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ABSTRACT:

Industrial chemical accidents involving fires, explosions, or toxic vapors impose external costs on nearby communities. We examine changes in residential property values using nationwide data on chemical facilities, accidents, and residential transactions within a spatial difference-in-differences framework. We find that accidents with direct offsite impacts lower home values within 5.75 km by 2-3%, an effect that remains for at least 15 years. We estimate an average loss of $5,350 per home, which translates to a $39.5 billion loss to communities around the 661 facilities where an offsite impact accident occurred. We assess the assumptions needed for a formal welfare interpretation and conclude these results roughly approximate losses experienced by nearby residents.

Keywords: chemical accident, hedonic, nonmarket valuation, property value, Risk Management Plan, welfare effects

JEL Classification: D61, L50, Q51, Q53

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I. INTRODUCTION

Accidents at industrial chemical facilities occur with a frequency and intensity that may impose substantial social costs. These accidents involve fires, explosions, and drifting toxic vapors, all of which can directly impact nearby populations. Impacts include injuries and deaths, damages to nearby properties and the environment, and requirements that the surrounding community evacuate or take shelter to avoid potential harm. In 2016, EPA estimated that at least 40 million people (or about 12% of the U.S. population), and perhaps as many as 177 million (55%), were at risk of experiencing impacts from an accident at these facilities (U.S. EPA, 2016).[1] Evidence suggests that environmental justice is a concern as communities located near industrial chemical facilities have disproportionately larger income disparities, higher proportions of minority households, and live in houses with already depressed values (Guignet et al. 2022; Elliot et al. 2004). The social costs imposed by accidental chemical releases can exacerbate these existing inequalities. This paper provides the first ever national level estimates of the magnitude of such social costs.

To reduce the impacts of chemical accidents experienced by nearby communities, the US Environmental Protection Agency (EPA) administers the Risk Management Plan (RMP) program.[2] Section 112(r) of the 1990 Clean Air Act Amendments required EPA to publish regulations and guidelines to prevent accidents at facilities using certain hazardous chemicals. The Amendments followed public outrage at the mid-1980s catastrophe in Bhopal, India, where a pesticide production facility accidentally released a toxic cloud that killed thousands of people.[3] In 1996, EPA published a rule that established the RMP Program, requiring regulated facilities to (1) undertake hazard assessment; (2) develop an accident prevention program; and (3) plan emergency response activities in case of an accident. Facilities are covered by the program if they hold above a threshold quantity of a regulated substance.[4] At present, 140 toxic chemicals, including ammonia, chlorine, hydrofluoric acid, and methane, are regulated under the RMP Program.

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[1] In the Regulatory Impact Analysis for the 2017 "Accidental Release Prevention Requirements" rule, EPA reported that approximately 177 million people would be impacted if a hypothetical worst-case scenario accident occurred at all RMP facilities. However, under more likely alternative accident scenarios, EPA reports that approximately 40 million people are potentially at risk (US EPA, 2016). The estimated percentages of the U.S. population are based on the estimated total population of 324 million people at the end of 2016 (U.S. Census Bureau, 2016).

[2] The safety of workers is addressed by the U.S. Occupational Safety and Health Administration.

[3] US EPA, "Emergency Planning and Community Right-to-Know Act (EPCRA) Milestones Through The Years," Accessed at: https://www.epa.gov/epcra/epcra-milestones-through-years#:~:text=The%20Bhopal%20disaster%20was%20one,storage%2C%20releases%20and%20emergency%20response, 8 Aug 2022.

[4] More specifically, a facility is regulated under the RMP program only if it holds above a threshold quantity in a *"process"*, as opposed to consideration of sitewide quantities. Under the RMP rule, a "process" means any activity involving a regulated substance, including any use, storage, manufacturing, handling, or on-site movement of such substances, or combination of these activities. A single process includes any group of "vessels" that are interconnected, or separate vessels that are located such that a regulated substance could be involved in a potential release (40 CFR part 68.3). For example, the quantities of separate containers of the same regulated substance that are located such that they could be involved in a single accidental release event are aggregated into a single "process" for purposes of determining whether a threshold quantity is exceeded.)

As of 2020, the RMP program regulated close to 12,000 facilities that processed or stored certain high-risk chemicals. These facilities include a wide range of industrial categories ranging from complex petroleum refineries, chemical manufacturers, and paper producers, to less complex and more numerous food and beverage manufacturers, water and wastewater utilities, and agricultural chemical distributors and wholesalers. From 2004 to 2019, reports to EPA by RMP facilities show an average of 202 accidents per year. About a quarter of these accidents caused measurable impacts to offsite communities, including hospitalizations, other medical treatments, evacuations, shelter-in-place events, or property and environmental damage.

Despite the almost 25-year age of the RMP program, there are no estimates of the value of its social benefits. EPA updated the requirements for program facilities in 2017 and 2019, and most recently, proposed amendments in August 2022 (US EPA 2022a, 2022b). Among other provisions, the 2022 proposal would require root cause analysis of most accidents, third party compliance audits for certain facilities with multiple accidents, and enhanced worker authority to "stop work" in situations with a potential for a catastrophic release. Analyses accompanying these final and proposed rule updates included a comparison of regulatory costs to baseline accident damages, but lacked estimates of the social benefits from reducing the probability of accidents (US EPA 2016, 2019, 2022).

It is well-established that hedonic property value results generally lack a formal welfare interpretation in cases of non-marginal changes and when the hedonic price surface is changing over time (Klaiber and Smith, 2013; Kuminoff and Pope, 2014). Banzhaf (2021) recently proposed an approach that allows for inference of a formally valid, bounding welfare measure based directly on first-stage hedonic property value models that use a difference-in-differences (DID) design. Under this approach there is no need to estimate Rosen's (1974) second-stage bid and offer functions. To our knowledge, our study is the first to explore this approach in the context of chemical accident prevention, thereby facilitating a formal welfare interpretation of the results; and thus helping inform benefit-cost analyses of RMP and other chemical security policies that protect surrounding "fence-line" communities.

We start with nationwide data for 2004 to 2019 on facilities regulated by EPA's RMP program, including information on the number of accidents and their impacts. Regulated facilities are required to report such information, including details of onsite and offsite impacts. We combine this with Zillow's nationwide ZTRAX data of residential parcels and transactions. Within a hedonic regression framework, we use a DID design to examine differences in property prices before and after an accident. We compare those differences between homes that are near versus far from an accident. Our study is the first ever to assess the nationwide property value impacts of chemical facility accidents. Prior research on similar disamenties has focused on only one or a few accident cases (e.g., Carroll et al. 1996; Hansen et al. 2006; Grislain-Letremy and Katossky 2014; and Herrnstadt and Sweeney 2019), or on a sub-national region within the US (Guignet, et al. 2022).

