Property Value Losses Following a Freshwater Chemical Spill

ABSTRACT

In 2014, an above ground tank storing coal processing chemicals leaked into the Elk River near Charleston, West Virginia. This study quantifies the extent of home value losses associated with that event using difference-in-difference spatial regression models. Various buffer distances and timeframes are used to determine the magnitude and spatial-temporal persistence of changes in the sale price of single-family properties. Results suggest that homes sold within a year of the spill experience a significant price reduction—between $10,000 and $25,000—based on their proximity to the spill. However, sale prices rebound to pre-spill levels within 2 to 3 years.

Keywords: Contamination, Elk River, Hedonic Valuation, Water

JEL Codes: N52, Q25, K32

The Temporal and Spatial Extent of Property Value Losses Following a Freshwater Chemical Spill

1. INTRODUCTION

On the morning of January 9, 2014, residents of Charleston, West Virginia began reporting a licorice smell present in their drinking water. Within hours, investigators discovered that a tank at Freedom Industries, a manufacturer of coal processing chemicals, had broken and liquid had subsequently leaked into the Elk River, the main water source for local water utilities (Manuel 2014). The major water utility, West Virginia American Water Company (AWC), sampled and tested water in the river. By 5:50 in the afternoon, a "do not drink" order was announced for nearly 300,000 residents (Manuel, 2014). One day following the spill, 122 people sought medical attention for symptoms of nausea and vomiting (Guilfoos et al. 2018). While health impacts were generally mild and acute, an estimated 25,623 households had at least one person with symptoms attributed to the spill, including mild skin, respiratory, and/or gastrointestinal symptoms that resolved with no or minimal treatment. Within two weeks, approximately 10,000 gallons of contaminants[1] had been reported spilled. The "do not drink" order remained in place for 10 days and residents were dependent on bottled water for everyday needs until January 18th (Manuel, 2014). As a result of the spill, 40% of the working population did not attend work for the entirety of the drinking ban (Guilfoos *et al*., 2017), and economic losses were estimated at roughly $61 million (Manuel, 2014). One week after the spill, Freedom Industries had roughly twenty-five

[1] Chemicals identified in the spill include 4-Methylcyclohexanemethanol (MCHM), 4-Methoxymethylcyclohexylmethanol, Methyl 4-methylcyclohexanecarboxylate, 1,4-Cyclohexanedimethanol, Dimethyl 1,4-cyclohexanedicarboxylate, Propylene glycol phenyl ether, Dipropylene glycol phenyl ether, Crude MCHM, 4-Methylcyclohexanecarboxylic acid, Cyclohexanemethanol, 4-(ethenyloxy)methyl)-, Cyclohexanemethanol, alpha,alpha,4-trimethyl-, Phenoxyisopropanol, 2-methylcyclohexanemethanol, and Dowanol DiPPh glycol ether (NIH-NTP 2016).

lawsuits brought against them and subsequently filed for bankruptcy (White, 2014). Thus, the benefits of their production were privatized, but the costs of this spill were largely pushed onto the public. As such, the magnitude, temporal persistence, and spatial extent of these losses have significant implications for public welfare and policy.

Given the well-documented connection between water quality and housing prices (see, for example, Leggett and Bockstael 2000; Nicholls and Crompton 2018), this paper returns to the Elk River spill to estimate the spatial extent and temporal persistence of contamination on property values in the affected region. Specifically, we:

1. Estimate the impact of proximity to the contamination site on sale price of residential properties (before and after the spill);
2. Investigate whether property value losses are temporally acute or persist across time;
3. Estimate the effect of the spill on homes whose municipal water supply was contaminated, conditioning on spatial proximity to the spill site.

To understand the costs imposed on the public, we must better understand the spatial and temporal extent of these losses. For example, if home values near the spill rebound within months, then the long-term wealth and welfare implications are quite small for most homeowners. Conversely, if value losses persist for years or otherwise decrease the ability of property owners to sell, losses may be substantial. McCluskey and Rausser (2003) find that stigma—a negative attribute of real estate acquired by environmental contamination—can have long-term price effects. Despite the acknowledgement of this phenomena, few studies quantify real estate losses beyond their immediate decline following such events. Since the Elk River spill occurred in early 2014, sufficient time has passed (~6 years) to investigate the existence of stigma and measure the persistence of property value losses.

As a necessary first-step, the spatial extent and magnitude of loss must be quantified. Surprisingly little hedonic work was conducted following the Elk River spill, such that the relationship between proximity-to-spill and sale price is largely unknown, though the impact of contamination events on property sales is generally believed to decrease with distance (Epley 2012). To investigate these phenomena, hedonic valuation methods are used in spatially autocorrelated, difference-in-difference (DID) multivariate regression models.

Hedonic valuation is a revealed preference technique commonly used to quantify the costs and benefits associated with environmental (non-market) features (Champ et al. 2003). In the absence of market frictions, variation in external exposure to (dis)amenities will be capitalized into housing prices (Bishop et al. 2020), making it possible to indirectly estimate the value of such (dis)amenities through property sale prices. In an environmental context, hedonic analysis uses housing markets to reveal the willingness to pay for marginal changes in those (dis)amenities. Since properties have easily identifiable attributes (e.g. size, quality), residual values—portions of the sale price unexplained by property characteristics—can be attributed to locational characteristics linked to environmental (or other) assets of importance (Gopalakrishnan and Klaiber 2014). For half a century, results from hedonic research have been consistent; disamenities (pollution, noise, etc.) significantly decrease property values (Smith and Huang 1995; Nelson 2004; Turner et al. 2003; Deaton and Hoehn 2004; Walsh and Mui 2017).

