, utilizing a range of weighting schemes to account for clustering and primary estimate precision, and assessing and adjusting for publication bias. The meta-regression results suggest that drinking water contamination leads to a 4-5% decline in home values when contamination is detected, and that this depreciation increases in magnitude – to about 12-13% – when contamination levels exceed regulatory or health-based standards.

## II. THE META-DATA

### *II.A. Identifying Studies for Inclusion*

To develop our meta-dataset, we first comprehensively identified the relevant literature. Our interest is in primary studies that use statistical methods to estimate the effect or association between groundwater and/or potable water quality and home values. This includes hedonic studies specifically examining drinking water quality, no matter whether it is from a public or private source. Studies focused exclusively on water quantity or availability issues, or on surface water quality, are excluded. We erred towards inclusion when identifying candidate studies, and included peer-reviewed journal articles, dissertations, theses, and unpublished conference proceedings and working papers.

Based on our previous research and experience in this area, we started with a set of seven relevant studies. Building on this foundation, we then conducted a forward and backward citation search. We looked at studies cited by one of the original seven studies, and then used Google Scholar to identify potentially relevant studies that later cited one or more of the original studies.[1] This led us to identify an additional thirteen studies. In addition, based on past experience in this area, we were aware of six other potentially relevant studies, but they required further review.

We then conducted a broader search using the EconLit database and a predefined list of keywords.[2] We searched every pairwise combination of the keywords in Table A1 in Appendix A, reviewing the title and abstract for all returned entries. This led us to identify an additional thirteen candidate studies for potential inclusion in the meta-dataset. A total of 39 candidate studies were identified. Three additional papers were published or posted as a working paper during the development of the meta-dataset. Together, these efforts left us with 42 candidate studies for potential inclusion.

We then reviewed each of the 42 candidate studies to evaluate whether they met all three of the following inclusion criteria:

1. ***Primary study that uses hedonic price regression models or another statistical method to isolate the association between groundwater or drinking water quality and home values***.

[1] We conducted this Google Scholar citation search from February 11-12, 2025.
[2] We conducted this EconLit literature search from March 1-3, 2025.

2. ***Focuses on direct or indirect measures that primarily reflect groundwater or drinking water quality.*** Studies focused on proximity to contaminated sites, cleanups, etc., where groundwater may be a key concern, but where the measure of the environmental disamenity likely captures other considerations (e.g., aesthetics) are excluded. Included studies could utilize and isolate the price effect associated with a continuous measure of water quality (e.g., concentration of some contaminant, bacteria counts, metric of some water quality parameter, like pH). Studies using dummy variables denoting the presence of contaminants, concentrations above standards, etc., are also included. Studies using the number of drinking water violations, or other measures directly related to drinking water or potable groundwater quality, were also included.
3. ***Is the most recent publicly available version of a study*** (as of the time of our metadata collection in 2025). Studies that are earlier versions of a later published study, for example, are excluded.

After reviewing each study in detail, fifteen studies met all inclusion criteria and were thus included in the meta-data (as shown in Figures 1 and 2). Twenty-seven studies did not meet all the inclusion criteria. Of those, fourteen studies were excluded because of criterion 1, and fourteen based on criterion 2. One study was excluded under both criteria 1 and 2, and two studies excluded under criterion 2 were also excluded due to criterion 3.[3]

### *II.B. Formation of the Meta-data*

As can be seen in Figure 1, the fifteen included studies cover a range of areas across the contiguous United States. The states that are represented in the meta-dataset range from Florida to Maine, and then as far west as California. States that include multiple studies are indicated with an asterisk, and include Wisconsin, Florida, and Maryland.

The fifteen included studies were published or publicly posted anywhere from 1990 to 2026. Eight of the studies focus on groundwater and private well contamination, and the other seven studies focus on public water issues. As shown in Figure 2, each study contributes anywhere from 1 to 68 meta-observations to the meta-dataset. Two studies, Malone and Barrows (1990) and Dotzour (1997), give us just one meta-observation each, while Case et al. (2006) contributes the most, at 68 observations.

[3] Table A2 in the Appendix lists the candidate studies that were excluded and briefly describes the reasons for exclusion.

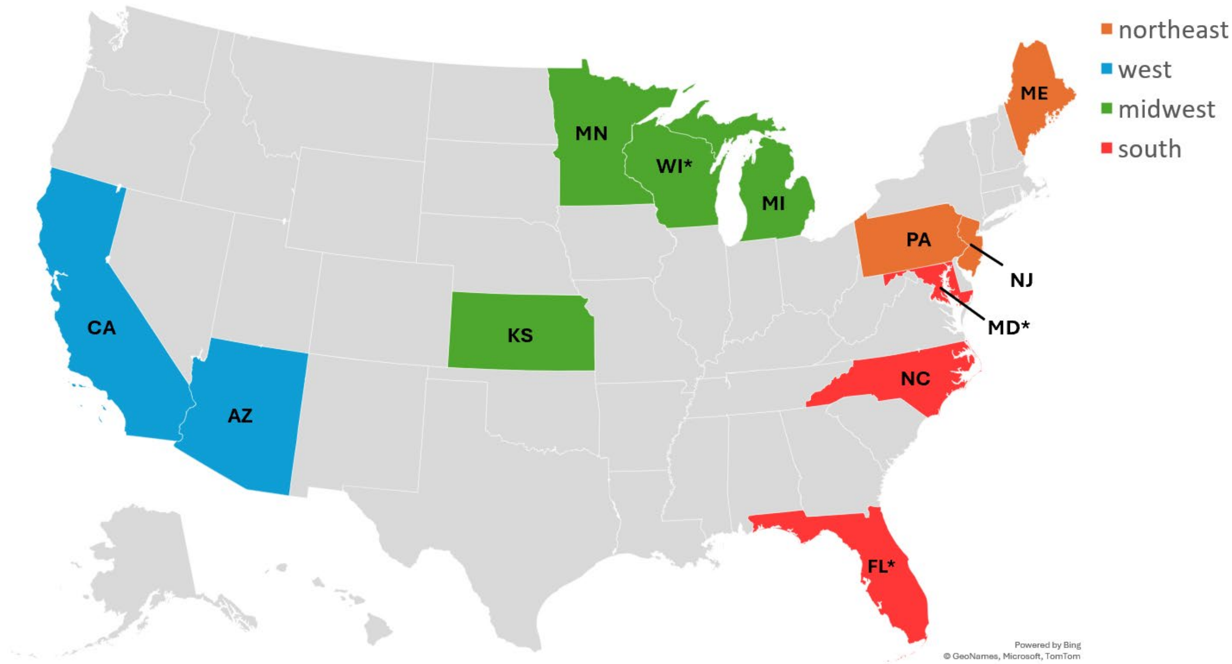


Figure 1 Locations of Studies Included in the Meta-Analysis Across the Contiguous United States

Each study can contribute multiple meta-observations for a variety of reasons. Some studies estimate multiple regression models, where each contributes a unique meta-observation. In other cases, multiple unique estimates stem from the same regression model. For example, within the same model we may be able to infer estimated percent changes in home prices at different contamination levels, or at different time periods between the date of the contamination test or event, and the later home transaction. In other words, some studies were explicitly interested in how any decrease in property values associated with water contamination evolve over time. In such cases we "construct" meta-observations for each year since a test, for example, following the functional form assumptions made in the primary study. Guignet et al. (2022) did something similar in their meta-dataset of hedonic property value study results on surface water quality, only Guignet et al. and that literature were focused more on how house price premiums evolve with distance, rather than time.

In any case, the construction of our meta-dataset required detailed, study-by-study and model-by-model derivations of the percent change in home prices associated with groundwater and drinking water contamination. When constructing the meta-dataset, focus is drawn to results presented in tables in the main text of the primary studies. Results that are exclusively presented in appendices or in figures for purposes of diagnostics and robustness checks are generally excluded from our meta-dataset.

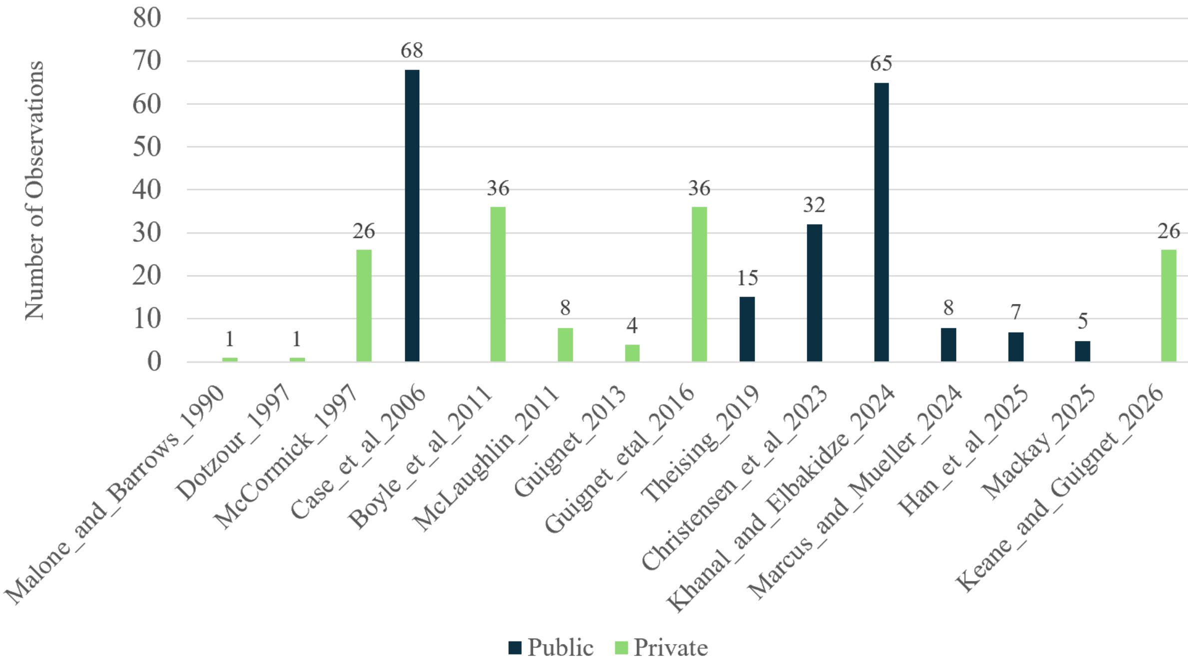


Figure 2. Number of Observations Given by Each Study

Although some studies estimate hedonic price regression specifications that utilize continuous measures of contamination, the majority of studies in the literature examine how home values respond to discrete changes or events. Therefore, in order to compare "apples to apples", we convert the estimates from each primary study into comparable measures of the percent change in price due to some discrete change in drinking water or groundwater quality. In some cases, this is with respect to the discovery of contamination, a public announcement of contamination, contamination levels exceeding some regulatory-related threshold, and/or remediation of contamination. Appendix B details the study and model-specific derivations for each of the n=338 percent change in price estimates in the meta-dataset.

To derive the corresponding standard errors for each of the n=338 percent change in price estimates, we use the original standard errors reported in the primary studies to conduct a Monte Carlo simulation where we re-estimate each of the n=338 estimated price changes 100,000 times.[4] The resulting empirical distributions gives us an estimate of the standard errors for the originally inferred estimates, which as discussed in Section III is important for purposes of weighting and assessing publication bias in meta-analyses.[5]

[4] Note that covariance matrices are not often reported in the empirical literature, and so a covariance of zero is assumed in our Monte Carlo simulations for the 90 (26.6%) meta-observations that involved more than one regression coefficient estimate.

[5] The full meta-dataset, data formatting code, and analysis code will be made publicly available after publication.

### *II.C. Descriptive Statistics*

Table 1 presents descriptive statistics for the full sample of 338 observations. The table reports the mean, standard deviation, minimum, and maximum values for the dependent variable, commodity characteristics, and study and methodological variables included in the analysis.

The outcome variable is the percent change in price (%Δp). The mean percent change is −7.58%, indicating that, on average, studies report a decrease in home prices due to contaminated potable water. However, the relatively large standard deviation (14.62) and wide range (−53.52 to 123.14) indicate substantial variation across estimates and primary studies. Several commodity-level variables describe environmental and informational conditions. Approximately 59.2% of observations involve public water systems, while contamination is detected in 94.1% of cases, indicating that most estimates evaluate confirmed contamination scenarios rather than perceived risks alone. About 67.5% of the meta-observations correspond to situations where contamination levels exceed regulatory standards, and 37.0% occur following public informational events. The average number of years observed after contamination events is 4.3 years, with a minimum of zero years and a maximum of 16.5 years, suggesting both short- and long-term price effects are represented.[6] Only about 8.0% of observations are missing information on the relative timing of an observed price effect.