Our paper contributes three additional unique analyses. The effects on home prices of accidents of different severity are estimated, as are the different effects of single versus multiple accidents. We also examine the persistence of any adverse price impacts over time.

The results suggest that homes as far as 5.75 km away are impacted by a chemical accident, but the adverse price effects are limited to the most severe cases; i.e., accidents resulting in deaths or injuries to people in the surrounding community, damage to offsite properties and environmental systems, and/or the evacuation or sheltering-in-place of offsite populations. Among those homes, an average price decline of 2% to 3% is experienced. We do not find evidence of systematically different price declines among homes that experience multiple chemical accidents, but do find that home values remain depressed for at least 15 years after an offsite impact accident occurred.

The average loss in a home's value is about $5,350 (2021$ USD), and this translates to a $39.5 billion loss due to the offsite impact accidents that occurred at 661 different facilities from 2004 to 2019. The loss to the community where an offsite impact accident occurs was, on average, $59.8 million (the median loss was $24.9 million). We provide evidence that the depreciation in prices due to an offsite impact accident may be constant over our study period, which is a necessary assumption to support interpretation of these results as a theoretical upper bound of the ex post welfare loss to nearby residents (Banzhaf, 2021). For smaller shocks, such as may be the case for our estimated 2% to 3% loss, the bounding estimate better approximates the true ex post welfare loss to nearby residents (Banzhaf, 2021).

The remainder of this paper includes a brief description of EPA's RMP program, a literature review, details on our data and methods, and a summary of our results. We conclude with a discussion of the necessary assumptions to interpret the estimates as national-level ex post welfare impacts on nearby communities, and the analytical advantages afforded by detailed, broad-coverage datasets like that provided by Zillow's ZTRAX program.

II. LITERATURE

Soon after the first chemical facility accident data became public following establishment of the RMP Program, several publications explored factors that correlated with accidents occurring between 1994 and 2000. These studies examined how facility characteristics, applicable federal regulations, and firm financial variables related to accidents; and reported on the correspondence between accident risk and socioeconomic status of the surrounding communities (Kleindorfer, et al., 2003, Elliot, et al., 2003, Kleindorfer et al., 2004, Elliot et al., 2004). For example, Kleindorfer et al. (2004) identified a positive relationship between a facility's debt-to-equity ratio and accident propensity. Elliot et al. (2004) concluded that larger RMP facilities and those using a larger number of chemicals are disproportionately located in counties with higher median incomes, but also greater levels of income inequality and a higher proportion of African Americans.

Multiple hedonic case studies have examined home values near petroleum refineries, chemical plants, and natural gas pipelines, and find that prices decline following a chemical explosion (Flower and Ragas, 1994; Carroll et al., 1996; Hansen et al., 2006; Liao et al., 2022). Such adverse effects may vary from case to case. Focusing on homes near pipelines in San Bruno, California, Herrnstadt and Sweeney (2019) find that a 2010 pipeline explosion and subsequent mail notifications to all households living within 2,000 feet of a natural gas pipeline resulted in no impact on prices.

In a nationwide analysis of properties near natural gas distribution pipelines, Cheng et al. (2021) find that home values within 1 km decline by 7.4% after an explosion, compared to a control group of homes 1-2km away. Cheng et al.'s spatial difference-in-differences approach is similar to the identification strategy implemented in our analysis, as well as to hedonic studies of similar types of disamenities and releases of hazardous chemicals. Guignet et al. (2018) examine property value changes around high-profile releases from underground storage tanks (USTs) at retail gas stations and find that homes within 3 km depreciate an average of 6%. Guignet and Nolte (2021) conduct a nationwide study of hazardous waste treatment, storage, and disposal facilities (TSDFs). They caution against a causal interpretation but do find evidence that home values within 750 meters may decrease up to 5% after the discovery of contamination.

Our study also relates to a branch of literature on air pollution and home values. In general air quality improvements increase home values (e.g., Chay and Greenstone 2005; Bayer, et al. 2009; Grainger 2012; Bento et al. 2015; Lang 2015; and Amini et al. 2021). Much of this literature focuses on "criteria air pollutants" as designated under the Clean Air Act, rather than toxic pollutants. However, there are several notable exceptions focusing on EPA's Toxic Release Inventory (TRI) Program. The TRI Program requires firms with threshold quantities of reportable chemicals to disclose fugitive emissions. Currie et al. (2015) examine residential transactions near 1,600 industrial facilities in five U.S. states and conclude that the opening of a facility that reports toxic air emissions to the TRI led to an 11% price decrease of homes within 0.5 miles. Mastromonaco (2015) examines house price changes in several California counties with existing firms newly required to report to the TRI in 2001 and finds up to 11% lower prices within one mile. Mastromonaco interprets the house price impacts in this context as responses to firms maintaining threshold chemical quantities, rather than to changing emissions levels. A working paper by Moulton et al. (2018) examines nationwide home values around facilities newly required in March 2000 to report pollution releases to the TRI. They find that home prices within a half mile of firms emitting at high levels decrease by approximately 8%, with smaller price declines experienced by homes up to 5 miles away. Banzhaf (2021) examines the effect of changing the number of plants required to report to the TRI on house values in the Los Angeles area between 1995 and 2000. He finds that homes located within a mile of reporting plants experience negative and significant price effects relative to homes located 1 to 2 miles away.

Most reported emissions to the TRI entail routine and intentionally emitted pollutants. In contrast, pollution incidents reported under the RMP Program are exclusively the result of infrequent, accidental air emissions and the resulting explosions, fires, and clouds of toxic vapors. The results of hedonic studies on criteria air pollutants and TRI facilities are not necessarily transferable when examining the impacts of the RMP program.

To our knowledge, there is only one nonmarket valuation study specifically on the RMP Program. In an earlier study, Guignet et al. (2022) use DID and triple difference approaches, along with coarsened exact matching techniques, to examine the impact of chemical accidents on home prices in a tri-state region of the US (Michigan, Ohio, and Pennsylvania). They find that the typical accident yields no effect on surrounding home prices, but homes within 5 km of an accident that impacts surrounding populations (i.e., leads to offsite injuries, property damage, shelter-in-place, or evacuations of people in the surrounding community) experience a 5% to 7% decline in price.