In a recent comprehensive review, a statistically significant relationship between water quality and home values was found in forty-six out of forty-eight studies (Nicholls and Crompton 2018).

While the review provides extensive background on the history of hedonic valuation applications in water quality, the majority of the included studies examine the effect of water clarity, quality, or general nuisance (e.g. pH, algal blooms, turbidity) on mainly waterfront properties, and are therefore less applicable to the Elk River context, where health and clean water supply concerns were more salient.

Chronic pollution, such as Superfund sites or locations near the EPA's Toxics Release Inventory (TRI), have also been linked to persistent home price depression (Decker, Nielsen and Sindt 2005; Kiel and Williams 2007). The Cheat River Watershed—also located in West Virginia—has been chronically impaired by acid mine drainage, which exerts an implicit cost of $4,783 on residential properties near the waterway (Williamson, Thurston and Heberling 2008). While, these and other studies justify the use of hedonic methods to value environmental contamination, they do not evaluate the persistence of value loss due to acute contamination events.

One such event, was the Dan River coal ash spill. In a comprehensive evaluation of the Dan River accident, Lemly (2015) estimated total costs (ecological, health, recreational, etc.) to be nearly $300 million dollars within 6 months of the spill and highlights the need for accurate (short- and long-term) real estate losses associated with such events. Boyle and Kiel also acknowledge the need for hedonic studies with longer time horizons in order to capture the dynamics of environmental goods on home prices and preferences (Boyle and Kiel 2001). Yet, few studies have examined the temporal aspects of these acute chemical spill events beyond their immediate impact on property values, particularly where such spills have affected municipal drinking water systems.

Hedonic valuation studies of large-scale, chemical spills in the United States remain limited (Winkler and Gordon 2013). As Winkler and Gordon (2013) point out, acute events are inherently different from the effect of other, more permanent disamenities (e.g. power plants) since they involve more uncertainty and are less likely to provide positive effects such as increased employment. Although hedonic research of acute chemical spills is rare, a number of such studies exist in response to oil spills specifically. For example, the Deepwater Horizon accident precipitated several studies. Siegel, Caudill and Mixon (2013) and Winkler and Gordon (2013) estimate the property value losses from that event to range from 1% to 15%, and largely dissipate within five months. However, these studies focus chiefly on waterfront or vacation properties. Other research that has examined the effects of acute spill or contamination events, find property value losses around 10%. In April of 2000 an oil pipeline ruptured in Prince George County outside of Washington DC. This spill impaired ten miles along the Patuxent River, which decreased the value of affected homes by 11% on average (Simons, Winson-Ceideman and Brian 2001). A similar decrease (10%) due to petroleum leakage from underground tanks was observed in Maryland (Zabel and Guignet 2012). Hansen et al. (2006) conduct an analysis similar to our own based on the perceived risk of living near an oil-pipeline after a spill event. Their work suggests that proximity to an oil pipeline decreases home values following a rupture (regardless of proximity to the actual spill), and such losses persist across time due to increased awareness.

The Elk River study site allows us to investigate several phenomena simultaneously and separately identify the effect of proximity to spill from that of acute drinking water contamination, which may affect property values across an entire city. Chemically degraded drinking water is not always visible, but once contamination events are identified, there are limited ways to mitigate risks. Such events often receive disproportionate televised coverage (Driedger 2007), which may indirectly decrease demand for real estate in the affected municipal water supply area regardless of actual risk. In the case of Elk River, local water utilities were contaminated, which resulted in a “licorice smell” across large service areas. Therefore, we can separately identify the effect of contaminated drinking water, which was present throughout American Water Company’s service areas and the effect of proximity to the spill site based on distance-buffer-treatments. Importantly, we revisit the spill after sufficient time has elapsed to estimate the temporal persistence of property value losses associated with such events. These findings are crucial to understanding the extent to which firm bankruptcies—following such event—push costs onto the broader public, since there is little recourse available to the average homeowner. Given the notoriety of the spill, other work has investigated its effect on health and economic growth in the area. Guilfoos et al. (2018) identified a 3% decrease in GDP in Kanawha County (although not statistically significant) as well as a statistically significant decrease in 5-minute Agar scores, used to measure infant health (Guilfoos *et al*., 2017). However, they did not specifically investigate changes in property values, nor did they have the additional subsequent years to include in their analysis.

Nevertheless, their (and others’) findings point to the complexity of perceptions and valuation of chemical contamination, since there are several mechanisms by which these events can affect value (perceived health risks, increased avoidance costs, reduced recreation, and numerous avenues of indirect effects related to changes in the local economy). Moreover, the autocorrelation of home sales may outlast any measurable impacts of the spill or create long-lasting stigma in the area. A neighborhood near the spill may see decreased home values in the short-term, and these lower prices are likely to affect future sales in nearby neighborhoods—even without explicit knowledge of the spill. For example, most realtors provide a "comps list" that explicitly compares recent nearby home sale prices for potential buyers. Thus, the lower sales price of a home sold directly after the spill, may lead to long-lasting depreciation of other homes in the area. In cases of perceived water supply failures, trust in local public and government entities decreases (Driedger, Mazur and Mistry 2014; Morckel and Terzano 2019), which may indirectly decrease real estate value. In the case of Elk River, two months after the spill, less than 5% of the locals in the Charleston area were using municipal water for cooking or drinking (Guilfoos *et al*., 2017). This increased reliance on expensive water sources—a common avoidance cost—is notable because it persisted long after the do not drink order ended, highlighting the complexity of valuing acute contamination events.