Study and methodological characteristics also vary across studies and meta-observations. The average publication year is 2015, with studies ranging from 1990 to 2026, demonstrating that the meta-data span several decades of research. Some model specifications appear with relatively low frequencies, including Box-Cox (2.1%), linear (21.6%), and double log (2.1%) functional forms. Spatial econometric methods are used, but are less common. A spatial lag of neighboring home prices (LeSage and Pace 2009) is included in only 0.3% of the models. In contrast, spatial fixed effects are used in 76.9% of the meta-observations. Approximately 45.9% of the estimates explicitly account for spatial autocorrelation, either through a spatial error model (LeSage and Pace 2009) or through clustering based on geographic area. Additionally, 38.8% of observations use a difference-in-differences design, reflecting the increased prevalence of quasi-experimental approaches in this literature.

Table 1. Meta-data descriptive statistics.

| Variable | Obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| % Change in price (%Δp) | 338 | -7.58 | 14.62 | -53.52 | 123.14 |
| % Change in price std. error | 338 | 11.61 | 114.93 | 0.32 | 2113.23 |

[6] In many instances, the variable denoting time since the contamination event could be directly inferred from the model specification assumed in the primary study (see Appendix B). In other cases, we based the time variable on the observed midpoint in the primary study sample. For example, if a hedonic regression model was estimated using home transactions that took place 0 to 3 years after a private well test, then the midpoint of 1.5 years was assumed.

| | | | | | |
|---|---|---|---|---|---|
| **Commodity variables** | | | | | |
| Water not used | 338 | 0.003 | 0.054 | 0 | 1 |
| Public water | 338 | 0.592 | 0.492 | 0 | 1 |
| Contamination detected | 338 | 0.941 | 0.236 | 0 | 1 |
| Contamination above standard | 338 | 0.675 | 0.469 | 0 | 1 |
| Post informational event | 338 | 0.370 | 0.483 | 0 | 1 |
| Time (years) | 338 | 4.3 | 4.0 | 0 | 16.5 |
| Missing: time | 338 | 0.080 | 0.272 | 0 | 1 |
| **Study and Methodological variables** | | | | | |
| Year published | 338 | 2015.2 | 9.2 | 1990 | 2026 |
| Unpublished | 338 | 0.290 | 0.454 | 0 | 1 |
| Box-cox specification | 338 | 0.021 | 0.143 | 0 | 1 |
| Linear specification | 338 | 0.216 | 0.412 | 0 | 1 |
| Double log specification | 338 | 0.021 | 0.143 | 0 | 1 |
| Spatial lag of price | 338 | 0.003 | 0.054 | 0 | 1 |
| Spatial fixed effects | 338 | 0.769 | 0.422 | 0 | 1 |
| Spatial autocorrelation | 338 | 0.459 | 0.499 | 0 | 1 |
| Difference-in-differences | 338 | 0.388 | 0.488 | 0 | 1 |
| Inferred % change in price | 338 | 0.506 | 0.501 | 0 | 1 |
| Assumed zero covariance | 338 | 0.266 | 0.443 | 0 | 1 |

## III. METHODS

The meta-analytic methods that we employ entail a combination of techniques, including the derivation of observation weights to account for the clustered structure of the meta-dataset and precision of primary study estimates; an approach to assess and control for publication bias; and meta-regression models to account for price effect heterogeneity.

### *III.A. Meta-analytic Weights.*

When calculating mean unit values and estimating meta-regression models, meta-analysts will often weight the meta-observations. There are two primary motivations when deriving such weights: (i) to account for the clustered nature of the meta-dataset; and (ii) to give more weight to more statistically precise primary estimates, under the pretense that higher-precision estimates are of higher quality and better reflect the true price effect of interest (Guignet and Newbold 2026).

The two conventional precision-based weighting schemes are Fixed Effect Size (FES) and

Random Effect Size (RES).[7] The FES weights are simply the inverse variance of each primary study estimate, and are appropriate when each meta-observation is believed to represent a draw from the same underlying population distribution or data generating process (Nelson and Kennedy, 2009; Borenstein et al., 2010; Nelson, 2015; Havránek et al., 2020; Schütt, 2021; Vesco et al., 2020). More formally, the FES weight for primary estimate *i* from model specification *s* in study *j* can be expressed as:

$$w_{isj}^{FES} = \frac{1}{v_{isj}}, \tag{1}$$

where $v_{isj}$ is the variance of the primary estimate of interest; in our case an estimate of the percent change in price $\%\Delta p_{isj}$. The RES weights are slightly more complicated, and are more appropriate when the meta-observations are thought to be drawn from different underlying distributions (Harris et al., 2008; Borenstein et al., 2010; Nelson, 2015). The RES weights are:

$$w_{isj}^{RES} = \frac{1}{v_{isj} + T^2}, \tag{2}$$

where $T^2$ represents the "excess heterogeneity" among the meta-observations, and can be estimated as:

$$T^2 = \frac{Q - (n-1)}{\sum_{i=1}^{n} w_{isj}^{FES} - \left(\frac{\sum_{isj=1}^{n}\left(w_{isj}^{FES}\right)^2}{\sum_{isj=1}^{n} w_{isj}^{FES}}\right)}, \tag{3}$$

where $Q = \sum_{i=1}^{n} \frac{\left(\%\Delta p_{isj} - \%\Delta \bar{p}^{FES}\right)^2}{v_i}$, $n$ is the sample size of the meta-dataset, and $\%\Delta \bar{p}^{FES}$ is the FES-weighted mean.

To account for the clustered nature of the meta-dataset – i.e., that some studies contribute multiple, perhaps redundant meta-observations, meta-analyses sometimes use cluster-based weights based on the number of observations from a primary study or otherwise defined cluster (e.g., Mrozek and Taylor 2002; Guignet et al. 2022). Let $k_j$ denote the number of meta-observations from study $j$. The cluster-based weights are simply the inverse of the cluster size:

$$w_{isj}^{K} = \frac{1}{k_j}, \tag{4}$$

[7] The FES and RES terminology should not be confused with the commonly referenced Fixed Effects and Random Effects panel models often utilized in econometrics. These concepts are different. The FES weights are named as such because when employed one is assuming that the effect size estimates all have the same (or fixed) expected value; meaning that sampling variability is assumed to be the only reason primary study estimates vary. In contrast, the RES weights allow for additional heterogeneity (or randomness) among the expected values of the effect size estimates.

where the *K* superscript is simply the general label for cluster-based weighting schemes.

As described by Guignet et al. (2022), the inverse cluster size weight in equation (5) can be considered a specific case of a more general cluster-based weighting scheme. Consider the incorporation of a weight re-allocation parameter $r_{isj}$, where $0 \leq r_{isj} \leq k_j$. The more general cluster-based weights can be expressed as:

$$w_{isj}^{K} = \frac{1}{k_j} r_{isj}, \tag{5}$$

The weights expressed by equation (5) are a generalization of the inverse cluster size weights in equation (4), where $r_{idj} = 1$. Equation (5) is also a generalization of the approach taken by some meta-analysts who select a single "preferred" estimate from each cluster; in which case $r_{isj} = k_j$ for the preferred estimate, and $r_{isj} = 0$ otherwise.

Labelled as Variance Adjusted Cluster (VAC) weights, Guignet et al. (2022) proposed a weighting scheme that uses the FES weights from equation (1) to determine the reallocation parameter, as follows:

$$r_{idj} = \left( \frac{w_{isj}^{FES}}{\sum_{i=1}^{k_j} \left( w_{isj}^{FES} \right)} \right) k_j, \tag{6}$$

This weighting scheme still gives the same overall weight to each study *j* in the meta-dataset, but reallocates the weight given to each estimate *within* a study, giving more weight to more precise estimates, and less weight to relatively imprecise estimates.

An alternative weighting scheme that accounts for both the clustered structure of the metadata and statistical precision of the primary study estimates is the Random Effect Size Cluster Adjusted (RESCA) weights (Guignet et al. 2022). The RESCA weights are simply the product of the conventional RES weights and the inverse cluster size weights shown in equations (2) and (4), respectively. More formally:

$$w_{isj}^{RESCA} = \frac{w_{isj}^{RES}}{k_j}, \tag{7}$$

The RESCA weights take the conventional RES weights, which give less weight to less precise primary estimates both within and across clusters or studies, and then further reduces the weight given to primary estimates from studies that contribute more meta-observations (i.e., where $k_j$ is greater).

The different weighting schemes are later applied to the primary study estimates when calculating the mean unit values and when estimating the meta-regression models. They are also applied in some of our tests and corrections for publication bias, discussed next.

***III.B. Publication Bias.***

As a first step to examine possible selection concerns, we create a funnel plot of the $\%\Delta p_{isj}$ estimates (Stanley and Doucouliagos 2012, 2014), where the x-axis is the $\%\Delta p_{isj}$ estimates and the y-axis is the corresponding inverse standard errors of those primary study estimates. If the plot exhibits a symmetric inverted funnel shape, then this provides a visual signal that the meta-data does not suffer from a publication bias. In contrast, any asymmetries in the funnel plot would suggest a possible selection bias. The intuition is that if there is no publication bias, then the inverted funnel shape will center around the "true" effect or value of interest, with the most precise estimates at the top. As one moves down the y-axis, if there is no selection bias then primary study estimates are equally as likely to be an over- or under-estimate, implying a symmetric inverted funnel shape.

Following this same rationale, Stanley and Doucouliagos (2012) propose a more formal funnel-asymmetry test (FAT) and precision-effect test (PET). To carry out their FAT-PET procedure, we estimate the following meta-regression model:

$$\%\Delta p_{isj} = \beta_0 + \theta SE_{isj} + \varepsilon_{isj} \quad (8)$$

where $SE_{isj}$ is the standard error from the primary study estimate of the percent change in price associated with potable water contamination ($\%\Delta p_{isj}$), $\varepsilon_{isj}$ is an unobserved disturbance term, and the parameters to be estimated are $\beta_0$ and $\theta$.

The null hypothesis under the FAT is $H_0: \theta = 0$, which would suggest no evidence of publication bias. The intuition behind this null hypothesis ties back to the funnel plots. If $\theta = 0$, then the magnitude of an observed price change estimate is independent of its statistical precision; implying that estimates will be randomly and symmetrically distributed around the true parameter of interest (Stanley and Doucouliagos, 2012). Under the PET, $\beta_0$ represents the true effect or value of interest. The null hypothesis $H_0: \beta_0 = 0$ would suggest that the true parameter of interest is zero, after controlling for any publication bias.

Simulation studies have suggested that including the $\%\Delta p_{isj}$ estimate variances $v_{isj} = SE_{isj}^2$ in equation (8), instead of $SE_{isj}$, yields a better estimate of the true effect of interest (Stanley and Doucouliagos, 2012, 2014). Referred to as the precision-effect estimate with standard error (PEESE), $\beta_0$ can be interpreted as true mean $\%\Delta p$ value of interest, stripped of any potential publication bias (Stanley and Doucouliagos, 2012, 2014). With such tests it is important to control for large sources of heterogeneity (Stanley and Doucouliagos, 2019), and we do so in several of the regression models discussed next.

### *III.C. Meta-regression Model.*

The outcome variable of interest is the percent change in home price associated with a discrete change in potable water quality (e.g., a contaminant being detected or found at levels above the health-based regulatory or guidance threshold). In a meta-analysis, the outcome variable of interest is an estimate itself from an earlier primary study. As before, $\%\Delta p_{isj}$ denotes percent change in price estimate *i* from model specification *s* in study $j$. The vector $x_{isj}$ denotes characteristics of the "commodity", such as the level of contamination; whether the water is from a public water system, as opposed to a private groundwater well; time since the contamination test, or since information was released or an event took place; etc. The vector $z_{sj}$ encompasses methodological attributes of the primary study and the corresponding regression model specification, including the assumed functional form, approaches to account for spatially correlated confounders, etc. The meta-regression model to be estimated is:

$$\%\Delta p_{isj} = \beta_0 + x_{isj}\beta_1 + z_{sj}\beta_2 + \varepsilon_{isj} \tag{9}$$

where $\varepsilon_{isj}$ is an unobserved disturbance term, and the parameters to be estimated are $\beta_0$, $\beta_1$, and $\beta_2$.

Subsequent models account for publication bias by following Stanley and Doucouliagos (2012, 2014), and include the primary estimate variance $v_{isj}$ as an independent variable, as follows:

$$\%\Delta p_{isj} = \beta_0 + x_{isj}\beta_1 + z_{sj}\beta_2 + \theta v_{isj} + \varepsilon_{isj} \tag{10}$$

Finally, to explicitly address our third research question of whether any price effects persist or diminish over time, we extend equation (10) by adding a measure of years since the contamination test or event occurred, $yrs_{isj}$, as shown:

$$\%\Delta p_{isj} = \beta_0 + x_{isj}\beta_1 + z_{sj}\beta_2 + \theta v_{isj} + \delta yrs_{isj} + \varepsilon_{isj} \quad (11)$$

In this simple linear specification with respect to time, if $\delta > 0$ then any negative price effects diminish over time, on average. But if $\delta \leq 0$ then any negative price effects associated with potable water contamination persist, or perhaps even intensify over time.