We expand on Guignet et al.'s (2022) regional case study in multiple ways. First, we include a more current study period, and examine national scale price impacts. This is important as it will enable assessment of national-level policies and programs. By expanding our study area and time period, we include more facilities and home sales in our analysis. The larger sample size allows us to determine the appropriate spatial extent of any price impacts using higher resolution 250-meter bins, rather than the one-kilometer bins used by Guignet et al. (2022). Second, we examine how price impacts vary not just by whether the accident resulted in offsite impacts or not, but also if an accident included any onsite impacts that were required by EPA to be reported. Third, we examine the role of multiple accidents in updating residents' perceived risks, and the subsequent price effects.

An additional important contribution enabled by the larger sample size, is that we can look more in-depth at how price impacts evolve over time. After an accident, property values in nearby communities could experience a brief period of decline or might suffer a persistent negative impact. Stigma is a phenomenon explored in the economics literature, although mostly in relation to cleanups of contaminated sites such as those on the National Priorities List (NPL). Messer, et al. (2006) examine up to 30 years of house price fluctuations in metropolitan areas neighboring prominent NPL sites. The study concludes that cleanups occurring over lengthy 10+ year periods do cause stigma, and that neighboring property values do not rebound enough to compensate for losses from the original contamination. One mechanism through which prices may remain depressed is the re-sorting of households following a contamination event (or chemical accident), whereby higher income families move away from contamination and, because they cannot afford otherwise, lower income families move toward it. Cleanup would lead to the opposite effect – i.e., gentrification. Banzhaf (2012) provides a discussion of gentrification that clearly identifies potential distributional concerns. A persistent price decline from chemical accidents would affect house values that are already lower than average due to proximity to an industrial facility.

Studies in the context of toxic air emissions and pipeline explosions have found some evidence of stigma leading to a persistent discount in house prices. In their study of toxic air emissions, Currie et al. (2015) find that the initial decline in house prices due to the opening of a facility remains, even after the plant is closed. Hansen et al. (2006) study home sales located within a mile of two pipelines to estimate the impacts of a 1999 fuel pipeline explosion in Bellingham, Washington.

Following the accident, property prices were significantly lower, with the effect diminishing with distance, from a 4.6% decline for a property 50 feet from the pipeline to 0.2% at 1,000 feet away. They find that prior to the explosion neither of two regional pipelines affected nearby property values, but for the five-year-time period following the event there was a significant negative effect of proximity to the pipeline that experienced the explosion (though it diminished in magnitude with each passing year). The researchers attribute the persistent five-year effects to households receiving new information about the location and risks of the pipeline, but also to attention-grabbing media coverage that may have led people to overestimate risk.

In contrast, other studies of site contamination find little evidence of persistent negative effects. Taylor, et al. (2016) compare the impact on home prices of commercial properties with no known contamination to commercial properties with remediated contamination and find that any differences in price are largely indistinguishable. The paper concludes that stigma does not persist once a contaminated site is remediated. Guignet, et al. (2018) similarly find no evidence of stigma in highly publicized cases of leaking and remediated underground storage tanks, nor do Guignet and Nolte (2021) at remediated hazardous waste sites. Both studies find surrounding home values rebound after cleanup is complete. We contribute to this persistence and stigma literature by examining how initial price declines due to a clearly noticeable chemical accident evolve over time.

One of our most important contributions is to assess a formally valid, welfare interpretation of our hedonic results. DID is an increasingly popular estimation approach in the hedonic property value literature (Parmeter and Pope, 2013; Guignet and Lee, 2021), and for causal inference in general. However, the results from hedonic property value studies generally lack a formal welfare interpretation in cases of non-marginal changes and when the hedonic price surface is changing over time (Klaiber and Smith, 2013; Kuminoff and Pope, 2014). Though many approaches have been suggested, there is no commonly agreed upon best approach to improve the interpretation of hedonic estimates as welfare changes (Bishop et al., 2020).

With a specific focus on the DID design, Banzhaf (2021) demonstrates that a change in price along the same ex post price gradient is a lower bound of the Hicksian equivalent surplus for an improvement in quality. Conversely, it can be interpreted as an upper welfare bound to the nearby community for a decrease in quality, as is the case for chemical accidents at industrial facilities. In later models we allow the entire hedonic price surface to vary over time, which allows for a formal ex post (i.e., post-accident) welfare interpretation of the results.

To our knowledge, our study is the first comprehensive, nationwide non-market valuation study of accidents at chemical facilities. Our analyses better characterize price impact heterogeneity and the potential persistence of price effects over time, thus providing more detailed insights about the impacts of industrial accidents and similar disamenities. Furthermore, our estimated capitalization effects and assessment of a formal welfare interpretation can inform benefit-cost analyses of federal regulations, as well as state and local decision-making. This is particularly relevant in light of climate change and the vulnerability of industrial operations to increasingly severe storms, floods, and wildfires (Flores, et al. 2021; US Chemical Safety Board, 2017; Chemical Industries Association, 2015). Our results can inform more socially efficient decisions regarding the RMP program and other federal chemical security policies, as well as local land use decisions and climate adaptation strategies.

III. DATA

The empirical analysis focuses on home transactions from 2004 to 2019 in the contiguous U.S. that occurred within 10 km of an RMP facility where a chemical accident was reported. Data describing all RMP facilities and reported accidents were provided by EPA's Office of Emergency Management. We spatially and temporally link facilities with reported accidents to transaction data of single-family homes from Zillow's ZTRAX database.