Although it is difficult to separately identify the underlying mechanisms of home-value losses associated with the chemical spill, a difference-in-difference (DID) regression analysis will provide an appropriate counterfactual by which the effect of the spill can be measured across space and time. Since randomized experimental design is not possible—or at least ethical—in the case of chemical contamination, the DID approach leverages the naturally occurring event to separate treatments from controls. The approach is well-established and one of the most widely applicable design-based estimators in the field on economics (Angrist and Pischke 2008).

2. METHODS

This analysis follows best practices suggested by Bishop et al. (2020). Exogenous variation in an amenity is observable by prospective buyers (*e.g.* distance from an unexpected spill). Data on the prices and physical attributes of properties, together with location-specific measures for amenities are used to estimate flexible functions predicting sale price. The DID method in a natural experiment creates quasi-random treatments, thus reducing sources of endogeneity or bias. We do not directly survey residents as Bishop suggests and rely on the assumption that buyers and sellers have knowledge of the spill to influence their decisions, although such knowledge can be imperfect (see Kiel and McClain (1995) for a discussion on information sets in hedonic valuation).

DID specifications are used to estimate the effect of the spill on property values across three model specifications. In Model 1, treatments are assigned based on property's proximity to the spill. In Model 2, we test the persistence of these value losses across time, and in Model 3 we attempt to separate the effects of proximity from the effect of being on a municipal water system that has been contaminated. Each model assumes property prices, y, are comprised of their underlying attributes such that $y_i = f(h_i, l_i, , x_i, s_i, p_i)$, where:

h_i represents property characteristics,
l_i represents locational characteristics,
x_i represents the year of the sale
s_i denotes spill treatments, $s_i \in [0,1]$
p_i denotes if the sale occurred after the spill, $p_i \in [0,1]$.

2.1 Regression Models

The initial DID models capture the property value loss using proximity to spill and post-spill occurrence as binary treatment variables, the interaction of which is the DID term of interest. The DID approach allows us to isolate the effect of the chemical spill, accounting for differences across housing groups before and after the spill occurred, separating the effect of the spill from overall trends in property values. The basic model is expressed as: $\beta_{DID} = \left[y_{s=1,p=1} - y_{s=1,p=0}\right] - \left[y_{s=0,p=1} - y_{s=0,p=0}\right]$ where $p = 0$ denotes the sale occurred before the spill and $p = 1$ denotes the sale occurred after the spill. The treatment $s = 1$, defines whether the home falls within the "close to spill" treatment, with the expectation that value loss estimates decrease as the buffer size denoting treatment increases. The welfare loss to a property owner is therefore the price that would have been received without the spill minus the actual price observed in the sale.

Although there is no consensus on the precise specification of hedonic housing models, explanatory variables were included based on previous work and intuition of household characteristics likely to affect property value, including parcel acreage, size of house, age, quality, home style (ranch, colonial, etc.), associated tax code (in- or outside of municipal taxing authority, structure used for business, etc.), flood risk, and proximity to amenities (Smith and Huang 1995; Cameron 2006; Williamson et al. 2008; Paterson and Boyle 2002; de Koning, Filatova and Bin 2019). A thorough set of control variables is therefore included in each model specification (complete list presented in Table 1), such that the variation in price leftover is likely due to environmental factors.

All models are estimated using log transformed sale price as the dependent variable. The log linear model is commonly used in hedonic residential studies to reduce the influence of outliers, allow price to change proportionally, and generally improve the normality of residuals (Winkler and Gordon 2013; Bigelow, Ifft and Kuethe 2020; Moore et al. 2020), however it also leads to biased predicted sale values if not corrected.[2]

As is common in hedonic studies of real estate, the model includes a spatial weighting matrix, since residential home sales are likely to suffer from high levels of spatial correlation (Basu and Thibodeau 1998; Neill, Hassenzahl and Assane 2007; Anselin 2013).[3] In our own data, Moran's I test strongly rejects the null of no autocorrelation (p-value<0.00). Thus, an inverse distance weighting matrix, truncated at 0.25 miles, is used to account for any unobserved features that result in correlation of sale price among nearby homes. Model 1 is therefore:

$$y_i = h_i'\phi + l_i'\tau + \beta_0 s_i + \beta_1 p_i + \beta_{DID}(s_i * p_i) + x_i'\delta + \gamma W y_i + \epsilon_i \qquad (1)$$

where y is the observed sale price of house i, h_i is a vector of property characteristics, including presence of a full basement, age, flood risk, parcel size, a set of 11 dummies denoting home style, and a vector of square-footage-quality interactions. Quality ranges from A+ to F- within Kanawha county, with 15 distinct categories. This size-quality specification improves fit considerably but is rarely seen in previous literature. The interaction is also more likely to represent the underlying data-generating process, since an additional square-ft of high-quality

[2] $E[y|x] \neq e^{(x`b)}$ See Woolridge (2010) or Ciane and Fisher (2018) for a full discussion on the need for this correction.

[3] The ongoing debate around spatial autocorrelation methods is not discussed here (See Gibbons and Overman 2012).

marble is more valuable than that of vinyl. Locational characteristics are represented by vector l_i, which includes waterfront (binary) designations and distance to downtown, x_i is a vector of dummy variables for each year in our sample. Annually dummies are used to account for interest rates and other macroeconomic conditions that may vary from year to year. W is the spatial weighting matrix and ϵ_i represents idiosyncratic error.[4] ϕ, τ, δ, ρ, are vectors of parameters to be estimated, γ is the estimated parameter for spatial correlation. The set of β's are coefficient parameters associated with control-treatment and β_{DID} represents the primary coefficient of interest. Model 1 is run 5 times with different buffer distances denoting $s_i = 1$ as within one, two, three, four, or five miles of the spill site and 0 otherwise.