## IV. RESULTS

### *IV.A. Mean Unit Values*

We start with calculating simple unit value estimates of the mean price effect, following the weighting schemes discussed in Section III.A, equations (1) through (7). As shown in Table 2, the mean values are robust across the weighting schemes, ranging from a 5.6% depreciation to an almost 9.0% decline. The unweighted mean unit value of a 7.6% price decrease is statistically insignificant, but otherwise the mean unit value estimates are statistically significant across all weighting schemes. The inverse cluster size weights account for the fact that some studies contribute more meta-observations than others, and re-weights the sample so that each study yields the same influence on the mean. In doing so, we see that the literature generally suggests that contamination issues with potable water is associated with a significant 8.4% decline in home values, on average. The FES and RES weights account for statistical precision, but not the potential redundancy of estimates from the same study. The unit values are fairly similar, suggesting a 5.6% and 8.3% respective decline in home values. Finally, the VAC and RESCA weights account for both statistical precision and the dependence of estimates from the same study, and suggest an 8.1% and almost 9.0% depreciation, respectively.

Table 2. Mean Unit Value Estimates of Percent Change in Price

| Unweighted | Inverse Cluster Size | Fixed Effect Size (FES) | Random Effect Size (RES) | Variance-adjusted Cluster (VAC) | RES Cluster -adjusted (RESCA) |
|---|---|---|---|---|---|
| -7.583 | -8.387** | -5.611*** | -8.336*** | -8.104*** | -8.983*** |
| [-19.879, 4.714] | [-16.102, -0.671] | [-5.809, -5.413] | [-8.671, -8.000] | [-8.838, -7.370] | [-9.586, -8.380] |

Note: Sample mean and weighted mean values of the percent change in price associated with potable water contamination (n = 338 meta-observations). * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

### *IV.B. Assessing Publication Bias*

We next investigate potential publication bias in these meta-data by first generating a funnel plot graph as suggested by Stanley and Doucouliagos (2012, 2014). As shown in Figure 3, the plot does generally depict an inverted funnel shape, but there is a cluster of estimates around a negative percent change in price of about 40%. There is also a greater density to the left of the central estimates, in general. Together these asymmetries suggest a potential publication bias. More specifically, this may suggest that estimates illustrating the expected negative sign may be more likely to be published in the literature and thus present in the meta-dataset.

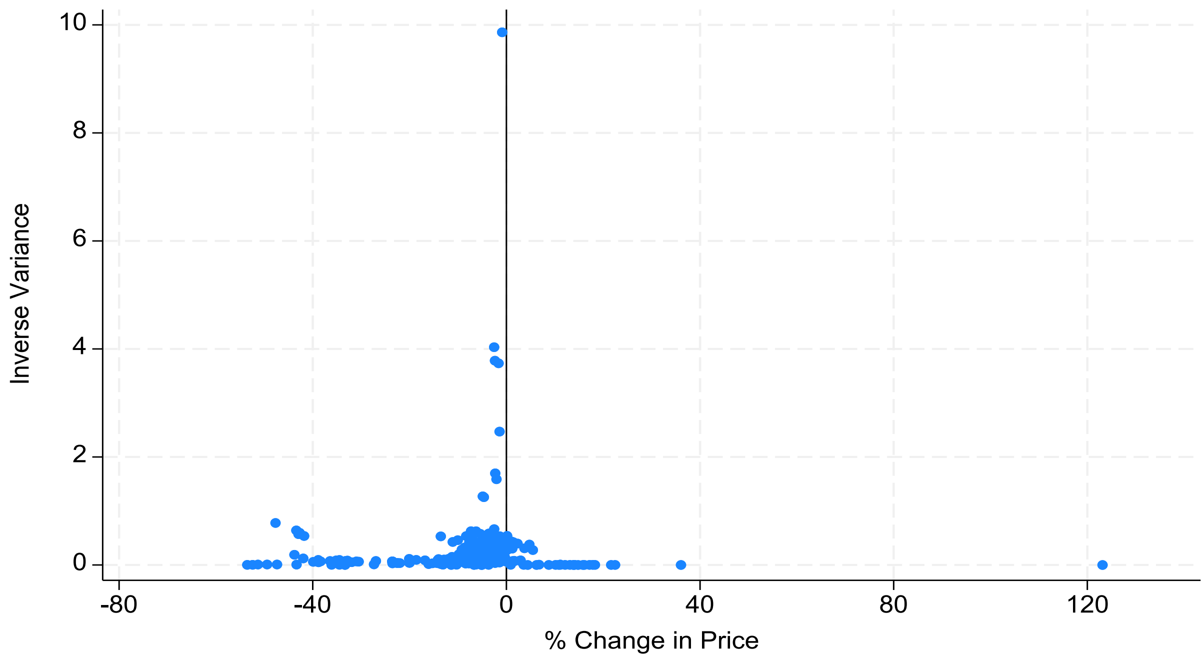


Figure 3 Publication Bias Funnel Plot.

In Table 3 we carry out Stanley and Doucouliagos's (2012) more formal FAT-PET procedure to test for publication bias (see equation (8)). The statistically significant coefficients corresponding standard error variable suggest such bias, but the direction of the bias seems to vary depending on the assumed weighting scheme, as seen when comparing columns (1) through (3) in Table 3. The more sophisticated weighting schemes, and in particular the VAC and RESCA weights that account for statistical precision and multiple estimates from each study, suggest no publication bias, as demonstrated by the statistically insignificant coefficients on the $\%\Delta p$ standard error variable in the first row of columns (5) and (6). This highlights a potential benefit of these dual-purposed weights in minimizing publication bias.

Table 3. FAT-PET Regression Models to Test for Publication Bias.

| | Unweighted | Inverse Cluster Size | Fixed Effect Size (FES) | Random Effect Size (RES) | Variance-adjusted Cluster (VAC) | RES Cluster -adjusted (RESCA) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Std Error %Δp | 0.06*** | 0.06*** | -1.83* | -0.35 | 0.30 | -0.18 |
| | (1.46e-03) | (2.08e-03) | (1.04) | (0.62) | (0.20) | (0.62) |
| Constant | -8.32*** | -8.91*** | -2.87 | -7.30** | -9.10** | -8.51* |
| | (2.43) | (2.93) | (2.38) | (2.93) | (3.48) | (4.16) |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| Adj. $R^2$ | 0.247 | 0.165 | 0.050 | 0.008 | 0.012 | -0.002 |

Note: The dependent variable is the estimated percent change in price estimates from the primary studies. Regression models are estimated via Weighted Least Squares (WLS) using the corresponding weighting scheme denoted in each column header. Clustered standard errors in parentheses, clustered at the study level. * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

Table 4 illustrates the PEESE-derived unit value estimates, which account for any potential publication biases (Stanley and Doucouliagos, 2012, 2014). The statistically significant constant terms suggest that potable water contamination is associated with a 5.6% to almost 9.0% decline in home values, on average. After controlling for publication bias, the estimates are quite robust across weighting schemes, and this range is similar to the mean unit values in Table 2. Stanley and Doucouliagos (2019) emphasize the importance in controlling for sources of effect size heterogeneity when implementing these corrections for publication bias, and we do so in the meta-regressions discussed next.

Table 4. PEESE Regression Models to Estimate Mean Unit Values after Controlling for Publication Bias.

| | Unweighted | Inverse Cluster Size | Fixed Effect Size (FES) | Random Effect Size (RES) | Variance-adjusted Cluster (VAC) | RES Cluster -adjusted (RESCA) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Variance %Δp | 2.94e-05*** | 2.95e-05*** | -1.48e-04 | 5.67e-05 | 1.00e-04*** | 7.17e-05 |
| | (5.56e-07) | (6.61e-07) | (2.88e-04) | (5.29e-05) | (2.42e-05) | (5.06e-05) |
| Constant | -7.97*** | -8.63** | -5.61** | -8.34*** | -8.11** | -8.98** |
| | (2.47) | (2.94) | (2.01) | (2.45) | (2.91) | (3.12) |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| Adj. $R^2$ | 0.236 | 0.156 | -0.003 | -0.003 | -0.003 | -0.003 |

Note: The dependent variable is the estimated percent change in price estimates from the primary studies. Clustered standard errors in parentheses, clustered at the study level. * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

## *IV.C. Meta-regression Results: Investigating Price Effect Heterogeneity*

A series of meta-regression models following equations (9) and (10) are estimated.[8] The initial meta-regression models in Table 5 do not control for publication bias. Model 1 starts simple, including just two indicator variables to control for whether the $\%\Delta p$ estimate was based on detected levels of contamination, or contamination levels above the regulatory standard or health advisory level for public water systems. The constant term suggests that studies examining drinking water contamination find an average 8.17% decline in home values in cases where contamination is not unambiguously confirmed or detected (the omitted category). These are usually cases where contamination is suspected or risks are potentially perceived, but were not objectively confirmed.[9] The marginally significant positive coefficient corresponding to contamination being detected suggests a 5.04% appreciation relative to the omitted category. This positive association is unexpected, but may be due to heterogeneity in the cases that are analyzed across studies and our categorization of estimates where the presence of contamination is not confirmed (i.e., *Detected* = 0). The remainder of the results from Model 1 match initial expectations. In cases where contamination is confirmed to be above the corresponding regulatory or health-based standards, we see an additional 9.92% decline in the estimated price effects.

The lower panel in Table 5 displays the price effects that can be inferred from Model 1 when contamination is above or below the regulatory standard. These predicted values are calculated based on equation (9) and the estimated coefficients from Model 1. When contamination is detected, but at levels below the standard (i.e., *Detected* = 1 and *Above Standard* = 0), Model 1 suggests an average 3.13% decrease in home prices. When contamination is detected at levels above the corresponding standard (i.e., *Detected* = 1 and *Above Standard* = 1), we find a larger average decline in home prices of 13.05%.

Model 2 adds an indicator denoting whether the estimates come from a study examining public water contamination or private groundwater wells. The negative 7.03 coefficient suggests that studies of public water systems generally reveal greater declines in home values, but this difference is not statistically significant. This pattern is also suggested by the predicted values from Model 2, as shown in the lower panel of Table 5.

As seen by Model 3, however, any difference in price effects across studies of public water systems versus private groundwater well contamination may be driven, at least partly, by differences in

[8] The RESCA weights are used to estimate the main regression models because this weighting scheme accounts for both the clustered nature of the meta-data and statistical precision of the primary estimates. The RESCA weights also account for relative precision across studies, and do not impose that each primary study is necessarily treated equally when estimating the meta-regressions. Similar to the earlier results, the key findings are robust to the alternative weighting schemes, and in particular, to the VAC weights, which also account for clustering and primary estimate precision.

[9] There are n = 20 such instances in the meta-data. Such examples include cases where contamination in a private well was suspected and tested for, but was not necessarily confirmed (Guignet 2013; Guignet et al. 2016); where homes were located in a high groundwater risk area and sold after additional disclosure (McLaughlin 2011); and where contamination was merely perceived but not present, because homes were near a contaminated public water system but were not connected to that system (Khanal and Elbakidze 2024).

methodological attributes of the primary studies themselves. Model 3 yields estimates that are generally similar in terms of the constant term, and the coefficients on contamination being detected and found to be at levels above the standard. The public water coefficient, however, is now positive and marginally significant. This change in the public water coefficient estimate is largely due to the inclusion of the indicator denoting estimates obtained from primary studies utilizing Difference-in-differences (DiD) methods.

All else constant, DiD models yield price effect estimates that are 13.68 percentage points lower. This could be driven by methodological decisions made by the primary study researchers, but we believe it is also because most DiD applications in this literature are focused on extremely high-profile cases. Christensen et al. (2023) focused on the nationally recognized lead contamination case in Flint, MI. Marcus and Mueller (2024) examined the highly publicized PFAS contamination case in Paulsboro, NJ. Both studies found price declines sometimes in the range of 40%.

Table 5. Primary Meta-regression Results.

| | (1) | (2) | | (3) | |
|---|---|---|---|---|---|
| Detected | 5.04* | 6.29* | | 4.37* | |
| | (2.60) | (3.06) | | (2.43) | |
| Above Standard | -9.92* | -5.70 | | -8.20* | |
| | (5.43) | (4.25) | | (4.63) | |
| Public Water | | -7.03 | | 8.19* | |
| | | (4.57) | | (4.33) | |
| Linear Specification | | | | 5.89 | |
| | | | | (4.25) | |
| No Spatial Fixed Effects | | | | 1.26 | |
| | | | | (2.01) | |
| Difference-in-differences | | | | -13.68* | |
| | | | | (6.81) | |
| Constant | -8.17*** | -7.91*** | | -8.45*** | |
| | (2.40) | (2.50) | | (2.54) | |
| Estimated %Δp | | Private | Public | Private | Public |
| Below Standard | -3.13** | -1.63 | -8.66** | -4.07*** | -4.84* |
| | (1.29) | (1.82) | (4.22) | (1.53) | (2.70) |
| Above Standard | -13.05** | -7.33** | -14.36** | -12.28*** | -13.05*** |
| | (5.27) | (3.61) | (5.70) | (4.70) | (4.56) |
| Observations | 338 | 338 | | 338 | |
| Adjusted R Squared | 0.136 | 0.182 | | 0.291 | |

Note: The dependent variable is the estimated percent change in price estimates from the primary studies. RESCA weights are used when estimating the Weighted Least Squares (WLS) models. Clustered standard errors in parentheses, clustered at the study level. * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

The other two methodological variables in Model 3 are indicators denoting when a linear hedonic price regression model was assumed, or when no spatial fixed effects were included in the primary study model. The corresponding coefficients for both variables are positive, but statistically insignificant (both individually and jointly, at least marginally so with $p = 0.11$).