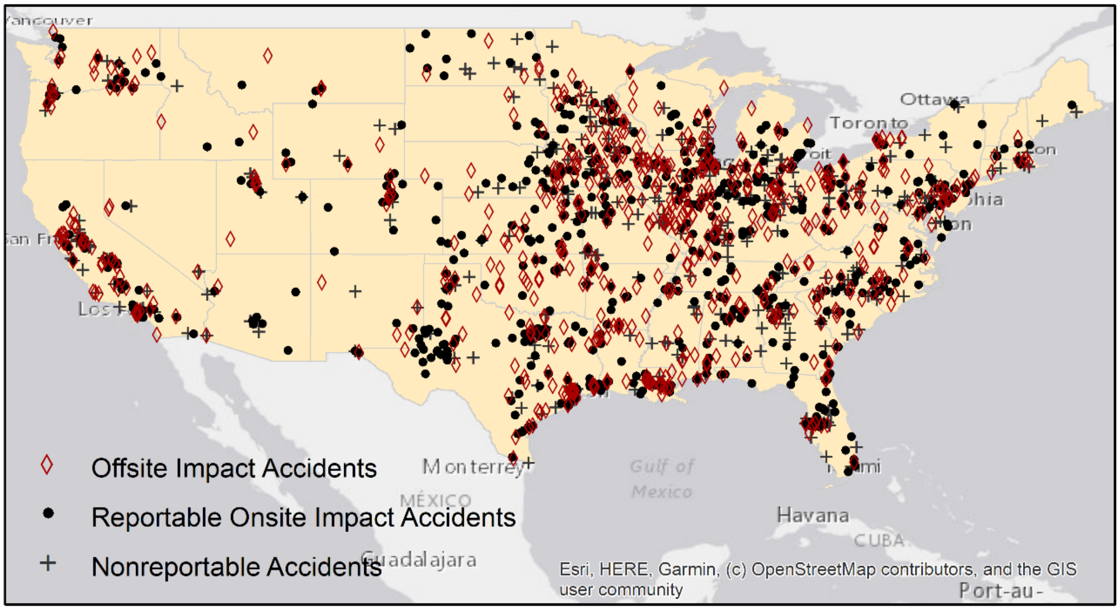
III.A. RMP Facilities and Accidents

The EPA maintains a nationwide database of all facilities regulated under the RMP program. Every five years, regulated facilities must identify and describe any accidents with reportable impacts that occurred over the prior five years. Reportable impacts include onsite fatalities, injuries, and property damage, as well as offsite fatalities, hospitalizations, people in need of medical treatment, number of people evacuated, number of people who were sheltered-in-place, and finally offsite property and environmental damage.[5] As a result, the RMP national database contains a continuous record of accidents from regulated facilities, beginning five years prior to facilities' initial submissions at the program's inception in 1999. Our analysis focuses on the 1,822 facilities where at least one chemical accident was reported to have occurred from 2004 to 2019. Figure 1 shows that these facilities and accidents are quite dispersed across the contiguous U.S., but with a higher spatial concentration in the rust belt around the Great Lakes, along the east coast and Gulf of Mexico, and in portions of California and the Northwest. Facilities participate in a variety of industrial activities, with the six most common being farm supplies wholesalers (13.1%), organic and inorganic chemical manufacturing (7.7%), refrigerated warehousing and storage (6.0%), poultry processing (5.0%), water supply and irrigation systems (4.9%), and petroleum refineries (4.7%).

These facilities all reported at least one accident, with a mean of 1.8 accidents, and a median of one. There is, however, noticeable variation in the number of accidents reported. Most facilities report just one accident (68.5%), but 31.5% report multiple accidents. The 90th and 95th percentiles are three and five accidents, and a maximum of 30 accidents is reported by one facility.

[5] See 40 CFR 68.42.

Figure 1. Study area and RMP accident sites.



A total of 3,236 chemical accidents are reported by the 1,822 RMP facilities from 2004 to 2019, an average of 202 accidents per year. As shown in Table 1, most of the accidents were at least partly due to equipment failure (62.5%), followed by human error, issues due to maintenance activities or a lack thereof, and unexpected weather conditions. Most accidents involved the release of a hazardous gas into the air (66.8%), but liquid spills and subsequent evaporation, chemical fires, and even explosions are somewhat common. Only 34 accidents (1.1%) resulted in uncontrolled chemical reactions. Of the 140 hazardous substances regulated under the RMP program, the chemicals most often reported as released include ammonia, chlorine, hydrofluoric acid, propane, sulfur dioxide, hydrogen sulfide, methane, butane, and a general "flammable mixture" category.

Most of the accidents (2,275 or 70.3%) were required to be reported under the RMP regulations, but 961 (29.7%) were not required to be reported, meaning that the accident did not result in RMP reportable impacts (i.e., deaths, injuries, significant property damage, environmental damage, or the shelter-in-place or evacuation of people in the surrounding community). In Figure 1, the nonreportable and reportable onsite impact accidents are denoted by the black crosses and dots, respectively. We include all reported accidents and examine for potential heterogeneity in the housing price impacts. Almost a fourth of the accidents (789) resulted in impacts that were *not* limited to the facility itself, directly affecting the surrounding environment and community. As shown by the diamonds in Figure 1, we label such accidents as having offsite impacts. These accidents resulted in offsite environmental damage (e.g., defoliation to trees, surface water contamination, dead or injured animals), damage to properties located offsite, injuries or deaths to offsite populations, and/or the evacuation or shelter-in-place of people in the surrounding community.

Details of both onsite and offsite impacts can be found in the lower portion of Table 1. About 1.5% (48) accidents resulted in one or more deaths to people onsite, including facility workers and first responders. Among those 48 accidents, there was an average of two deaths. One accident resulted in a maximum of 15 deaths. About 42% of accidents resulted in injuries onsite, and among those accidents the number of people injured ranged from one to 250. Onsite property damage was reported in 780 cases, with onsite damages assessed at $8.01 million (2021$ USD), on average.[6]

Damage to the surrounding environment was reported among 5.9% of the accidents. Fortunately, only one accident resulted in the death of an individual located offsite, but there were 249 accidents (8.0%) that resulted in injuries to the surrounding population. The number of people injured offsite among those accidents ranged from one to over 14,000, with an average of 61 people injured per accident. Offsite property damage occurred in 89 incidents, with an average assessed damage of $2.06 million. The evacuation and shelter-in-place of people in the surrounding community occurred in 312 (9.6%) and 220 (6.9%) cases, respectively; and impacted 307 and 2,369 people, on average. Thirty-nine accidents resulted in more than 1,000 individuals being evacuated or sheltered-in-place.

Table 1. Chemical accident descriptive statistics.

Variable[a]	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Causes of accident[b]					
Equipment failure	3,236	0.6252	0.4842	0	1
Human error	3,236	0.4796	0.4997	0	1
Maintenance activity/inactivity	3,236	0.1792	0.3836	0	1
Weather	3,236	0.0374	0.1897	0	1
Type of accident[b]					
Gas release	3,236	0.6681	0.4710	0	1
Liquid spill and evaporation	3,236	0.3446	0.4753	0	1
Fire	3,236	0.1165	0.3209	0	1
Explosion	3,236	0.0405	0.1971	0	1
Chemical Reaction	3,236	0.0105	0.1020	0	1
Impacts of accident					
Onsite deaths	3,236	0.0148	0.1209	0	1
# onsite deaths (people)	48	2.04	2.63	1	15
Onsite injuries	3,236	0.4203	0.4937	0	1
# onsite injuries (people)	1,356	2.34	9.01	1	250
Onsite property damage	3,236	0.2420	0.4283	0	1
Total onsite property damage (2021$ USD)	780	8,019,896	4.21E+07	1	5.94E+08
Environmental damage	3,236	0.0590	0.2357	0	1
Offsite deaths	3,236	0.0003	0.0176	0	1

[6] All nominal dollar values converted to 2021$ USD based on the Bureau of Labor Statistics annual US city average "All Urban Consumers" consumer price index (CPI), available at: https://www.bls.gov/cpi/tables/supplemental-files/historical-cpi-u-202206.pdf, accessed 31 July 2022.