Model 2 estimates the persistence of these losses across time. This model includes binary "treatments" as years-since-spill, for each year following the spill. As such, 5 binary variables, ν_{ij}, are interacted with the "close to spill" dummy. In this model, close to spill designation is informed by results from Model 1 and defined as within 3 miles from the spill. Thus, a set of 5 year-specific treatments is created, where each is specific to the number of years between the spill and the sale. This model is used to estimate the persistence of value loss across time. By introducing year-treatment as a dummy variable, we allow the spill effect to vary across time without imposing linear (or quadratic) decay, though the annual step imposes its own assumption. Model 2 is similar to Equation 1, but replaces $\beta_{DID}(s_i * p_i)$ with $\sum_j^5 \beta_{DID_j}(s_i * \nu_{ij})$, where β_{DID_j} is five, year-specific coefficients.

[4] Each model presented is also estimated without the spatial correlation term, $\gamma W y_i$. Qualitative results are similar and included in the appendix.

Models 1 and 2 inform both the spatial and temporal extent of the spill on home values. However, in the case of the Elk River spill, water supplies for 300,000 citizens were contaminated. As such, proximity to the spill may not adequately reflect the impact of the contamination, since water mainlines supply areas many miles from the spill site. If property values decreased because they are within the water utilities' affected service area, Models 1 and 2 would underestimate the total and value loss, since the control group would also have experienced decreases in property values. As such, we include a third model, incorporating two treatment dummies, one for proximity (<3 miles) and one for being within the affected service area. Thus, this specification investigates the possibility that homes supplied contaminated water experience a decrease in value, regardless of proximity. Model 3 is similar to the Model 1 but includes additional interaction term, g_i, to indicate if the property is within the affected service area:

$$y_i = \phi h_i + \tau l_i + \beta_0 s_i + \beta_1 p_i + \beta_3 (s_i * p_i) + \beta_4 g_i + \beta_5 (p_i * g_i) + \delta x_i + \gamma W y_i + \epsilon_i \qquad (3)$$

Each β is estimated, such that we can separately identify proximity to the spill from being in an affected utility's service area. However, a pure triple difference model, as used by Muehlenbachs et al (2012) or Maas and Watson (2018) is not possible because the triple-difference term $(s_i * p_i * g_i)$ is perfectly colinear with $(s_i * p_i)$ since homes close to the spill are necessarily within the utility service areas. Thus, there are two "treatments" in this model such that each household is either 1) next to the spill and within the public utility service area, or 2) within the public utility service area, but far from the spill. The baseline of comparison is therefore homes far from the spill (>3 miles) and not within the utility service area.

2.2 Data

Models 1 and 2 are estimated using county assessors' data for Kanawha county only. The sample for these models was limited to Kanawha county over concerns that more rural counties would not be an appropriate counterfactual. To estimate Model 3, the sample was expanded to include nine counties adjacent to the spill (Boone, Clay, Jackson, Kanawha, Lincoln, Logan, Putnam, Roane, and Cabell county. Figure 1 outlines the extent of the affected spill area and provides reference for readers unfamiliar with region.

FIGURE 1: Map of spill location and counties included in analysis.

All parcel characteristics were accessed through the GIS department of West Virginia University which include: 1) parcel-level assessor's data, 2) recorded sale price tables, 3) and shapefiles. Property characteristics that were not directly available in assessors' data (e.g. distance to downtown) were calculated using GIS. Each parcel in the sample was assigned a distance to spill—the coordinates of Freedom Industries, distance to downtown Charleston (nearest city), and a binary variable to indicate waterfront property (defined as <50 meters to a body of water).

Sales data were cleaned to a sample of single-family residential properties based on reasonable criteria. Observations were omitted from the analysis if lot size exceeded 4 acres because this may reflect agricultural activity, which provides revenue and therefore is inherently different than a residential home sale. Transactions less than $10,000 and sale prices that were outside of one standard deviation of the assessed value were also dropped to include only "arm's length" transactions and avoid other potential sale factors unobserved to the researcher. Sales with otherwise missing data were also dropped.

After cleaning, properties identified as single family residential that sold within 3-years before and 1-year after the spill total 2,705 for Kanawha county (used in Model 1). Model 2 includes houses sold up to 5 years after the spill, increasing total observations to 4,288. Model 3 uses the same timeframe as Model 1 but includes nine adjacent counties for a total of 5,072 observations. Descriptive statistics for the final sample are presented in Table 1. Mean home size for properties in Kanawha is ~1,400 sq-ft and the sale price follows an approximate log normal distribution with mean of $98,000. Mean calculated acre in the sample is 0.32 acres (Table 1). The 9-county sample on average has slightly larger lots, (0.37 acres), bigger houses (1,520 sq-ft) and higher sale prices (~$113,000). These differences are, in part, why the sample used in Models 1 and 2 is limited to Kanawha.

TABLE 1: Descriptive statistics of property sales

The DID approach requires that treatment and control groups trend together pre-treatment, such that any pre- and post-spill comparisons are not simply a result of existing trends (Kahn-Lang and Lang 2020). Figure 2 shows 10 years of average home sale prices before the spill occurred. The estimated annual trend coefficients for both the (future) treated group, properties sold within 3 miles of the spill site, and the untreated group, properties sold outside of 3 miles of the spill site, are statistically identical at $765 and $612 respectively. The treated group exhibits larger deviations year to year, but this variation is likely a result of the fewer number of home sales classified as near the spill.