The estimated percent changes in price derived from Model 3 are shown in the second panel of Table 5. We calculated these estimated price changes slightly differently to account for (i) the fact that in this literature to date, DiD specifications were only implemented in studies on public water system contamination (not on private wells); and (ii) that, although powerful in establishing causal inference, the DiD methodology is not applicable in all settings.

When using meta-regressions for benefit transfer, one can generally plug in policy site characteristics in order to predict a site-specific percent change in price. In the case of methodological characteristics one can plug in values denoting best methodological practices. The predicted values from the meta-regression model would then reflect the value estimate that the literature predicts for the policy site if best practices are used (Boyle and Wooldridge 2018). If there are methodological variables where there are not unambiguously determined best practices, then one could plug in the average from the meta-dataset, in which case the predicted values would reflect what the average study in the literature would predict (Boyle and Wooldridge 2018).

Hedonic price functions that are assumed to be linear, or do not include spatial fixed effects to account for spatially correlated confounders, are generally considered subpar in the hedonic literature (Bishop et al. 2020; Bockstael and McConnell 2006; Guignet et al. 2022). Therefore, we set the linear specification and no spatial fixed effects indicators equal to zero when predicting the $\%\Delta p$ estimates shown in the lower panel of Table 5. Although the DiD identification strategy is generally considered superior for causal inference, the technique is not applicable in all contexts. Therefore, instead of setting the DiD indicator equal to one when estimating $\%\Delta p$ for the various scenarios under Model 3, we set it equal to the subsample averages in the meta-dataset for private well and public water studies, which correspond to values of zero and 0.655, respectively. In other words, none of the hedonic property values studies on private groundwater well contamination to date have utilized the DiD approach. In contrast, among the studies focusing on public water system contamination, 65.5% of the $\%\Delta p$ estimates were from DiD regression models.

After controlling for methodological characteristics and subsample averages for the DiD indicator, the Model 3 estimates in the lower panel of Table 5 illustrate no substantial difference in the estimated price effects based on whether the contamination pertains to private groundwater wells versus a public water system. When contamination is detected but at levels below standards, we see average price depreciations of 4.07% and 4.84%. When contamination is at levels above the regulatory or health-based standards, we see a 12.28% decline in the value of homes on private wells, and a corresponding 13.05% for homes connected to the public water system. The results are virtually identical when we re-estimate Models 1-3 and account for publication bias by including the primary study $\%\Delta p$ variances as an independent variable (Stanley and Doucouliagos, 2012, 2014).[10]

[10] See Table A3 in Appendix A.

***IV.D. Meta-regression Results: Do Price Effects Diminish over Time?***

In the final set of meta-regression models, we account for how long ago contamination was discovered or tested for. In doing so, our goal is to assess what the literature suggests in aggregate regarding the potential permanence of potable water contamination on home values. The literature is generally mixed regarding the persistence of any price effects, with some studies suggesting that any adverse effects on home values decline within 3 to 5 years (Boyle et al. 2010; Case et al. 2006; Guignet et al. 2016), and other studies finding price declines that persist over time (Christensen et al. 2023; Keane and Guignet 2026; Marcus and Mueller 2024). Public distrust and stigma towards neighborhoods, even after contamination issues are resolved, are often cited as key contributing factors towards permanent declines in home values (Christensen et al. 2023; Marcus and Mueller 2024: Messer et al. 2006).

The following meta-regressions allow us to quantitatively synthesize the findings from the literature and assess how any decrements in home values evolve over time, on average. The full meta-regression results are presented in Table A4 in Appendix A. We estimate two different sets of model variants; in the first we assume any price effects associated with potable water contamination evolve linearly over time, and in the second we allow for a quadratic relationship. The first two models following the linear and quadratic specifications only include time (i.e., years since) on the right-hand side. The second two models (Models (3) and (4) in Table A4) build off of the earlier models by accounting for methodological characteristics in the primary study hedonic price models, as well as the %Δp variance to control for any potential publication bias. Given our goal of assessing general trends in the effects of potable water contamination on home values over time, we do not include commodity characteristics in these models (such as the indicators denoting when contamination is detected or at levels above the corresponding standard). The public water indicator is also excluded for this same reason, and because earlier results suggested no difference in the price effects based on private versus public water sources.

As seen in Table A4, except for the constant term, almost all the coefficients are statistically insignificant. Nonetheless, we can calculate the predicted price effects for each year after contamination was suspected or discovered, based on the parameterized models. The predicted price effect estimates based on Models 3 and 4 in Table A4 are shown in Figure 4. Similar to the earlier exercise, we set the indicators denoting subpar linear or no spatial fixed effect specifications to zero, and plug the overall sample average of 0.388 in for DiD model indicator. Based on the same logic of plugging zeros in for indicators denoting subpar methodological decisions, we plug zero in for the %Δp variance term. In doing so, we account for and strip out any influence of publication bias on the predicted %Δp estimates over time.

As can be seen in Figure 4, both the linear (top panel) and the quadratic (bottom panel) specifications suggest similar patterns, illustrating initial declines in home values of 13.93% or 10.56%, respectively. Both specifications then suggest that, on average, the adverse price effects associated with potable water contamination slowly diminish over time, remaining negative and statistically significant for about 11 years after the initial contamination event.

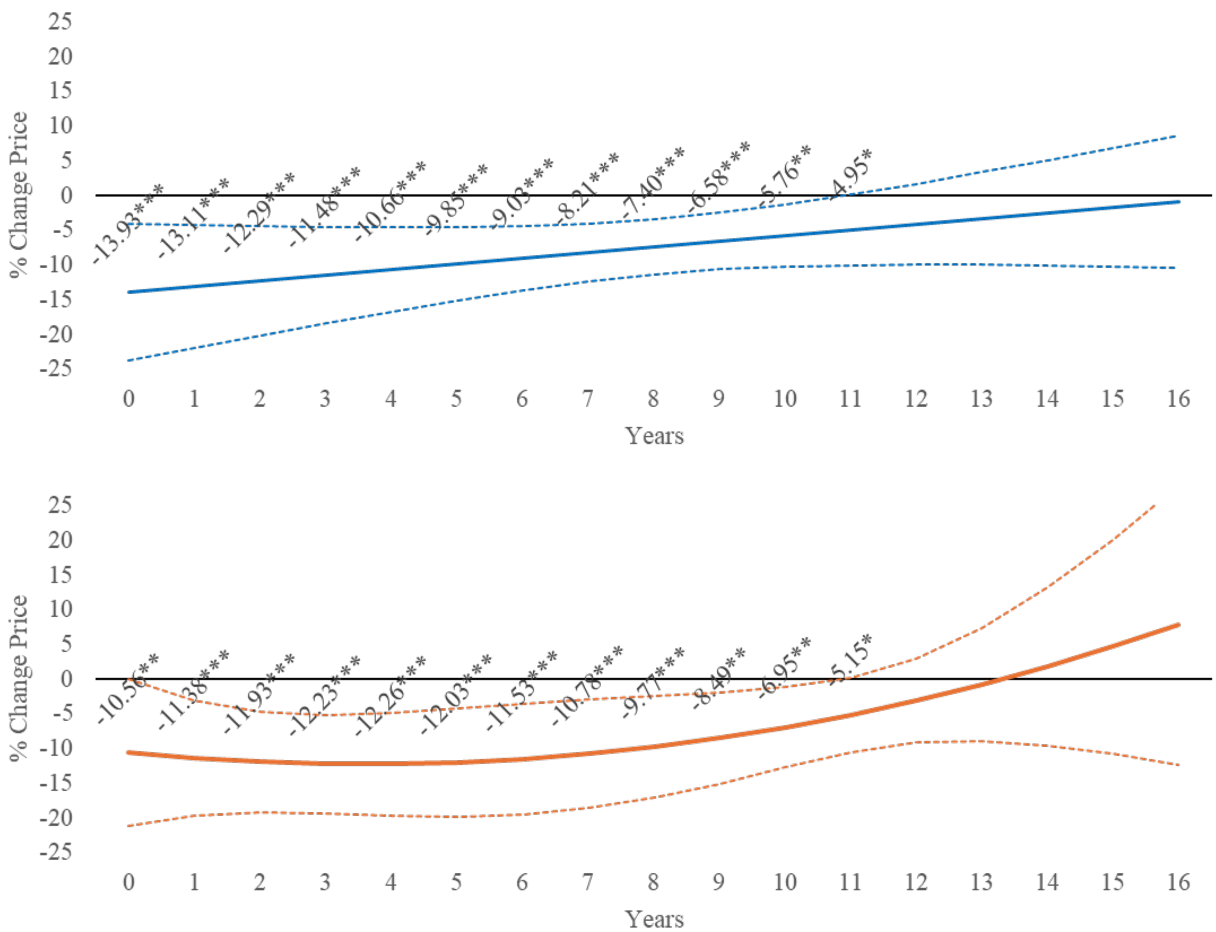


Figure 4. Estimated Percent Change in Price Over Time.

## V. CONCLUSION

We constructed a novel meta-dataset of hedonic property value studies examining the effects of potable water contamination on home values. We examined the robustness of the results across alternative meta-analytic weighting schemes, and test and control for publication bias. We estimate a series of meta-regression models to examine heterogeneity in the price effects across public water versus private groundwater well sources, based on the severity of contamination, and to account for primary study methodological characteristics. Finally, we assessed how any adverse effects of potable water contamination on home values tend to evolve over time.

Overall, we find robust evidence across alternative weighting schemes that potable water contamination does affect home values. The mean unit value estimates range from a 5% to 9% decrease in home values. We find evidence of potential publication bias in this branch of the hedonic property value literature, but this bias does not seem to substantively affect the meta-analysis results, especially when employing weights that account for statistical precision.

The meta-regression analysis yields a few key conclusions. First, when conducting a meta-analysis it is important to account for methodological decisions made in the primary studies. Similar findings have been noted in past meta-analyses of hedonic studies on surface water quality (Guignet et al. 2022; Heberling et al. 2024). Second, conditional on methodological attributes, we find that the adverse effects of potable water contamination on home values are the same no matter the water source – i.e., a public water system versus private groundwater wells. Third, as expected, the estimated price effects are greater in situations with more severe water contamination. When contamination is merely detected, we find an average decrease in prices of about 4-5%. When contamination is found at levels that exceed the regulatory or health-based standard, we find decreases in home values around 12-13%, on average. Lastly, on average these adverse price effects seem to persist for at least 10 years after the contamination was first tested for or detected.

There are several important limitations to keep in mind regarding our meta-analysis. For example, despite our best efforts to identify a comprehensive set of hedonic studies focusing on potable water contamination, we could only identify 15 such studies. Several of these studies, especially those on public water systems, are focused on particularly high-profile contamination incidents. This could imply a selection bias, although we at least partially address this issue using Stanley and Doucouliagos's (2012, 2014) publication bias corrections. Several of the studies are fairly dated, with about half of them being published before 2015. The housing market, types of contaminants, and econometric methods available have notably changed over time. There are also gaps in geographic coverage, particularly in the northwest, western mountains, and south central regions of the U.S. Future hedonic property value studies to help fill some of these gaps in geographic coverage, levels of severity, and types of contaminants, as well as to utilize more contemporary econometric methods (e.g., Difference-in-differences), would facilitate more robust meta-analysis and benefit transfer procedures. In addition, more comprehensive meta-data would allow for future meta-analyses to explore additional sources of heterogeneity in the estimated effects of potable water contamination on home values. Such efforts may entail more comprehensive meta-regression models, or perhaps utilize more flexible data-driven meta-analytic techniques, such as the random forest procedures recently proposed by Johnston and Moeltner (2026).

Despite these limitations, the constructed meta-dataset and meta-analysis can be used for purposes of benefit transfer, in order to inform benefit-cost analyses of local land use and public water program decisions, as well as for federal regulatory decisions under the Safe Drinking Water Act. The results can also be used to help inform and motivate homeowners, as well as state and local health agencies, dealing with private groundwater well contamination issues. Our findings can aid in damage litigation cases pertaining to drinking water contamination, including those dealing with issues of lead contamination, PFAS, volatile organic compounds, petroleum bi-products, and other contaminants like arsenic, manganese, and nitrates. Although original, context specific analyses are generally preferred, our meta-analysis provides easy-to-use unit values and transfer functions that allow for rough estimates of the effects of potable water contamination on home values.