# offsite deaths (people)	1	1.00	-	1	1
Offsite injuries	3,236	0.0803	0.2719	0	1
# offsite injuries (people)	249	61.19	887.22	1	14,003
Offsite property damage	3,236	0.0275	0.1636	0	1
Total offsite property damage (USD$)	89	2,062,809	1.72E+07	58	1.62E+08
Offsite evacuations ordered	3,236	0.0964	0.2952	0	1
# offsite people evacuated	312	307.05	2,861.53	1	50,000
Offsite shelter-in-place ordered	3,236	0.0686	0.2528	0	1
# offsite people sheltered-in-place	220	2,368.65	8,342.48	1	55,000

Note: The total number of observations is 3,236 chemical accidents.
(a) Variables are binary indicator variables unless otherwise noted.
(b) Cause and type of accident categorical variables are not necessarily mutually exclusive.

III.B. Residential Property Transactions

Residential parcels are individually linked to any of the 1,822 RMP accident sites that are within 10 km. We account for the timing of accidents relative to transactions of those parcels between 2004 and 2019. A total of 10,428,442 arms-length transactions of single-family homes are observed within 10 km of one or more of the RMP accident sites.[7] The data includes residential transactions in 47 of the 48 states across the contiguous U.S.[8]

Distance of a home from an RMP facility is accounted for using 250-meter incremental distance bins. A continuous distance measure to the nearest accident site was not an appropriate measure in our context because a home can potentially be near multiple RMP facilities that have experienced accidents. Accounting for proximity using bins allows us to track the number of RMP facilities and accidents in each incremental distance zone. We wanted to maintain a high-spatial resolution while also ensuring a sufficient number of transactions within each bin for initial empirical diagnostics. We judged 250-meter incremental bins as an appropriate size considering these tradeoffs. The number of sales observed in each 250-meter bin from a facility both before and after an accident are displayed in Figure A.1 of Appendix A.

Key variables and descriptive statistics are provided in Table 2. Several variables describing the home are derived from ZTRAX's transaction and assessment databases. Attributes of the location of a home were provided by the Private-Land Conservation Evidence System (PLACES) at Boston University. PLACES uses assessor parcel numbers to link ZTRAX data to parcel boundaries based on county and town-specific deductive string pattern matching and geographic quality controls (Nolte, 2020). For each parcel, we identified the census tract using spatial joins, computed Euclidean distances to the nearest highway (using TIGER road data), lake (>4ha) and river (using

[7] We focus solely on full, arms-length transactions of single-family homes. Data cleaning and formatting details are provided in Appendix A.
[8] We exclude Washington, D.C. because it is a unique housing market, and Wyoming is excluded because it is a non-disclosure state and no transactions from the available data were of homes within 10 km of an RMP accident site. Limited available sales data for the other states often cited as non-disclosure states (Wentland et al., 2020) are maintained in our analysis, including Idaho, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, Texas, and Utah.

the waterbody polygons from the National Hydrography Database), as well as the proportion of developed land cover within a 500-meter circular buffer around each home (using the 2011 National Land Cover Database).[9]

The average home sells for just under $260,000 (2021$ USD), is on a 0.28-acre lot, and is 1.3 stories high. The average number of bathrooms is 1.9, and the interior square footage and age of a home, on average, are about 3,300 sq ft and 40 years. As can be seen by the companion missing variable indicators for the house structure and acreage variables, the percent of observations missing are most noticeable for the number of bathrooms (30%) and stories (16%). Missing values are coded as zero, and are included in the later hedonic regression models, along with the corresponding missing value indicators.

Table 2 reports location attributes showing that, on average, 52% of the land within 500 m of a home is developed. About 36% of sales are of homes within 500 m of a highway, and 4.6% and 2.2% are within 500 m of a lake and 250 m of a river, respectively. The subsequent hedonic regression models include spatial fixed effects at the census tract level, but location attributes are included to capture local, within tract variation of amenities and disamenities near each home.

Table 2. Residential transactions descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Price (2021$)	10,428,442	259,182	190,929	15,000	999,972
Transaction year	10,428,442	2011.13	4.85	2004	2019
Quarter	10,428,442	2.52	1.06	1	4
Acres	10,272,126	0.2834	0.2709	0.05	2
Missing: Acres†	10,428,442	0.0150	0.1215	0	1
Stories	8,802,167	1.34	0.48	1	3
Missing: Stories†	10,428,442	0.1559	0.3628	0	1
Bathrooms	7,310,276	1.94	0.76	1	4.5
Missing: Bathrooms†	10,428,442	0.2990	0.4578	0	1
Interior square footage	9,845,806	3,312.90	2,345.69	750	15,000
Missing: Interior square footage†	10,428,442	0.0559	0.2297	0	1
Age (years)	9,702,115	39.70	29.07	0	120
Missing: Age†	10,428,442	0.0696	0.2546	0	1
% Land Developed w/in 0-500m	10,428,442	52.44	23.36	0	100
Highway w/in 500m†	10,428,442	0.3568	0.4791	0	1

[9] Census tract data comes from the National Historical Geographic Information System (Manson et al., 2018), and are based on the tract boundaries from the 2016 American Communities Survey. Land cover data comes from the 2011 National Land Cover Database (Dewitz, 2019). The highways data is from the US Census Bureau's TIGER/Line shapefiles (2019).

Lake w/in 500m†	10,428,442	0.0456	0.2087	0	1
River w/in 250m†	10,428,442	0.0216	0.1452	0	1

Note: The final sample includes n=10,428,442 single-family home transactions. Descriptive statistics for some variables are for a smaller sample due to missing values, as reflected by the corresponding missing value indicators. Variables denoted with † are binary indicators.

IV. METHODS

This section explains our empirical design and presents models of the price impacts of chemical accidents, cumulative price effects and their attenuation over time, and the welfare effects experienced by nearby residents.