FIGURE 2: Pre-treatment trends

3. RESULTS

Given the large number of covariates, the results presented below are truncated to only include some house attributes and coefficients related to the Elk River spill (Full results tables are included in the Appendix). Estimates from Model 1 are presented in Table 2. We include results for treatment buffer distances starting at 1 mile and increasing to 5 miles from the spill site.

TABLE 2: Model 1 Difference in Difference Results, $\boldsymbol{ln}(\boldsymbol{Y_i})$

Coefficients for parcel characteristics are stable across each distant treatment and in-line with expectations. Direct interpretation of the logged model coefficients is difficult, but the marginal impact of household characteristics can be back-transformed to estimate the marginal impact of each attribute on estimated sale price.[5] The price of homes in Kanawha county increase an average $7,000 per additional acre included in the sale. Having a full basement increases home value by approximately $5,800. Home price significantly decreases the farther the parcel is from downtown Charleston. Waterfront properties exhibit a strong price premium, increasing value by ~$15,000. Older homes experience a decrease in value of between $288 and $330 for each year of age. Values associated with home style and quality-sf are highly significant but omitted here for conciseness. As an example, after accounting for direct and indirect effects, results indicate that an additional sq.-ft in a 1600 sq.-ft home is worth $97.80 in an A+ quality home, $85.92 in a B+ quality home, and $67.90 in a C+ home (See Appendix for complete results). Homes listed as D-, F, and F- have negative values associated with increased square footage, presumably because they may be "tear-downs" such that increased size increases the cost of demolition. Model fit is

[5] $\widehat{y}_i = e^{\hat{y}_i} e^{\left[\frac{\Sigma(y_i-\hat{y}_i)}{2(N-k)}\right]}$. This correction assumes the errors in the log-model are normally distributed and may not appropriately capture spatial correlation if error is also spatially correlated.

high across all model specifications (R-squared values ~ 0.58). Homes near the spill exhibit a slightly lower sale price on average, and the DID coefficient is significant at the 5% level for each treatment specification less than 3 miles.

3.1 Model 1: Change in sale price of residential properties before and after the spill based on proximity to the contamination site.

The DID coefficient estimates from Model 1 suggests that homes close to the spill experience large and statistically significant decreases in value after the spill (compared to homes farther away). As expected, the effect decreases as the size of the treatment buffer-ring increases across model specifications. Because coefficients from the log-transformed model are difficult to interpret directly; the estimates are back-transformed using the Duan correction (Duan, 1983). Pre- and post-spill DID estimates are presented in Figure 2 for each of the treatment (distance) classifications. Transformed estimated prices include the indirect effect due to spatial correlation.

FIGURE 2: Before and After Spill Difference in Estimated Sale Price

If treatment is defined as less than 1 mile from the spill site, treated homes experience a substantial decrease in sale price ($25,959) after the event. If treatment is defined as 2-miles, value loss is estimated at ~$14,200; when defined as 3-miles, loss is estimated at ~$9,900. In line with regression results from Table 2, the change in sale price attributed to the spill dissipates with treatment specifications larger than 3 miles. Results therefore suggest a large value-loss conditional on proximity (< 3 miles) to the spill, though point estimates are sensitive to the choice of "treatment" distance.

Given the average home sale price in Kanawha is about $100,000, the results defining treatment as 3 miles are in-line with the approximate 10% decrease in value observed in other studies investigating acute spills (Simons, Mikelbank and Winson, 2001). However, when the model is specified to define treatment as within a mile of the spill, estimated losses are considerably greater. This additional loss may be attributed to the well-documented contaminated water supply in this case, which has been shown to reduce homes values by more than twenty percent (Case et al. 2006).

3.2 Model 2: Temporal persistence of proximity effects.

Here, the temporal effect of the spill on home prices is estimated. Although there is no clear buffer distance to define "treatment", based on results from Model 1, the buffer distance used to define s_i in Model 2 is < 3 miles. This term is interacted with each year after the spill to capture any temporal or dynamic effects of the spill on sale price. The transformed estimates of sales price within and outside of the treatment buffer price for five years after the spill are presented in Figure 3. As expected, a substantial decrease in price, approximately $9,000, occurred immediately following the spill within the treatment buffer. Homes outside the treatment buffer see a small increase in price across the same time. While the effect of the spill is initially large, prices begin to rebound in year 3. By year 4, there is no significant difference in estimated sale price within and outside of the 3-mile buffer. Thus, the effect of the spill on home prices is significant and negative, but ephemeral.

FIGURE 3: Estimated sale prices for five years after the spill.

3.3 Model 3: Effect of being within the contaminated municipal water supply service area

Equation 3 is used to estimate the effect the "do not drink"—denoting contaminated municipal drinking water—had on home prices. In this model, two treatment dummies are included, one for proximity to spill (<3 miles) and another for being within the affected area. We find no evidence that properties within the “do not drink” boundary experience a decrease in property value. Properties within the do not drink boundary sold for approximately $105,000 both before and after the spill occurred. By comparison, homes within both the affected area and within three miles of the spill site experience a marked decrease in value (~$10,000). It is difficult to estimate the value of homes post-spill, near the spill site, but outside of the “do not drink” order area, because all homes near the spill site are necessarily in the affected service area. Results are presented in Table 3.

TABLE 3: Estimated Price of Homes from Model 3

Overall, results support the underlying hypothesis that proximity to acute environmental contamination events negatively impact home values, though we do not observe a utility-wide effect caused by the subsequent “do not drink” order. Across all three model specifications, we observe a similar decrease in price for homes sold near the spill. While the initial loss is statistically and economically significant, home values rebound to pre-contamination levels within a few years.