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**APPENDIX A. Supplemental Details and Results.**

Table A1. Literature Search Keywords.

| Keyword 1 | Keyword 2 |
|---|---|
| groundwater | hedonic |
| ground water | property value |
| potable | home value |
| drinking water | home price |
| public water | property price |
| private well | housing |
| well water | |
| groundwater well | |
| water well | |
| public well | |
| community well | |

Table A2. Table of identified but excluded studies.

| Study name | Primary reason for exclusion |
|---|---|
| Gopalakrishnan and Klaiber 2014 | Excluded due to **criterion 2**. Primary measures are the number or count of shale gas wells near a home. Although groundwater quality is surely affected, proximity to and the number of these sites capture other disamenities as well. Also includes "risk" measure, but this is calculated based solely on the number of wells (or sites) and average proximity to those sites. |
| Andersson and Lavaine 2018 | This study examines how the price of homes in France are affected by location in a "vulnerable" zone. The zones are classified as vulnerable if nitrate levels in surface and groundwater exceed 40 mg/l. The study does not differentiate between surface water quality and groundwater quality, however, and is thus excluded under **criterion 2**. |
| Barnwal et al. 2017 | This study uses a field experiment to estimate the demand for well water testing. The study does not examine how home values are affected by |

| | |
|---|---|
| | contamination and is thus excluded under **criterion 1**. |
| Chappells et al. 2014 | This study is excluded based on **criterion 1**; it does not examine house prices. This study focuses on private well water contamination and how levels of arsenic affect public health. |
| Chattopadhyay et al. 2005 | This study focuses on how property values are affected by nearby hazardous sites, not water quality. We can exclude it due to **criterion 2** because the main focus is on proximity to toxic sites and cleanup. |
| Chaudhry et al. 2024 | This study only looks at the value of farmland, not home values, so it is excluded under **criterion 1**. |
| Choumert et al. 2015 | This study is excluded because although it touches on drinking water, it focuses on *access* to drinking water and sanitation, and not explicitly on quality. Therefore, it can be excluded under **criterion 2**. It is also an earlier version of Choumert et al. (2016), and can thus also be excluded under **criterion 3**. |
| Choumert et al. 2016 | This study focuses on how *access* to water and sanitation affects housing prices, and not on water quality. It can therefore be excluded under **criterion 2**. |
| Coelli et al. 1991 | This study is excluded under **criterion 1**. The focus is on public water being funneled to farmlands in Australia, not on impacts to home values. |
| Cassidy et al. 2022 | This study looks at how the cleanup of contaminated sites under RCRA increases home value. The cleanup targets are based on two environmental indicators: (1) Current Human Exposures Under Control and (2) Migration of Contaminated Groundwater Under Control. This study should be excluded under **criterion 2** because it is based on proximity to the RCRA site and does not necessarily isolate the price effects specific to groundwater quality. |
| Dendup and Tshering 2018 | This study looks at the demand for piped drinking water and residents' willingness to pay for such an amenity. It is excluded under **criterion 1**; the focus is not on the quality of drinking water but on accessibility. |
| Hill and Ma 2017 | Excluded under **criterion 1**. This study looks at water quality, but is not an analysis of house prices. |
| Kaur and Janmaat 2023 | This study is excluded under **criterion 1**. It is a theoretical and simulation study, and is not a statistical analysis that estimates the effect of drinking water quality on home values using actual data. |

| | |
|---|---|
| Kovacs and Rider 2023 | This study can be excluded under **criterion 1**. The focus here is on the demand for saturated thickness of the alluvial aquifer in Arkansas using a hedonic price model on the sale of agricultural land. It does not focus on home values, nor the quality of groundwater in the aquifer. |
| Muehlenbachs et al. 2012 | Excluded under **criteria 2** and **3**, it is an earlier working paper version of Muehlenbachs et al. (2015), and examines price effects based on proximity (see below). |
| Muehlenbachs et al. 2015 | This study is excluded under **criterion 2**. It focuses on shale gas development and how the development of these sites affects house prices. The study does take into account groundwater use, but the study relies on proximity and does not isolate the price effects associated solely with groundwater quality. |
| Liou et al. 2019 | This study looks at the spillover effects of soil and groundwater-contaminated sites on people's willingness to pay to avoid the contaminated sites. They do not look at the quality of the groundwater but rather focus on the distance to the sites and how much people are willing to pay for housing closer or further from the site. Therefore, this study can be excluded under **criterion 2**. |
| Melstrom and Wilkinson 2022 | This study is excluded under **criterion 2** because it estimates the effect of environmental remediation on housing prices in the Milwaukee Estuary Area of Concern. They are focused on housing prices related to clean-ups and distance from a contaminated site. |
| Ngyuen et al. 2022 | This study can be excluded under **criterion 2** as it focuses on climate change-related flooding on housing prices, as opposed to groundwater quality. |
| Phaneuf et al. 2008 | This study examines how changes in land use for residential development affect water quality. Since water quality is the outcome of interest, and not property values, this study is excluded under **criterion 1**. |
| Poe 1993 | This study looks at nitrate levels in private wells using stated preference survey methods. It can be excluded under **criterion 1** because the primary results are based on stated willingness to pay and groundwater protection programs. It does not examine property values. |
| Sakhri 2014 | This study can be excluded under **criteria 1 and 2.** The focus is on how access to groundwater affects poverty in India. It does not focus on groundwater quality or home values. |

| | |
|---|---|
| Tapsuwan et al. 2009 | This study focuses on the value of urban wetlands in Australia and, therefore, can be excluded under **criterion 2** since it does not evaluate the quality of drinking water or groundwater. |
| Weiwei 2020 | This study is excluded under **criterion 1** because the focus is on the overuse of groundwater, not quality. |
| Yang et al. 2020 | This study can be excluded under **criterion 1** as the study focuses on human health effects of arsenic-contaminated drinking water rather than water quality on home values. |
| Alzahrani and Collins 2022 | During a more detailed review, we decided to exclude this study due to **criterion 2**. This study focuses on the impact of boil water notices on property values. It focuses on water main breaks and the flow of contaminants in that water due to the breaks. However, boil water notices reflect other things as well, including aesthetics, reduced flow, etc. The authors describe it as a measure of water service reliability, and not necessarily a measure of water quality. |
| Page and Rabinowitz 2007 | This paper focuses on toxic chemical contamination of groundwater and how that affects home values. But it uses a "case study" approach with no formal statistical analysis, and is thus excluded under **criterion 1**. |

Table A3. Meta-regression Results after Controlling for Publication Bias

| | (1) | (2) | (3) |
|---|---|---|---|
| Detected | 5.04* | 6.28* | 4.37* |
| | (2.61) | (3.06) | (2.43) |
| Above Standard | -9.92* | -5.70 | -8.21* |
| | (5.44) | (4.26) | (4.64) |
| Variance %Δp | 9.80e-05 | 5.02e-05 | 8.43e-05 |
| | (6.10e-05) | (5.35e-05) | (5.69e-05) |
| Public Water | | -7.03 | 8.19* |
| | | (4.58) | (4.34) |
| Linear Specification | | | 5.90 |
| | | | (4.25) |
| No Spatial Fixed Effects | | | 1.26 |
| | | | (2.01) |
| Difference-in-differences | | | -13.68* |
| | | | (6.82) |
| Constant | -8.17*** | -7.91*** | -8.45*** |
| | (2.40) | (2.50) | (2.54) |

| | (1) | (2) GW | (2) PW | (3) GW | (3) PW |
|---|---|---|---|---|---|
| Estimated %Δp | | GW | PW | GW | PW |
| Below Standard | -3.13** | -1.63 | -8.66** | -4.08*** | -4.84* |
| | (1.29) | (1.83) | (4.23) | (1.53) | (2.71) |
| Above Standard | -13.05** | -7.33** | -14.36** | -12.28*** | -13.05*** |
| | (5.27) | (3.61) | (5.71) | (4.71) | (4.56) |
| Observations | 338 | 338 | | 338 | |
| Adjusted R Squared | 0.133 | 0.179 | | 0.289 | |

Note: The dependent variable is the estimated percent change in price estimates from the primary studies. RESCA weights are used when estimating these Weighted Least Squares (WLS) models. Clustered standard errors in parentheses, clustered at the study level. * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

Table A4. Meta-regression Results of Price Effects over Time

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Time (Years) | 0.56 | -1.54 | 0.55 | -1.54 |
| | (0.43) | (1.59) | (0.44) | (1.62) |
| Time Missing | 9.93 | 6.18 | 9.89 | 6.18 |
| | (6.07) | (5.10) | (6.24) | (5.16) |
| Time^2 | | 0.16 | | 0.16 |
| | | (0.13) | | (0.13) |
| Linear Specification | | | 6.55 | 6.00 |
| | | | (4.56) | (4.54) |
| No Spatial Fixed Effects | | | 1.20 | 0.90 |
| | | | (1.61) | (1.94) |
| Diff-in-diff | | | -10.60 | -10.67* |
| | | | (6.18) | (5.98) |
| Variance %Δp | | | 3.96e-05 | 4.87e-05 |
| | | | (4.28e-05) | (4.30e-05) |
| Constant | -12.57** | -8.82** | -9.82** | -6.42 |
| | (5.24) | (4.08) | (3.46) | (4.70) |
| Observations | 338 | 338 | 338 | 338 |
| Adj. R2 | 0.068 | 0.098 | 0.284 | 0.304 |

Note: The dependent variable is the estimated percent change in price estimates from the primary studies. RESCA weights are used when estimating these Weighted Least Squares (WLS) models. Clustered standard errors in parentheses, clustered at the study level. * ≤ 0.10, ** p ≤ 0.05, and *** ≤ 0.01.

**APPENDIX B. Study-by-study Derivations into Common Price Effect Measures.**

This appendix details the study-by-study, and model-by-model derivations of the percent change in price estimates associated with potable water contamination. When constructing the meta-dataset, focus is generally drawn to results presented in tables in the main text of the primary studies. Results that are exclusively presented in primary study appendices or in figures where the actual estimates and standard errors cannot be ascertained are generally excluded.

To the fullest extent possible, we convert the estimates from each primary study into comparable measures of the percent change in price due to some discrete change in drinking and/or groundwater quality. In some cases, this is with respect to the discovery of contamination, a public announcement of contamination, contamination levels exceeding some regulatory-related or health-based threshold, and/or the remediation of contamination. Common notation is introduced below to facilitate comparison of the calculations across primary studies. Note that for notational ease, the disturbance term, as well as subscripts denoting cross-sectional and temporal unit of observation, are not represented in the following hedonic price equations and subsequent derivations. Additional details can be found in the meta-data data preparation Stata do-file: "metadataprep_code2026_02_13.do."

$p =$ sale price (or an alternative measure of house value).

$d =$ dummy variable denoting whether a well was tested, or whether contamination was present or at levels above the detectable limit.

$s =$ dummy variable denoting contamination is at levels above some threshold or regulatory standard.

$c =$ continuous variable denoting concentration of a contaminant, with subscripts denoting units (when necessary).

$E =$ dummy variable denoting that some event occurred related to potable water contamination levels. This is a generic variable used when the event of interest does not fit under the $d$ or $s$ variable definitions above.

$x =$ vector of other control variables that are not of primary interest (e.g., home characteristics, such as the number of bathrooms, interior square footage, etc.).

$T =$ scalar or vector denoting time. This is explicilty represented because some primary study hedonic models examine how the price effects associated with potable water contamination vary over time.

$\beta =$ coefficients of primary interest, which correspond to water quality related variables (*d, s,* and *c*). When multiple water quality measures are presented in same model, subscripts denoting the corresponding variables are used.

$\theta =$ coefficients corersponding to $x$, which are not of primary interest.