IV.A. Stacked spatial difference-in-differences design

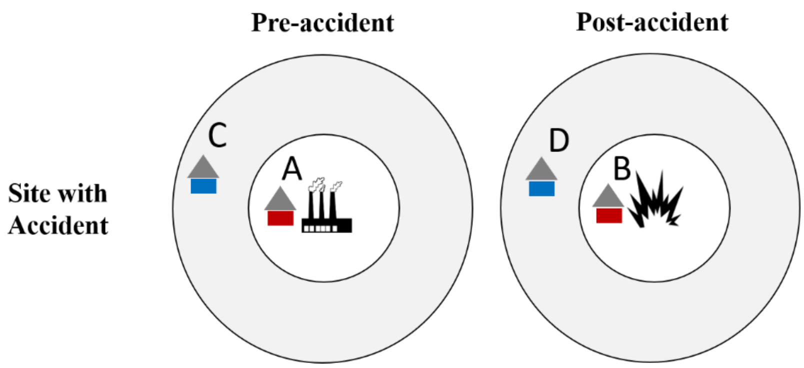
Spatial difference-in-differences (DID) is a popular approach to infer causal impacts in hedonic pricing models (Parmeter and Pope 2013; Guignet and Lee 2021). Davis's (2004) application in valuing the implicit price of pediatric cancer risks, and Linden and Rockoff's (2008) analysis of how proximity to registered sex offenders impacts home values, are among the first to demonstrate the appeal of the DID strategy in a property value setting. The approach has since been used in numerous environmental hedonic applications (e.g., Horsch and Lewis 2009; Atreya et al. 2013; Bin and Landry 2013; Muehlenbachs et al. 2015; Haninger et al. 2017; Guignet et al. 2017).

The DID strategy closely resembles a classical experimental design. Figure 2 depicts homes near an RMP facility, both before and after a chemical accident. "Treatment" in this quasi-experimental setting is defined as being near an industrial facility where a chemical accident occurs. Homes denoted by group A are the treated group, pre-treatment; and those in group B are the treated group, post-treatment. The impacts of the chemical accident on the price of homes in group B are of primary interest, but identifying the appropriate counterfactual is critical.

A simple before and after (or first differences) estimate would entail the difference in price between groups B and A (i.e., $P_B - P_A$). Such a comparison, however, is susceptible to temporally varying confounders. If the price of homes in a neighborhood are changing due to other unobserved factors, then a first differences estimate would suffer from an omitted variable bias. Such concerns are partially alleviated because our analysis is a stacked treatment design (Cengiz et al. 2019; Deshpande and Li 2019; Fadlon and Nielsen 2021), where RMP accidents occur at different locations and at different times. Confounding factors would have to be temporally correlated across many RMP accidents and nearby neighborhoods to bias the first differences results, but it is still possible. For example, a plausible situation might be that an industrial facility is no longer as profitable as it used to be, and cost-savings measures may imply an increased risk of an accident. Such facilities could tend to be in neighborhoods that are experiencing ongoing economic decline.

The DID strategy can further alleviate omitted variable bias concerns, and bolster causal inference, by using homes in the broader neighborhood as a counterfactual. The intuition and key assumption are that the price of homes in the broader neighborhood are affected by the same unobserved trends as the treated group, but are too far away to be impacted by the chemical accident. The homes in these farther distance bins (denoted by groups C and D) serve as the control group, and so the second difference in the DID strategy allows one to difference out the broader neighborhood trends that could otherwise bias the price effects of interest. The DID estimate is $(P_B - P_A) - (P_D - P_C)$.

Figure 2. Illustration of the Difference-in-differences approach.



This DID strategy is applied within a traditional hedonic price regression model, where the dependent variable is the natural log of the price of home i, in neighborhood j (i.e., census tract), in housing market m (i.e., county), at time t $\left(p_{ijmt}\right)$. The independent variables include a vector of house and location characteristics $\left(\boldsymbol{x}_{ijmt}\right)$, county-by-year and county-by-quarter fixed effects $(\boldsymbol{\tau}_{mt})$, and neighborhood fixed effects $\left(\upsilon_{jm}\right)$.

We set out to answer five main research questions. First, does the typical accident tend to impact the value of nearby homes? Second, how do the price impacts vary based on severity of an accident? Third, what are the cumulative effects on home prices due to multiple accidents? Fourth, do the price impacts tend to attenuate over time? And fifth, what are the formal welfare implications?

IV.B. Price impacts of chemical accidents

Our empirical analysis largely follows equation (2) below, but for purposes of exposition we start with the simplest model:

$$(1) \qquad ln\left(p_{ijmt}\right) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \boldsymbol{\rho}\boldsymbol{RMP}_i + \delta post_{it} + \boldsymbol{\gamma}(\boldsymbol{RMP}_i \times post_{it}) + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

where ε_{ijmt} is a normally distributed disturbance term (which we allow to be correlated for all transactions within the same county). The subscripts on the parameter $\boldsymbol{\beta}_{mt}$ reflect that the slope coefficients of the house and location attributes are allowed in some models to vary over time and by market. Although not explicitly represented for notational ease, in our most comprehensive models these attributes are interacted with market and year indicators, or even with market-by-year indicators. We are estimating a nationwide hedonic price model, but the hedonic price surface is an equilibrium result. The "law of one price" states that identical houses should sell for the same price throughout the entire assumed market (Bishop et al. 2020). Assuming the entire nation is a single housing market would surely violate this principle. The inclusion of these interaction terms allows the equilibrium price surface to vary across space and time with respect to the house and location attribute dimensions.

$\boldsymbol{RMP}_i$ is an indicator denoting that an RMP facility is in close proximity to the home (i.e., 0 to 5,750 meters). Section V.A describes how the distance used to define being in close proximity to an RMP facility (i.e., within the treated zone distance) is established. For the "treated" group of homes, no matter whether the sale occurs before or after an accident, $\boldsymbol{RMP}_i = 1$, and so the coefficient $\boldsymbol{\rho}$ captures the baseline price differences associated with an RMP facility being nearby. In some later models we allow for heterogeneity of the price effects within the assumed treated zone, and in such cases $\boldsymbol{RMP}_i$ is a vector of indicator variables corresponding to 250-meter incremental bins.

The indicator denoting that an RMP facility had an accident nearby, or in the broader vicinity of, a home ($post_{it}$) reflects the post-treatment period, irrespective of being in the treated or control group. In other words, the parameter δ captures temporally varying, and otherwise potentially confounding, factors affecting prices. Given the inclusion of year-by-county and quarter-by-county fixed effects, δ may be redundant, capturing only average within year and within quarter variation associated with the pre- and post-accident periods. Nonetheless, we include $post_{it}$ to be as thorough as possible in controlling for temporally correlated confounders.

The variable of primary interest is the interaction term $\boldsymbol{RMP}_i \times post_{it}$, which equals one when a chemical accident occurred at an RMP facility near the home, as of the time of sale. The key parameter $\boldsymbol{\gamma}$ thus captures the average effect of the treatment on the treated (ATT).