4. DISCUSSION AND CONCLUSIONS

Hedonic valuation has been consistently used in valuing the impacts of water quality—and to a lesser extend other acute environmental contamination events—on property values (Nicholls and Crompton, 2018). Using home sales in West Virginia, we document the impact Freedom Industries’ chemical spill had on residential property values in the surrounding market. The immediate reduction in property value is largely limited to homes within three miles of the spill and is estimated between 10% and 25% of total value. Unlike Hansen et al. (2006), we find the loss in sale price is transitory such that prices rebound to their pre-spill levels within 3 years.

This difference in our results may be related to the nature of both events. Hansen et al. examined proximity to an active pipeline, which is likely to pose a more salient and continued threat than storage tanks from a nearby chemical company.

Each estimated model includes different assumptions around the “treatment” designation, and it is clear that results are sensitive to this choice. As expected, limiting treatment definitions to nearer distances results in larger loss estimates. At larger treatment buffers, the effect is small and insignificant.

Given the divergence in results across studies and the sensitivity to treatment choices within our own study, future work should continue to elucidate the complexities of environmental contamination in human perception and housing markets. Further, loss estimates from this work should be viewed as a lower bound, since they only account for value losses associated with property sales and do not include avoidance (or other) costs imposed by the spill on communities in the region. Within three miles of the spill there are 20,122 homes implying a back-of-the-envelope loss of $201,220,000. Although, the true welfare loss depends on how accurately observed sales reflect buyers and sellers in the area. In reality, consumers have heterogeneous preferences for water supply attributes (Awad et al. 2021), pollution risk perceptions and preferences are will likely drive changes in welfare and housing market equilibria. For example, if individuals with the strongest aversion to chemical spills list their homes immediately after the event, the reduced price may not reflect the disutility of those who did not list their homes. A similar argument could be made for buyers. The presence of such heterogeneity in buyers and sellers seems reasonable and has implications for new market equilibria and total welfare estimates, which are beyond the scope of this paper, but a fertile area for future work.

While the overall results of our models are compelling, it is possible that other factors also influencing home values close to the Freedom Industries spill site after 2014. Namely, our estimates may include a structural change in the regional economy following the bankruptcy of Freedom Industries. West Virginia coal production has been declining since 2008 to 40-year lows in 2016. Such a change in employment opportunities may spillover into housing markets. All such indirect effects are impossible to characterize but should be considered in similar analyses.

The point estimates provided here are in line with previous work in other locations, but benefit cost transfers and external validity should be evaluated carefully before generalizing our results. Lastly, this analysis is applied in nature, and therefore relies on well-established methods in lieu of new methodological advancements. Recent work suggests hedonic estimation results may depend on the estimation method. For example, gradient boosting methods may improve accuracy of predictions, though they also increase volatility (Mayer et al. 2019).

Despite limitation, our results have implications for property owners and policy makers as they provide insight into the implicit and potential long-term costs of environmental contamination. Freedom Industries declared bankruptcy shortly after the incident and has therefore largely negated any legal recourse or compensation to affected residents. One solution to address the sustained decrease in property values identified herein could be the use of reclamation funds for industries with contamination risks, where an escrow account can be set aside to guarantee compensation in the event of a spill. The magnitude of these reserve funds should depend on the spatial and temporal extent of potential losses. These fund may also provide benefits for water utilities, many of which are trying to address infrastructure investment needs as they move toward integratted water managment (Grigg et al. 2018). Indeed, while Freedom Industries declared bankruptcy to avoid making conpensaotry payments, American Water settled for over $100 million over the handling of the spill, a cost which is ultimately pushed to the rate payer.

Understanding the extent to which property values and demand decrease after contamination events has significant implications for property owners, insurance companies, real estate agents, and brokerage and property management firms, investors, and regulators. While results from this analysis are robust, further work is needed to evaluate the indirect impacts of acute environmental contamination on residents and the economy. For instance, our analysis does not include demographic information, so we cannot say whether the change in housing prices disproportionately impacts minorities, the poor, or underrepresented groups. In addition, understanding how policies shape incentives for developers or industry decisions around industrial organization, risk mitigation, or production decisions is crucial in land-use planning and polices. Understanding these incentives could be used to induce firms to internalize potential hazards to water supply and health.