### *Boyle et al. (2010)*

Boyle et al. contribute 36 observations to the meta-dataset. Boyle et al. examined how house prices vary with the concentration of arsenic in the groundwater, and how this price effect varies over time. Given our interest in examining price effect heterogeneity over time in the meta-analysis, we decided that rather than simply plugging in a sample average, we could construct representative meta-observations for each of the years encompassed in the primary study data.[11]

Their hedonic price models estimated by Boyle et al. are generally of the form:

$$ln(p) = x\theta + \beta_1(c \times s) + (c \times s \times T)\beta_2 \qquad (1)$$

where $c$ denotes a neighborhood-specific concentration of arsenic, based on the nearest tested well where concentrations exceeded the EPA standard for arsenic in public drinking water at the time (0.05 mg/L). In their paper, the concentration variable $c$ is implicitly interacted with the dummy variable $s$ because the Arsenic concentrations are only observed when above the corresponding standard for public drinking water. $\boldsymbol{T}$ is a vector of year dummies, ranging from 1992 to 2003 (where 2003 is the omitted category). Arsenic contamination became public knowledge in the study area in 1992. Equation (1) can be rewritten as:

$$p = e^{x\theta + \beta_1(c \times s) + (c \times s \times T)\beta_2} \qquad (2)$$

Let $p_0$ denote the price with no contamination. If there is no contamination then the level of arsenic is below the regulatory standard, $s = 0$. Plugging this into equation (2) yields:

$$p_0 = e^{x\theta} \qquad (3)$$

Based on equation (2), we can specify the price when contamination is above the regulatory standard $(s = 1)$ as:

$$p_1 = e^{x\theta + \beta_1 c + (c \times T)\beta_2} \qquad (4)$$

Similar to the transformation first advocated by Halvorsen and Palmquist (1980), we then express the percent change in price for having contamination above the regulatory standard ($s$) in each year $\boldsymbol{T}$ as shown:

$$\%\Delta p^s = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 \qquad (5)$$

Plugging in equations (3) and (4) into equation (5) yields the derivation of the corresponding percent change in price for each year in vector $\boldsymbol{T}$.

$$\%\Delta p^s = \left(\frac{e^{x\theta + \beta_1 c + \beta_2(c \times T)} - e^{x\theta}}{e^{x\theta}}\right) \times 100$$

[11] Note that in their meta-analysis of surface water quality, Guignet et al. (2022) took a similar approach with respect to distance from a waterbody. They constructed representative meta-observations at different distances based on the functional form of the distance gradient assumed in each primary study, when applicable. Our approach to the meta-dataset construction here is similar, except we are accounting for price effect heterogeneity over time rather than distance.

$$\%\Delta p^s = \left(\frac{e^{x\theta}\left(e^{\beta_1 c+\beta_2(c\times T)}-1\right)}{e^{x\theta}}\right) \times 100$$

$$\%\Delta p^s = \left(e^{\beta_1 c+\beta_2(c\times T)} - 1\right) \times 100 \quad (6)$$

We then plug in the sample mean for arsenic concentration ($\bar{c}$) to get the corresponding average percent change in price when arsenic concentrations are above the regulatory standard, for each year in vector $\boldsymbol{T}$.

$$\%\Delta p^s = \left(e^{\beta_1\bar{c}+\beta_2\bar{c}} - 1\right) \times 100$$

$$\%\Delta p^s = \left(e^{(\beta_1+\beta_2)\bar{c}} - 1\right) \times 100 \quad (7)$$

Using equation (7) and the regression coefficient estimates from the three models in Table 2 of Boyle et al., we obtain numerous estimates of $\%\Delta p^s$, which vary by the year since 1992, which is when contamination was first made public.

In some models, Boyle et al. pool the data cross two towns and include interaction terms to allow the $\%\Delta p^s$ to also vary by the town (Buxton versus Hollis). In such cases, a separate estimate for each town, and for each corresponding year, is obtained. Let *B* denote a dummy variable denoting homes in the town of Buxton. The hedonic price function can be written as:

$$ln(p) = x\theta + \beta_1(c \times s) + (c \times s \times T)\beta_2 + \left(c \times s \times \tilde{T} \times B\right)\beta_3 \quad (8)$$

where the vector $\tilde{T}$ is a subset of years in $T$. The corresponding derivation of the $\%\Delta p^s$ for Hollis is the same as in equation (7), but for the subset of years where there is an interaction with the Buxton indicator, the percent change in price for homes in Buxton would be:

$$\%\Delta p^s = \left(e^{(\beta_1+\beta_2+\beta_3)\bar{c}} - 1\right) \times 100 \quad (7)$$

### *Case et al. (2006)*

Case et al. contribute 68 observations to the meta-dataset. Each of their estimated models contribute one to up to 17 meta-observations. Similar to Boyle et al. (2010), Case et al. explicitly examine how home prices in a contaminated area vary based on the amount of time after contamination was discovered and publicly announced. As detailed below, they do this by interacting a linear "time since" variable with their contamination variables. Given our interest in examining price effect heterogeneity over time in the meta-analysis, we again construct representative meta-observations for each of the years encompassed in the primary study data.

Although the study never explicitly stated the contamination concentrations nor whether those concentrations were above any regulatory standard, we assume contamination levels were above any corresponding standard because the public water system shut down the contaminated wells, and the contaminated area was later declared a Superfund site. Case et al. estimate a repeat sales model to identify the price effects of interest, but for simplicity in exposition, the underlying hedonic price function for their simplest models examining contamination (Models 2 and 3) can be expressed as follows:

$$ln(p) = x\theta + \beta_1 s \tag{1}$$

We can re-arrange this and specify the price with contamination ($s = 1$) and without contamination ($s = 0$) as $p_1 = e^{x\theta+\beta_1}$ and $p_0 = e^{x\theta}$, respectively. Here by "with contamination" we mean that the home is in the groundwater contaminated area and sold after the (roughly) 1982 public announcement of contamination. For this simplest model that does not account for time since the 1982 announcement of contamination, the percent change in price due to the presence of contamination is calculated as:

$$\%\Delta p^s = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{e^{x\theta+\beta_1} - e^{x\theta}}{e^{x\theta}}\right) \times 100$$

$$\%\Delta p^s = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

Subsequent models by Case et al. allow the association between contamination and home prices to vary over time. Their Models 2a and 3a allow this temporal variation to follow a linear trend, as follows:

$$ln(p) = x\theta + \beta_1 s + \beta_2(s \times T) \tag{3}$$

where *T* in this case is a scalar denoting time since the contamination announcement in 1982. Similar to the above steps, we calculate the with and without contamination price as of year *T* as $p_1 = e^{x\theta+\beta_1+\beta_2 T}$ and $p_0 = e^{x\theta}$, respectively. And in turn calculate the percent change in price for a given *T years* after the contamination announcement as follows:

$$\%\Delta p^s = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{e^{x\theta+\beta_1+\beta_2} - e^{x\theta}}{e^{x\theta}}\right) \times 100$$

$$\%\Delta p^s = \left(e^{\beta_1+\beta_2 T} - 1\right) \times 100 \tag{4}$$

The sample of sales goes from 1980-1998. The contaminated-related price discounts start in 1982, when contamination was discovered and publicly announced, implying that we can calculate separate $\%\Delta p^s$ estimates for 17 different post-announcement years based on Models 2a and 3a, *T=0,…, 16*.

Models 2b and 3b by Case et al. allow the effect of contamination over time to vary freely from year to year, and so the models are of the form:

$$ln(p) = x\theta + (s \times T)\beta_1 \tag{5}$$

where now ***T*** is a vector of dummy variables denoting the corresponding year, from 1982 through 1998. Similar to before, the price with and without contamination can be used to calculate the percent change in price for each year, as shown in equation (6). This results in a vector of 17 estimates of $\%\Delta p^s$ for each year, as shown in equation (6).

$$\%\Delta p^s = \left(e^{\beta_1} - 1\right) \times 100 \tag{6}$$

### *Christensen et al. (2023)*

Christensen et al. contribute 32 observations to the meta-dataset. Each model contributed two meta-observations based on different treatment events. Multiple models were estimated based on the included control variables, alternative sample criteria in terms of the minimum price threshold for inclusion, and alternative control groups (i.e., a matched-city design versus a control group consisting of other cities where an emergency manager was put in place).

The hedonic price function estimated by Christensen et al. is generally of the form:

$$ln(p) = x\theta + \beta_1 E_1 + \beta_2 E_2 \tag{1}$$

where $E_1$ is an indicator denoting the treated group (i.e., homes in Flint, MI) after the first treatment event (the public water system's switch to an alternative water source that spurred much of the lead contamination issues). $E_2$ is an indicator denoting the subsequent emergency declaration. The models by Christensen et al. follow a Difference-in-differences (DID) approach, but we exclude some of the additional variables here, and focus only on the estimates of interest to ease exposition.

First, focusing on the switch in water sources ($E_1$) that led to the lead contamination issues, the before and after prices are represented as: $p_0 = e^{x\theta}$ and $p_1 = e^{x\theta+\beta_1}$. The percent change in price associated with the water switch can then be derived as

$$\%\Delta p^{E_1} = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{e^{x\theta+\beta_1} - e^{x\theta}}{e^{x\theta}}\right) \times 100$$

$$\%\Delta p^{E_1} = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

Similarly, the percent change in price following the emergency declaration ($E_2$), relative to *before* the water switch, can be calculated as

$$\%\Delta p^{E_2} = \left(\frac{e^{x\theta+\beta_1+\beta_2} - e^{x\theta}}{e^{x\theta}}\right) \times 100$$

$$\%\Delta p^{E_2} = \left(e^{\beta_1+\beta_2} - 1\right) \times 100 \tag{3}$$

Note that Christensen et al. interpret their presented results directly as percent changes in price, but this is slightly incorrect. They never mention the above transformation via Halvorsen and Palmquist (1980) in the manuscript, and review of their analysis code confirms that their tables are of the regression coefficient estimates, and not the percent change in price calculations. We therefore follow equations (2) and (3) when translating Christensen et al.'s results into our meta-dataset.

Similar derivations following equations (1) through (3) are applied to the results from the "Emergency Manager Design" in Table 3 of Christensen et al., but where $E_2$ denotes the end of the financial emergency management period, which it seems is interpreted as a proxy for the timing of the public health emergency (for example, see text after Figure 5 in Christensen et al.). The same derivations following equations (1) through (3) are also applied to the robustness checks presented in Table 4 of Christensen et al., where they vary the lower-bound price threshold for inclusion of a home transaction in the sample.

### *Dotzour (1997)*

Dotzour contributes a single estimate to the meta-dataset. This primary study uses a two-sample t-test to compare the mean price in a groundwater contaminated area before, versus after contamination is discovered. No regression models are estimated, but their tests can be couched as a linear price function, as follows:

$$p = \theta_0 + \beta_1 E_1 \tag{1}$$

where $\theta_0$ is an intercept term, which reflects the price of the average home prior to contamination, $\beta_1$ captures the price differential post contamination discovery and announcement of groundwater contamination, and $E_1$ is the corresponding indicator denoting that event.

The analogous representation between the t-test of means and equation (1) can be further illustrated as follows. We have the following pre and post-announcement prices, respectively: $p_0 = \theta_0$ and $p_1 = \theta_0 + \beta_1$. The corresponding percent change in price is calculated as:

$$\%\Delta p^{E_1} = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{\beta_1}{\theta_0}\right) \times 100 \tag{2}$$

The price differential $\beta_1$ can be inferred by subtracting the pre-announcement mean sale price in the contaminated area from the post-announcement mean price (both averages are displayed in Table 2 and in Appendix B of Dotzour's paper). Dotzour provides no standard error, reporting just an F-statistic for the null hypothesis that the mean prices are equal – i.e., $H_0: p_1 = p_0$. However, this is sufficient to infer a standard error around the price differential, $p_1 - p_0$, which can be later used to simulate an empirical distribution and infer a standard error for $\%\Delta p^{E_1}$. The calculation is $SE = \frac{p_1 - p_0}{\sqrt{F}}$, where $F$ is the provided F-statistic from Appendix B in the study.

### *Guignet (2013)*

Guignet contributes four observations to the meta-dataset. The initial focus of this study was a spatial DID approach that examined how home prices near leaking underground storage tanks (mainly those at gas stations) respond to contamination leak and clean-up events. However, the study also utilized a binary measure denoting homes where the leak investigations led to home-specific groundwater wells being tested. It is this groundwater testing variable that is of primary interest for purposes of our meta-analysis. Guignet argues that this testing variable reflects suspected and actual contamination in private potable wells. Of the 50 home sales where the well was tested prior to the sale, only 23 had contamination levels above the detectable limit, and among those, only 10 had levels above the corresponding regulatory or health advisory standards for public water systems. Each of the four meta-observations from this primary study come from a different hedonic price model, where the models vary in terms of the estimating sample, included covariates and level of spatial fixed effects, and in some cases model specification (i.e., some models were estimated including spatial lag and autocorrelation terms).

Focusing only on the private groundwater well test variable of interest, the general model estimated is of the form:

$$ln(p) = x\theta + \beta_1 d \quad (1)$$

where $d$ denotes whether a well was tested due to contamination concerns. The estimates of interest from the first specification (Model D) in Table 4 of the primary study must undergo the same transformation first put forth by Halvorsen and Palmquist (1980) to obtain a valid percent change in price interpretation More specifically, we calculate the percent change in price as:

$$\%\Delta p^d = \left(\frac{p_1 - p_0}{p_0}\right) = \left(e^{\beta_1} - 1\right) \quad (2)$$

In subsequent models (Models E, F, and G in Table 4), Guignet already converts the estimates to $\%\Delta p^d$ following a similar transformation, as follows:

$$\tilde{\beta}_1 = \left(e^{\beta_1} - 1\right) \quad (3)$$

But notice that he did not multiply the provided estimate $\tilde{\beta}_1$ by 100, and so we do that additional step here:

$$\%\Delta p^d = \tilde{\beta}_1 \times 100 \quad (4)$$

### *Guignet et al. (2016)*

Guignet et al. contribute 36 observations to the meta-dataset. As documented below, often multiple estimates are inferred from a single regression based on varying levels of contamination. The various models vary in terms of the included level of spatial fixed effects, if any, and in terms of the temporal window considered when setting the various contamination indicators – i.e., time since the water contamination test.