We estimate variants of equation (1) to examine heterogeneity in any price effects based on severity of the accident. In an earlier case study of just three states (MI, OH, and PA), Guignet et al. (2022) found that the typical RMP accident did not affect home values on average, but significant price declines were found among homes near chemical accidents that impacted offsite populations. We explore such heterogeneity here with respect to offsite versus onsite impacts, as well as whether the accident resulted in *any* reportable impacts in general. (Recall that the data contain reported accidents that were not required to be reported under the RMP program.)

To examine heterogeneity in the housing price impacts with respect to accident severity, we include an interaction term with a vector of accident characteristics $\boldsymbol{acc}_{it}$, as follows:

$$(2) \qquad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \rho RMP_i + \delta post_{it} + \gamma(RMP_i \times post_{it}) + (RMP_i \times post_{it} \times \boldsymbol{acc}_{it})\boldsymbol{\theta} + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

The coefficient vector $\boldsymbol{\theta}$ captures incremental differences in the price effects of an accident, depending on whether the accident was reportable, or resulted in offsite impacts.

The percentage change in price for a non-reportable accident, a reportable accident resulting in only onsite impacts, and an accident exhibiting more severe offsite impacts are calculated, respectively, as:

(3a) $\%\Delta p^{nr} = \{exp(\gamma) - 1\} \times 100$

(3b) $\%\Delta p^{rep} = \left\{exp\left(\gamma + \theta^{[rep]}\right) - 1\right\} \times 100$

(3c) $\%\Delta p^{off} = \left\{exp\left(\gamma + \theta^{[rep]} + \theta^{[off]}\right) - 1\right\} \times 100$

where $\theta^{[rep]}$ is the first element of the coefficient vector $\boldsymbol{\theta}$, and captures the incremental effect of an accident with reportable onsite or offsite impacts, relative to a non-reportable accident. $\theta^{[off]}$ is the second element of $\boldsymbol{\theta}$, and reflects the incremental effect of an accident yielding offsite impacts, relative to an accident yielding only reportable onsite impacts. The percent change in price estimates described by equations (3a) through (3c) are the DID estimates of primary interest and represent the weighted average of the ATT.[10]

IV.C. Cumulative price effects and attenuation over time

In subsequent models we investigate the potential cumulative effects of multiple chemical accidents occurring near a home. We include additional interaction terms with the number of RMP sites (RMP_cnt_i) and accidents that occurred ($post\_cnt_{it}$), and the number of more severe accidents ($\boldsymbol{acc\_cnt}_{it}$), as shown:

(4)
$$\begin{aligned} ln\left(p_{ijmt}\right) = {} & \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \rho RMP_i + \rho^{add}(RMP\_cnt_i - RMP_i) \\ & + \delta post_{it} + \delta^{add}(post\_cnt_{it} - post_{it}) \\ & + \gamma(RMP_i \times post_{it}) + \gamma^{add}\left(RMP_i \times (post\_cnt_{it} - post_{it})\right) \\ & + (RMP_i \times post_{it} \times \boldsymbol{acc}_{it})\boldsymbol{\theta} \\ & + \left(RMP_i \times post_{it} \times (\boldsymbol{acc\_cnt}_{it} - \boldsymbol{acc}_{it})\right)\boldsymbol{\theta^{add}} + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt} \end{aligned}$$

The corresponding dummy variables are subtracted from the RMP and accident count variables, so that, for example, $post\_cnt_{it} - post_{it} = 0$ if there was just one accident (i.e., $post\_cnt_{it} = 1$

[10] Recent literature has cautioned against this average ATT interpretation in settings where the treatment events are staggered over time (Goodman-Bacon, 2021; Marcus and Sant'Anna, 2021; Roth et al., 2022; Sun and Abraham, 2021). The primary criticism is that in some settings a subset of treated observations can receive a negative weight if they serve as a control observation for subsequent treatment event comparisons. The spatial DID design implemented here and by numerous other hedonic property value applications (e.g., Linden and Rockoff, 2008; Haninger et al., 2017; Muehlenbachs et al., 2015; Guignet et al., 2018) utilize a clearly separate control group (i.e., farther away homes located around the same disamenity). This setup is essentially a stacked DID design (Cengiz et al., 2019; Deshpande and Li, 2019; Fadlon and Nielsen, 2021), which is one suggested approach to address concerns with staggered treatment events (Goodman-Bacon, 2021, Roth et al., 2022).

and $post_{it} = 1$); and $post\_cnt_{it} - post_{it} = 1$ if there were two accidents (i.e., $post\_cnt_{it} = 2$ and $post_{it} = 1$), and so on. In other words, the differenced variable ($post\_cnt_{it} - post_{it}$) is the number of *additional* accidents that occurred after the first. And so γ^{add} will capture the price impacts of each additional accident after the first, in a linear fashion. Each additional accident could lead residents to perceive the risks posed by the site as greater ($\gamma^{add} < 0$). On the other hand, additional accidents may not yield any new information towards the surrounding community's perceived risk, in which case additional price impacts may diminish and be negligible when multiple accidents occur ($\gamma^{add} = 0$). A similar interpretation follows for the differenced ($\boldsymbol{acc\_cnt}_{it} - \boldsymbol{acc}_{it}$) variable and $\boldsymbol{\theta^{add}}$ coefficient – the coefficient captures the incremental price effect for each additional more severe accident, relative to the least impactful (non-reportable) accident category.

A variant of equation (2) is also estimated to examine whether any adverse price effects attenuate over time, remain constant, or intensify. The coefficients corresponding to a chemical accident (γ_s) and characteristics of that accident ($\boldsymbol{\theta}_s$) are allowed to vary for each year *s* after the accident. We can then flexibly examine whether any adverse price effects attenuate over time (i.e., become less negative ($\gamma_s < \gamma_{s+1}, \forall\, s = 1, \dots, S$)), remain constant ($\gamma_s = \gamma_{s+1}$), or intensify (i.e., become more negative ($\gamma_s > \gamma_{s+1}$)).

$$(5) \qquad ln(p_{ijmts}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \rho RMP_i + \delta post_{it}$$

$$+ \sum_{s=1}^{S} \{\gamma_s (RMP_i \times post_{is}) + (RMP_i \times post_{is} \times \boldsymbol{acc}_{is})\boldsymbol{\theta}_s\}$$

$$+ \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

IV.D. Inferring welfare impacts to nearby residents

As discussed in section II, non-marginal results from first-stage hedonic price regressions generally lack a formal welfare interpretation. Although hedonic property value studies compose an increasingly large portion of the nonmarket valuation literature, they are often not used in benefit-cost analyses of environmental policy (Petrolia et al., 2021). The lack of a formal, non-marginal welfare interpretation is one reason why. Although several studies have provided guidance on ways to derive welfare estimates and bounds (see Bishop et al. 2020 for a review), only recently has progress been made to infer a formal, non-marginal welfare estimate in a DID setting.