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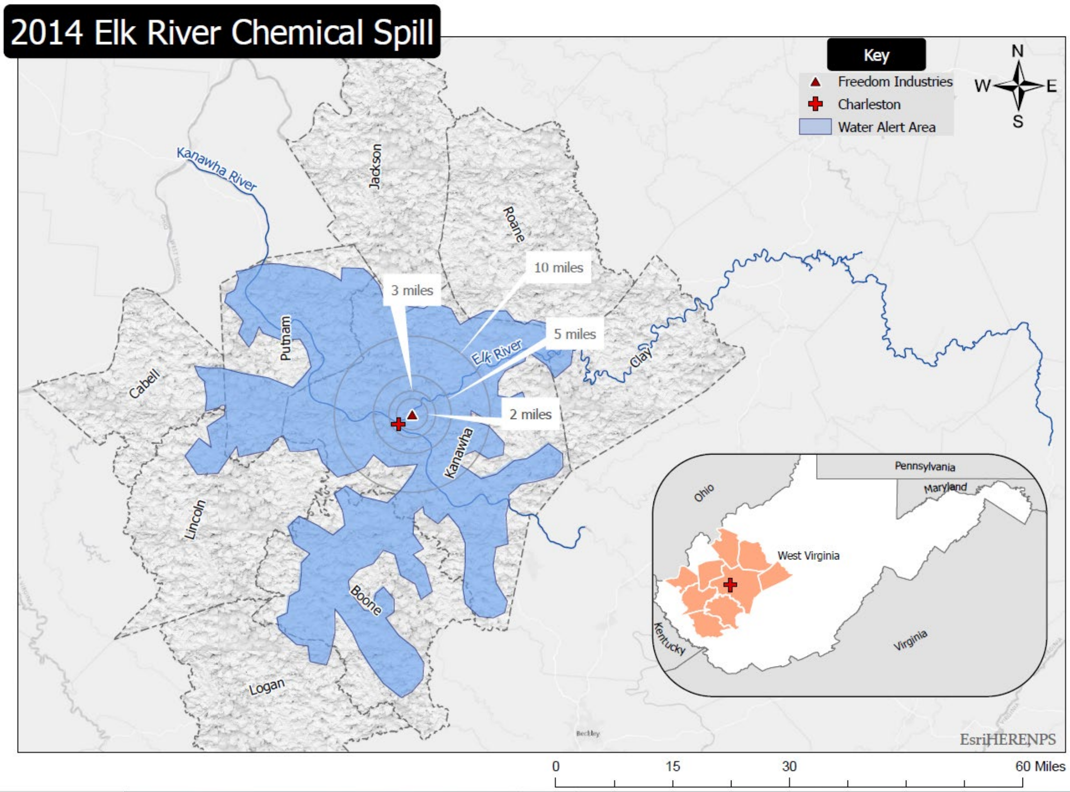

Figure 1: Map of spill location and counties included in analysis.

Table 2: Descriptive statistics of property sales

		Model 1 Sample		Model 3 Sample	
Variable	Units	Mean	St. Dev.	Mean	St. Dev.
Dependent Variable					
Sale Price	USD	98,114	73,438	112,790	85,197
DID Variables					
Sold Post Spill	[0,1]	0.247	0.431	0.253	0.435
Near Spill <2	[0,1]	0.08	0.28	-	-
Near Spill <3	[0,1]	0.18	0.38	0.098	0.298
Near Spill <4	[0,1]	0.28	0.45	-	-
Near Spill <5	[0,1]	0.37	0.48	-	-
Control Variables					
Size of home (1,000sq)	Sq.-ft	1.403	0.575	1.520	0.658
Age of home (100 years)	years	0.641	0.228	0.554	0.274
Parcel size (acres)	acres	0.323	0.423	0.369	0.488
Full basement	[0,1]	0.469	0.499	0.367	0.482
Distance to city center	miles	6.833	4.395	16.29	12.60
Waterfront	[0,1]	0.009	0.097	0.018	0.134
		N=2,705		N=5,072	

Summary statistics for flood risk (3 dummies), home style (11 dummies), and home condition (18 dummies) are included in the Appendix

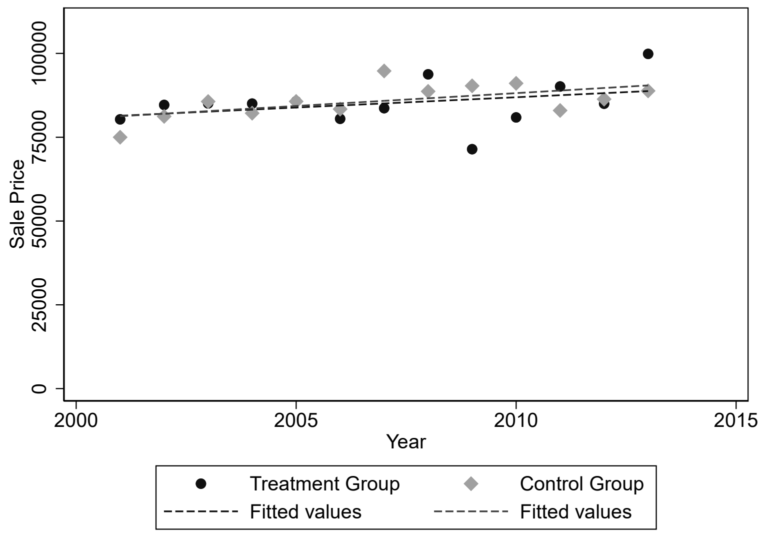

FIGURE 2: Pre-treatment trends

Table 2: Model 1 Difference in Difference Results, $ln(Y_i)$

VARIABLES	1 mile	2 miles	3 miles	4 miles	5 miles
Post-spill	-0.0089	-0.0029	0.0049	0.0044	-0.0077
	(0.0273)	(0.0279)	(0.0287)	(0.0305)	(0.0319)
Near site	-0.193**	-0.0986**	-0.210***	-0.117***	-0.126***
	(0.0934)	(0.0420)	(0.0342)	(0.0336)	(0.0367)
Post-spill* Near site	-0.417**	-0.181**	-0.130**	-0.0685	-0.0221
	(0.209)	(0.0918)	(0.0641)	(0.0534)	(0.0497)
Age of home	-0.406***	-0.402***	-0.339***	-0.373***	-0.374***
	(0.0573)	(0.0573)	(0.0576)	(0.0579)	(0.0581)
Parcel size (acres)	0.00731	0.00469	0.00307	0.00629	0.0113
	(0.0269)	(0.0270)	(0.0267)	(0.0269)	(0.0269)
Full basement	0.0968***	0.0928***	0.0921***	0.0950***	0.0974***
	(0.0224)	(0.0224)	(0.0222)	(0.0224)	(0.0224)
Distance to city	-0.0066**	-0.008***	-0.0158***	-0.0141***	-0.0159***
	(0.00296)	(0.00308)	(0.00323)	(0.00361)	(0.00411)
Waterfront	0.291***	0.275**	0.305***	0.290***	0.293***
	(0.108)	(0.107)	(0.106)	(0.107)	(0.108)
Spatial Correlation					
W	0.0140***	0.0131***	0.0128***	0.0139***	0.0140***
	(0.00321)	(0.00323)	(0.00318)	(0.00320)	(0.00320)
Observations	2,705				

Coefficients for sq. footage-quality interactions, county, year, style of home, flood risk, and condition of home are omitted from this table (See Appendix for complete results).