The hedonic price function estimated by Guignet et al. (2016) is generally of the form:

$$ln(p) = x\theta + \beta_1 d_1 + \beta_2 d_2 + \beta_3 s \quad (1)$$

where $d_1$ is an indicator denoting that a well was tested within some specified time window, $d_2$ indicates that contamination was detected from tests within that time window, and $s$ denotes when those levels were above the corresponding regulatory standard for public water. Note that $s$ is not included in all models. In the main model specifications, the specified time window is zero to three years prior to when a home is sold. Conveniently, Guignet et al. already converted the estimates to percent change in price estimates that could be readily entered into the meta-dataset, as-is. Following our standardized notation, the estimates for the percent change in price associated with testing due to contamination concerns, having contamination detected, and having contamination at levels above the regulatory standards, respectively, is as follows:

$$\%\Delta p^1 = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

$$\%\Delta p^2 = \left(e^{\beta_1+\beta_2} - 1\right) \times 100 \tag{3}$$

$$\%\Delta p^3 = \left(e^{\beta_1+\beta_2+\beta_3} - 1\right) \times 100 \tag{4}$$

In a secondary set of models Guignet et al. include indicators based on one-year increments for 1, 2, …, and 8 years prior to the sale, and estimates the percent change in price due to contamination being present $\%\Delta p^2$. Note that those models omitted $s$. The results are only presented in a figure (see Guignet et al. Figure 2), but the point estimates following equation (3) were also provided. The corresponding standard errors are not presented in the manuscript, but were obtained from the primary study authors. Guignet et al. also estimated models based on a continuous measure of total nitrates, using both linear and piecewise-linear spline specifications, but the model results needed to construct the corresponding meta-observations are not in the paper. The results for those models are only presented in graphical form and thus excluded from the meta-dataset.

### *Han et al. (2025)*

Han et al. contribute seven observations to the meta-dataset. The included meta-observations are derived from a single event study regression model, presented in Figure 13 of their main text, with additional details presented in Table 8 in their Appendix. Han et al. present estimates based on both a synthetic control approach and DID event study regression models. The synthetic control estimates are excluded because no corresponding standard errors around the estimates are presented. It is reassuring, however, that the synthetic control estimates are very similar to those from the DID event study regression models. Our focus is thus on the DID event study results. Although we generally consider event study estimates as a type of diagnostic test, and do not include event study estimates from other primary studies in our meta-dataset, we do include such estimates here because Han et al. do not present results from a more conventional DID model.

Han et al. estimate a DID event study model of the general form:

$$ln(p) = x\theta + \beta_1 E_1 \tag{1}$$

where $E_1$ in this instance is a vector of quarterly post-treatment indicators that denote homes in the affected public water system service area in a corresponding quarter after the high media attention pertaining to PFAS contamination in the Wilmington, NC public water system. Although the primary study authors interpret the vector $\beta_1$ as a percent change in price, there is no mention of any transformation following Halvorsen and Palmquist (1980), and the regression results tables and figures suggest that the presented results are of the direct regression coefficients. Therefore, similar to earlier derivations, we convert the estimates to percent changes in price as follows:

$$\%\Delta p^{E_1} = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

### *Keane and Guignet (2026)*

This study is a published version of an earlier working paper that was previously included in our meta-dataset (Keane and Guignet 2025). The published version contributes 26 observations to the meta-dataset. Most of the primary study models yield a single meta-observation. In some cases, a model will contribute two meta-observations, as documented below. The models vary in terms of the included independent variables and level of spatial and temporal fixed effects. Some models are estimated using the full dataset, and others are estimated using a matched sample. Different models also make alternative assumptions regarding the temporal window used to define the contamination indicators.

The hedonic price functions estimated by Keane and Guignet are generally of the form:

$$ln(p) = x\theta + \beta_1 d + \beta_2 s \quad (1)$$

where $d$ is an indicator denoting that contamination was detected in a home's private potable well within some specified time window prior to a sale (e.g., three years), and $s$ denotes when those levels were above the corresponding regulatory standard for public water. Note that $s$ is not included in all models. In the main model specifications, the specified time window is zero to three years prior to when a home is sold. Conveniently, Keane and Guignet already converted the coefficient estimates to percent changes in price, and so their estimates could be directly entered into the meta-dataset. Following our standardized notation, the estimates for the percent change in price associated contamination being detected, and having contamination at levels above the regulatory standards, respectively, are:

$$\%\Delta p^1 = \left(e^{\beta_1} - 1\right) \times 100 \quad (2)$$

$$\%\Delta p^2 = \left(e^{\beta_1 + \beta_2} - 1\right) \times 100 \quad (3)$$

Equation (2) denotes the percent change in home price when the potable well is contaminated, while equation (3) denotes the percent change in price when the levels of contamination for at least one tested chemical are above the corresponding health-based standard or advisory level for public water systems. Both are relative to tested homes where no contamination was found. In a secondary set of models Keane and Guignet define the $d$ contamination indicator based on tests within 0 to 1 years, 0 to 2 years, 0 to 3 years, and so on out to 0 to 10 years, and then any time prior to the sale of a home. Note that those models omitted $s$. The results are only presented in a figure (see Keane and Guignet Figure 2). The corresponding standard errors are not presented in the manuscript, but were provided in the primary study appendix (Table A5), and so those estimates are still included in the meta-dataset.

### *Khanal and Elbakidze (2024)*

Khanal and Elbakidze contribute 65 observations to the meta-dataset. These estimates largely stem from different models that vary in terms of the included level of spatial fixed effects, as well as what the assumed control group is. For example, much attention is given to minimizing confounding factors due to spatial spillovers, and so the models vary in the defined control group based on distance from the contaminated public water system and the extent of the spatial buffer between the treated and the control group – i.e., homes outside of the contaminated public water system service area but within X miles of the service area boundary are excluded from the sample. In some cases the control group homes come from another county entirely, or the model is estimated using a matched sample. In other models, multiple estimates are derived from a single model that allowed the price effect of interest to vary based on heterogeneity in home age and size, for example. Khanal and Elbakidze estimate these models by including interactions with corresponding indicators denoting ordinal groups. We do not explicitly represent these interactions in our stylized mathematical derivations below, but such estimates are included in the meta-dataset.

Within a DID framework, Khanal and Elbakidze estimate a series of linear hedonic price functions, all of which are of the following general form:

$$p = x\theta + \beta_1 E_1 \tag{1}$$

where $E_1$ denotes the discovery of PFAS contamination in a public water system, and that a home is located within that public water system.[12] The price without and without contamination, respectively, can be expressed as:

$$p_0 = x\theta \tag{2}$$

$$p_1 = x\theta + \beta_1 \tag{3}$$

The percent change in price can be calculated as:

$$\%\Delta p^{E_1} = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{\beta_1}{x\theta}\right) \times 100 = \left(\frac{\beta_1}{\bar{p}_0}\right) \times 100 \tag{4}$$

The second equality holds by plugging equations (2) and (3) in for $p_0$ and $p_1$ in the first part of equation (4), and the final expression is obtained by plugging the pre-contamination sample mean price $\bar{p}_0$ into the denominator.

### *Mackay (2025)*

Mackay contributes five observations to the meta-dataset. These estimates are derived from different DID models, which vary based on the interpolation approaches used to derive the CWS-by-year level observations in the primary data, or the approach used to address concerns associated with staggered treatment events over time in a DID setting.

Although our meta-dataset generally focuses on only results presented in the main text, the main text for this publication in *Applied Economic Letters* is much shorter, and so we include results presented in the Appendix, as long as they are also discussed in the main text. The five contributed

[12] In some models, Khanal and Elbakidze examine spillover effects, and define the "treatment" ($E_1$=1) as merely being near the contaminated public water system. We treat those meta-observations the same way when calculating $\%\Delta p^{E_1}$ but the moderator variables in the meta-dataset are coded to reflect no actual contamination in the drinking water at those homes (i.e., *detect* = 0).

meta-observations are based on the results presented in Panel A in Table A1 and in Table A2 of Mackay's Appendix. The corresponding event study estimates in Panel B of Table A1 are excluded because such estimates are considered more of a diagnostic test and in some sense can be considered redundant with the broader post-treatment price effect estimates associated with the more conventional DID estimates in Panel A of Table A1.

The hedonic price function estimated by Mackay is generally of the form:

$$ln(p) = x\theta + \beta_1 E_1 \tag{1}$$

where $E_1$ is an indicator denoting the treated group and after the treatment event (i.e., homes in a community water system after a notification event regarding nitrate pollution in that system). Although the primary study authors interpret the results as an approximate percent change in price, we do not believe a formal transformation following Halvorsen and Palmquist (1980) was undertaken. There is no mention of any transformations, and the main result is labelled as "$\beta$" in Figure 2, which corresponds to the coefficient notation in their primary model equation. Therefore, to make Mackay's estimates comparable to the rest of our meta-dataset, we carry out the following transformation:

$$\%\Delta p^{E_1} = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

### *Malone and Barrows (1990)*

Malone and Barrows contribute one observation to the meta-dataset. They estimate a single, linear hedonic price function, as follows:

$$p = x\theta + \beta_1 c \tag{1}$$

The main variable of interest is the concentration of nitrate contamination in a private well. At the time of the study, the regulatory threshold for nitrate was 10 ppm, and the mean concentration was $\bar{c}$ = 5.31 ppm, with a range in their data from 0 to 31 ppm. We infer a single estimate from Malone and Barrows' model, for a home going from zero to the mean concentration, as follows:

$$p_0 = x\theta \tag{2}$$

$$p_1 = x\theta + \beta_1 \bar{c} \tag{3}$$

We then calculate the percent change in price for the presence of nitrates at this average level as:

$$\%\Delta p^d = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{\beta_1 \bar{c}}{x\theta}\right) \times 100 = \left(\frac{\beta_1 \bar{c}}{\bar{p}}\right) \times 100 \tag{4}$$

The latter equality holds by plugging in the mean home price for the sample $\bar{p}$ into the denominator of equation (4). The mean price was not reported in by Malone and Barrows, but was reported as \$56,765 in Malone's (1987) earlier master's thesis using these same data and sample.

### *Marcus and Mueller (2024)*

Marcus and Mueller contribute 8 observations to the meta-dataset. Each was from a separate model presented in Table 2 or 3 of the primary study, where the level of spatial fixed effects and whether the models account for effects on other systems or spatial spillovers vary. Note that our focus for purposes of the meta-analysis is only on the direct effects on the Paulsboro community water system, and so estimates pertaining to potential effects on other systems or spatial spillovers are disregarded.

The hedonic price function estimated by Marcus and Mueller is of the form:

$$ln(p) = x\theta + \beta_1 E_1 \tag{1}$$

where $E_1$ is an indicator denoting the treated group (i.e., homes the affected public water system) after the treatment event, which in this case entailed public information, including media coverage and a subsequent health advisory letter to residents regarding elevated PFAS contamination in the water system. Like early transformations, we can convert this to a percent change in price following the high-profile informational event regarding elevated PFAS contamination as follows:

$$\%\Delta p^{E_1} = \left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

### *McCormick (1997)*

The dissertation by McCormick contributed 26 observations to the meta-dataset. Each of these results are often from a different model that uses an alternative functional form to describe the relationship between house prices and the concentration of nitrates in the potable well water (e.g., linear, log-linear, box cox, etc.). In some instances multiple estimates are derived from a single model that used a series of indicator variables denoting different levels of nutrient concentrations.

The nitrate levels in most of the hedonic price models estimated by McCormick enter as the concentration (or a transformation of the concentration). In some models, however, nitrate enters as a series of dummy variables denoting different levels, and in a final set of two models a spline is specified, allowing for a kink in the associated house price effect for nitrate levels above or below 10 ppm (the regulatory standard). We go through each model specification briefly here to illustrate the calculations and assumptions for the various percent change in price estimates.

First let's consider the series of models where the concentration of nitrates in a well enters the hedonic price models continuously, measured as parts-per-million (ppm). To standardize McCormick's results to match our meta-dataset, we calculate the percent change in price to go from no nitrate contamination (0 ppm) to the sample average of 4.05 ppm among homes with wells to a percent change in price. First consider the linear specification:

$$p = x\theta + \beta_1 c \tag{1}$$

A home with no contamination has a price of $p_0 = x\theta$, a home with the average concentration of nitrates has a price of $p_1 = x\theta + \beta_1\bar{c}$ . Calculating the percent change in price we get:

$$\%\Delta p^d = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{\beta_1 \bar{c}}{x\theta}\right) \times 100 = \left(\frac{\beta_1 \bar{c}}{\bar{p}}\right) \times 100 \tag{2}$$

As suggested by the last equality, we substitute the mean price of $202,719 among well water homes for $p_0$ in the denominator.