Standard errors in parentheses

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

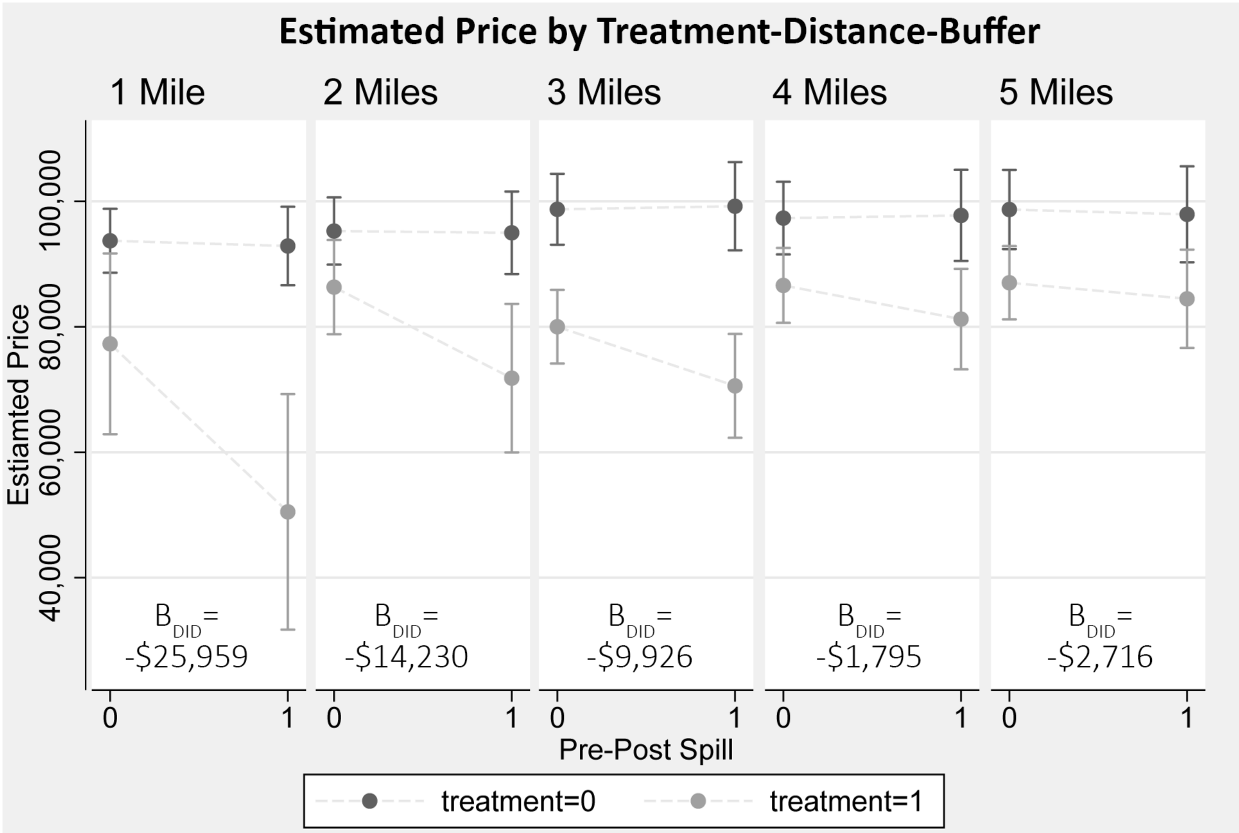

Figure 2: Before and After Spill Difference in Estimated Sale Price

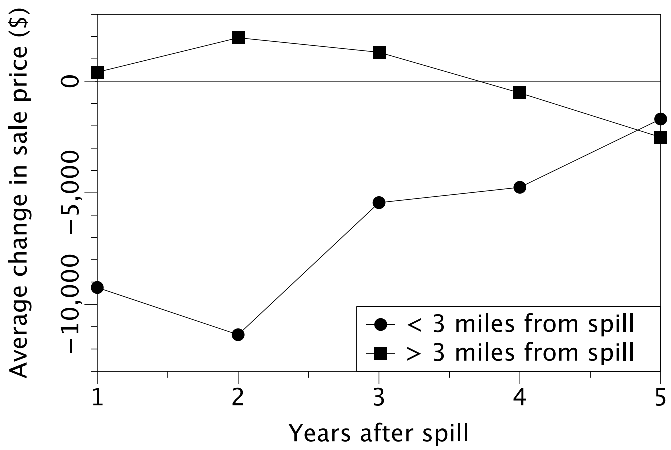

Figure 3: Estimated sale prices for five years after the spill.

Table 3: Estimated Price of Homes from Model 3

Property Treatments	Estimated Sale Price
Baseline	$111,777
In affect area	$104,826
Post Spill	$102,807
Post Spill & In affected area	$104,711
In affected area & < 3-miles from spill	$85,948
In affected area & < 3-miles from spill & Post Spill	$75,646