Next let's consider the semi-log model estimated by McCormick:

$$ln(p) = x\theta + \beta_1 c \tag{3}$$

which can rewrite as $p = e^{x\theta + \beta_1 c}$. The average price with no contamination and that at the average nitrate concentration level are, respectively: $p_0 = e^{x\theta}$ and $p_1 = e^{x\theta + \beta_1 \bar{c}}$. Plugging these into the $\%\Delta p^d$ formula yields:

$$\%\Delta p^d = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{e^{x\theta + \beta_1 \bar{c}} - e^{x\theta}}{e^{x\theta}}\right) \times 100 = \left(e^{\beta_1 \bar{c}} - 1\right) \times 100 \tag{4}$$

The same expression applies to McCormick's double log specifications (which he labels as "log-linear") . Some of the datasets included public water homes where *c* is assumed to be zero. The natural log of zero is undefined. It was not explicitly stated in the dissertation, but based on back-of-the-envelope comparisons to McCormick's average marginal price effects, it seems that *c* entered the double log models in linear form. In other words, the estimated double log models were of the form: $ln(p) = ln(x)\theta + \beta_1 c$. Assuming otherwise resulted in an average marginal effect estimate that was an order of magnitude less than the average marginal price effects that were presented. We believe the natural log transformation was only applied to the other covariates that were not of primary interest.[13] As such, the same calculations as in equations (3) and (4) apply to the double log models with nitrate concentrations entering continuously.

Similarly, back-of-the-envelope calculations of the average marginal effects presented for McCormick's Box-Cox specification suggest that the transformation was only applied to the covariates that were not of primary interest, and not to the nitrate concentration $c$. In contrast, assuming $c$ enters linearly and plugging in the sample averages result in similar marginal effect estimates. As such, we assume the Box-Cox model estimated by McCormick is of the following form:

$$\frac{p^{\vartheta} - 1}{\vartheta} = \frac{x^{\lambda} - 1}{\lambda}\theta + \beta_1 c \tag{5}$$

We can further solve for the price as follows:

$$p = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + \vartheta\beta_1 c + 1\right\}^{\frac{1}{\vartheta}} \tag{6}$$

The corresponding prices when contamination is zero or at the average level are:

[13] Additionally, McCormick uses the same functional form labels for the later specifications with binary indicator variables denoting different nitrate levels. Because one cannot take the natural log of binary variables that sometimes take the value of zero, this again suggests that the specified transformations are only applied to the other covariates that are not of primary interest.

$$p_0 = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + 1\right\}^{\frac{1}{\vartheta}} \tag{7}$$

$$p_1 = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + \vartheta\beta_1\bar{c} + 1\right\}^{\frac{1}{\vartheta}} \tag{8}$$

Plugging equations (7) and (8) into our usual calculation for $\%\Delta p^d$ yields:

$$\%\Delta p^d = \left(\frac{p_1 - p_0}{p_0}\right) \times 100 = \left(\frac{\left[\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+\vartheta\beta_1\bar{c}+1\right\}^{\frac{1}{\vartheta}}\right] - \left[\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+1\right\}^{\frac{1}{\vartheta}}\right]}{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+1\right\}^{\frac{1}{\vartheta}}}\right) \times 100 \tag{9}$$

Equation (9) can be further simplified as follows:

$$\%\Delta p^d = \left(\frac{\left[\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+\vartheta\beta_1\bar{c}+1\right\}^{\frac{1}{\vartheta}}\right]}{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+1\right\}^{\frac{1}{\vartheta}}} - 1\right) \times 100 \tag{10}$$

We can rewrite equation (7) as ${p_0}^{\vartheta} = \frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + 1$, and then plug this into the numerator of equation (10), and equation (7) into the denominator of equation (10) to yield:

$$\%\Delta p^d = \left(\frac{\{\bar{p}^{\vartheta}+\vartheta\beta_1\bar{c}\}^{\frac{1}{\vartheta}}}{\bar{p}} - 1\right) \times 100 \tag{11}$$

Next we will consider the specifications by McCormick that have nitrate contamination entering the models as a series of four dummy variables, denoting $0.01 < c \leq 4$ ppm, $4 < c \leq 7$ ppm, $7 < c \leq 10$ ppm, and $c > 10$ ppm. The latter denotes levels above the regulatory standard for nitrate contamination in public water systems. To make this distinction, we follow our standardized notation and denote the first three indicator variables with the vector $d$, and the final indicator as $s$, which explicitly represents nitrate concentrations above the standard for public water systems. The linear hedonic price function under this representation can be denoted as:

$$p = x\theta + \beta_1 d + \beta_2 s \tag{12}$$

A nitrate concentration of zero (technically $< 0.01$) is the omitted category, and so the $\%\Delta p$ calculations are straight forward. It can be shown that they simplify to:

$$\%\Delta p^d = \left(\frac{\beta_1}{x\theta}\right) \times 100 = \left(\frac{\beta_1}{\bar{p}}\right) \times 100 \tag{13}$$

$$\%\Delta p^s = \left(\frac{\beta_2}{x\theta}\right) \times 100 = \left(\frac{\beta_2}{\bar{p}}\right) \times 100 \tag{14}$$

where similar to before, the second equality holds based on our assumption of plugging in the sample mean price in for $x\theta$ in the denominator.

We can next go through similar derivations for the semi-log model variants, which are of the form:

$$ln(p) = x\theta + \beta_1 d + \beta_2 s \tag{15}$$

The price function can be re-written as $p = e^{x\theta+\beta_1 d+\beta_2 s}$, and the corresponding price changes for the various levels denoted by the vector of indicators $d$ or being above the standard $s$, can be expressed as:

$$\%\Delta p^d = \left(e^{\beta_1} - 1\right) \times 100 \tag{16}$$

$$\%\Delta p^s = \left(e^{\beta_2} - 1\right) \times 100 \tag{17}$$

Similar to the earlier discussion, the double log specifications for $\%\Delta p^d$ and $\%\Delta p^s$ are the same, because the indicator variables on the right-hand are not (and cannot be) log-transformed.

Finally, looking into the Box-Cox models where the nitrate levels enter as a series of dummy variables, we have:

$$\frac{p^{\vartheta}-1}{\vartheta} = \frac{x^{\lambda}-1}{\lambda}\theta + \beta_1 d + \beta_2 s \tag{18}$$

which can then be rewritten as:

$$p = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + \vartheta\beta_1 d + \vartheta\beta_2 s + 1\right\}^{\frac{1}{\vartheta}} \tag{19}$$

The corresponding prices with no contamination ($d = 0$ and $s = 0$), contamination levels below the standard ($d = 1$ and $s = 0$), and contamination levels above the standard ($d = 0$ and $s = 1$, in this context because the indicator categories are mutually exclusive), can be expressed as:

$$p_0 = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + 1\right\}^{\frac{1}{\vartheta}} \tag{20}$$

$$p_1 = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + \vartheta\beta_1 + 1\right\}^{\frac{1}{\vartheta}} \tag{21}$$

$$p_2 = \left\{\frac{\vartheta}{\lambda}\left(x^{\lambda} - 1\right)\theta + \vartheta\beta_2 + 1\right\}^{\frac{1}{\vartheta}} \tag{22}$$

Based on equations (20)-(22), the corresponding percent changes in price relative to the baseline no contamination price of $p_0$ are:

$$\%\Delta p^d = \left(\frac{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+\vartheta\beta_1+1\right\}^{\frac{1}{\vartheta}}}{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+1\right\}^{\frac{1}{\vartheta}}} - 1\right) \times 100 \tag{23}$$

$$\%\Delta p^s = \left(\frac{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+\vartheta\beta_1+1\right\}^{\frac{1}{\vartheta}}}{\left\{\frac{\vartheta}{\lambda}(x^{\lambda}-1)\theta+1\right\}^{\frac{1}{\vartheta}}} - 1\right) \times 100 \tag{24}$$

We then plug $p_0$ from equation (20) into the denominator of equations (23) and (24). Further re-arrangement of equation (20) yields ${p_0}^{\vartheta} = \frac{\vartheta}{\lambda}(x^{\lambda} - 1)\theta + 1$, which we then plug into the numerator of equations (23) and (24), thus yielding:

$$\%\Delta p^d = \left(\frac{\{{p_0}^{\vartheta} + \vartheta\beta_1\}^{\frac{1}{\vartheta}}}{p_0} - 1\right) \times 100 \tag{25}$$

$$\%\Delta p^s = \left(\frac{\{{p_0}^{\vartheta} + \vartheta\beta_2\}^{\frac{1}{\vartheta}}}{p_0} - 1\right) \times 100 \tag{26}$$

Similar to our earlier calculations, we plug the sample mean price of \$202,719 among well water homes in for $p_0$ when calculating our $\%\Delta p^d$ and $\%\Delta p^s$ estimates based on McCormick's results.

Finally, the last set of specifications considered by McCormick are spline models where nitrate concentrations enter continuously, but the relationship with price is allowed to differ for levels above the 10 ppm regulatory standard. This is estimated for both a double log and Box-Cox functional form, but as before, we assume these transformations are not applied to the nitrate concentration variable $c$. More formally, the double log model can be represented as:

$$ln(p) = ln(x)\theta + \beta_1 c + \beta_2(c \times \mathbb{1}(c > 10)) \tag{27}$$

where $\mathbb{1}(c > 10)$ is an indicator equal to one when nitrate concentrations exceed the 10 ppm regulatory standard, and zero otherwise.

The price with zero contamination and a nitrate level equal to the 4.05 ppm sample average $\bar{c}$ can be expressed as:

$$p_0 = e^{ln(x)\theta} \tag{28}$$

$$p_1 = e^{ln(x)\theta + \beta_1 \bar{c}} \tag{29}$$

The corresponding percent change in price for going from zero to the mean nitrate concentration is the same as in equation (4). This is because the spline interaction term never comes into effect when considering the percent change in price going from zero to the mean nitrate concentration; in other words, $\bar{c}$ = 4.05 ppm, and so $\mathbb{1}(\bar{c} > 10) = 0$.

Similarly, the percent change in price under the Box-Cox spline model is the same as in equation (11). The initial model is:

$$\frac{p^{\vartheta} - 1}{\vartheta} = \frac{x^{\lambda} - 1}{\lambda}\theta + \beta_1 c + \beta_2(c \times \mathbb{1}(c > 10)) \tag{30}$$

This starting point hedonic price function simplifies to equation (5) because $\mathbb{1}(\bar{c} > 10) = 0$ when considering a change in pollution from zero to the sample mean of $\bar{c}$ = 4.05 ppm.

### *McLaughlin (2011)*

The McLaughlin study contributed 8 observations to the meta-dataset. These observations are derived from four different models, presented in Table 6 of the primary study. McLaughlin reported the results of quantile regression models and presented the results evaluated at the median home price. The hedonic models were generally of the form:

$$ln(p) = x\theta + \beta_1 d + \beta_2 E \quad (1)$$

where $d$ denotes that the private well at a home was tested sometime prior to its sale, and that the contamination (trichloroethylene or TCE) was detected and no GAC filter was installed, and $E$ denotes homes within the special well construction area (SWCA), which acts as a proxy for homes that are currently located within the groundwater contamination plume or that could be in the future. McLaughlin estimated this model using two different samples. The first was from 1995-2002, and was before a 2003 information disclosure law went into place. The second was 2003-2006, which was after the information disclosure law went into place.

Similar to calculations for other studies, since $d$ and $E$ are dummy variables, we can calculate the percent change in prices due to contamination or being within the potentially contaminated area as, respectively:

$$\%\Delta p^d = \left(e^{\beta_1} - 1\right) \times 100 \quad (2)$$

$$\%\Delta p^E = \left(e^{\beta_2} - 1\right) \times 100 \quad (3)$$

Note that McLaughlin reports t-statistics for the coefficients, rather than standard errors, and so we infer the standard errors simply as $SE = \beta/t$.

### *Theising (2019)*

Theising's analysis of lead service line replacement was unique because it is the only study in our meta-dataset where the change of interest is an improvement in water quality. Theising analyzed how the replacement of lead service lines in the public water system impacted home values. Theising's analysis contributed 15 observations to the meta-dataset. This includes three models from Table 3 in the primary study, which were based on alternative samples (one including a propensity score matched sample).  Additional meta-observations were derived from the results presented in Theising's Table 5, including several observations from individual models examining price effect heterogeneity over time or by lead service line replacement cost quantiles, and estimates based on models from a slightly different sample or alternative nearest neighbor estimation approach.

The primary models estimated in this study are generally of the form:

$$ln(p) = x\theta + \beta_1 E \quad (1)$$

where $E$ denotes homes that had a lead service line replaced, and hence where potential or actual exposure to lead in their drinking water was eliminated. For most of the estimates taken from Theising's study, the percent change in price estimates of interest are calculated as:

$$\%\Delta p^E = -\left(e^{\beta_1} - 1\right) \times 100 \tag{2}$$

The negative sign at the front of the estimate is there so that it is comparable to the $\%\Delta p$ estimates from all other studies in the meta-dataset, which denote a decrease in water quality. The nearest-neighbor matching estimator utilized in Theising's study, however, presents the estimated percent change in price due to the presence of a lead service line, and so for that single estimate, we do not need to multiply it by negative one, as shown:

$$\%\Delta p^E = \left(e^{\beta_1} - 1\right) \times 100 \tag{3}$$

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