Banzhaf (2021) demonstrates that a change in price along the same ex post price gradient is a lower bound of the Hicksian equivalent surplus for an improvement in quality. Conversely, a decrease in quality, like that from a nearby chemical accident, would suggest a theoretical upper bound of the Hicksian equivalent surplus to affected residents. Banzhaf shows that this bounding estimate more closely approximates the true loss for smaller shocks, with the two equating as the shock approaches a marginal change.

To implement Banzhaf's approach, the hedonic price surface must be allowed to vary over time (ideally) with respect to all dimensions. For the current study, this includes not just $\boldsymbol{\beta}_{mt}$ (which is already allowed to vary over time in most of our model results), but also ρ, δ, γ, and $\boldsymbol{\theta}$. Building off equation (2), the model to be estimated is:

$$(6) \qquad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \rho_t RMP_i + \delta_t post_{it} + \gamma_t(RMP_i \times post_{it})$$

$$+(RMP_i \times post_{it} \times \boldsymbol{acc}_{it})\boldsymbol{\theta_t} + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

Additional interaction terms with transaction year indicators are added to allow ρ_t, δ_t, γ_t, and $\boldsymbol{\theta_t}$ to vary freely by year. The coefficient subscripts denote this increased flexibility, but the interactions with year indicators are not explicitly represented for notational ease.

Similar to equations (3a) through (3c) the percent change in price in a specific ex post year $\tilde{t}$ can be calculated. Banzhaf (2021) describes these estimates as a direct unmediated effect (DUE). It is unmediated because all other attributes are held constant, and it is direct because it only considers movement on the *same* ex post price surface.

The resulting estimates represent a theoretical upper bound of the monetized welfare loss to nearby residents from an accident, in a given ex post year $\tilde{t}$. If these estimates are constant over time, then more conventional calculations of the capitalization effects have the same welfare interpretation.

V. RESULTS

Results are presented regarding the spatial extent of the treatment effect on house prices, the estimated price impacts of chemical accidents of different severity and at different distances, an examination of potential cumulative price impacts from multiple accidents, and the attenuation of price effects over time. The section ends with an assessment of the parallel trends assumption.

V.A. Determining the Treated and Control Groups

When implementing a spatial DID approach where "treatment" assignment is based on proximity to an environmental amenity or disamenity, researchers often rely on a strategy first proposed by Linden and Rockoff (2008), and later adapted by Haninger et al. (2017), Muehlenbachs et al. (2015), and others. The basic idea is that the pre- and post-treatment event price gradients are first estimated with respect to distance from the environmental commodity. If the treatment of interest is believed to have a negative effect (as is the case for a chemical accident), then for homes nearest the site one would expect the post-treatment gradient to fall below the pre-treatment gradient. As distance from the disamenity increases, we would expect the post-treatment gradient to gradually increase, moving towards the pre-treatment gradient. The distance where the two lines converge marks the average spatial extent of the treatment effect on house prices, and informs the assumed cutoff point between the treated and control groups.

We first estimate a regression based on equation (2), but where separate interaction term vectors for proximity to a facility pre- and post-accident are included. The uninteracted $\boldsymbol{RMP}_i$ and $post_{it}$ variables are now excluded because they become perfectly collinear with the pre- and post-accident interaction terms.

$$(7) \qquad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta} + \boldsymbol{\gamma}^0(\boldsymbol{RMP}_i \times pre_{it}) + \boldsymbol{\gamma}^1(\boldsymbol{RMP}_i \times post_{it})$$

$$+(\boldsymbol{RMP}_i \times post_{it} \times \boldsymbol{acc}_{it})\boldsymbol{\theta} + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

Estimating the hedonic model in equation (7) allows us to use the estimates of $\boldsymbol{\gamma}^0$ and $\boldsymbol{\gamma}^1$ to graph the pre- and post-accident price gradients. Furthermore, by summing $\boldsymbol{\gamma}^1$ and $\boldsymbol{\theta}$ we can graph the post-accident price gradients for different types of accidents (i.e., non-reportable accidents, reportable accidents resulting in only onsite impacts, and offsite impact accidents). Distance from the accident site is measured using indicators denoting 250-meter incremental bins, going from 0-250 m through 9,500-9,750 m. The farthest 9,750-10,000 m bin is the omitted category. Finally, we note that in this initial diagnostic exercise we do not include interaction terms to allow $\boldsymbol{\beta}$ to vary by county and year, but the final regression models do allow for such flexibility.

The results are shown in Figure 3. The pre-accident price gradient suggests that in general, irrespective of an accident occurring, the prices of homes nearest an RMP facility are already significantly depressed; a finding that is in line with Guignet et al.'s (2022) case study of Michigan, Ohio, and Pennsylvania. Although this is not necessarily a causal effect, house prices nearest RMP facilities tend to be lower in value, even when no accident has occurred. For example, homes within one kilometer are associated with a 3% to 6% decline in price compared to homes in the farthest distance bin, all else constant. This negative association remains statistically significant ($p \leq 0.10$) out to 2 to 2.5 kilometers from the site.

The top panel (Panel (A)) of Figure 3 shows the price gradient for a nonreportable accident. Although generally lower, comparison of the post-nonreportable accident price gradient to the pre-accident gradient suggests little statistically significant effect from nonreportable accidents. This is not surprising given that no onsite or offsite damages, injuries, etc. resulted from these accidents. Nearby residents may not generally be aware that such nonreportable accidents even occurred.

Panel (B) of Figure 3 shows how prices are impacted by proximity to an accident that resulted *only* in reportable onsite impacts (e.g., injuries or deaths to workers or first responders, or onsite property damage). The differences between the pre- and post-reportable accident gradients are not always statistically significant, but we do generally see that prices nearest the site significantly declined after an accident. As distance increases, the post-accident gradient gradually converges to the pre-accident gradient.

The price gradient with respect to accidents that resulted in impacts to offsite populations, properties, and/or the environment provides the clearest evidence of the extent of impacts on house prices. As shown in Panel (C) of Figure 3, there is a stark decrease in house prices after an offsite impact accident. This negative effect diminishes with distance, becoming negligible around 5,750 meters from the site.

Based on this diagnostic exercise we assume a treated group of homes within 0 to 5,750 meters of an RMP facility, and a control group of homes 5,750 to 10,000 meters from the same set of RMP facilities. We discuss the validity of the assumed treated and control groups in section V.D.

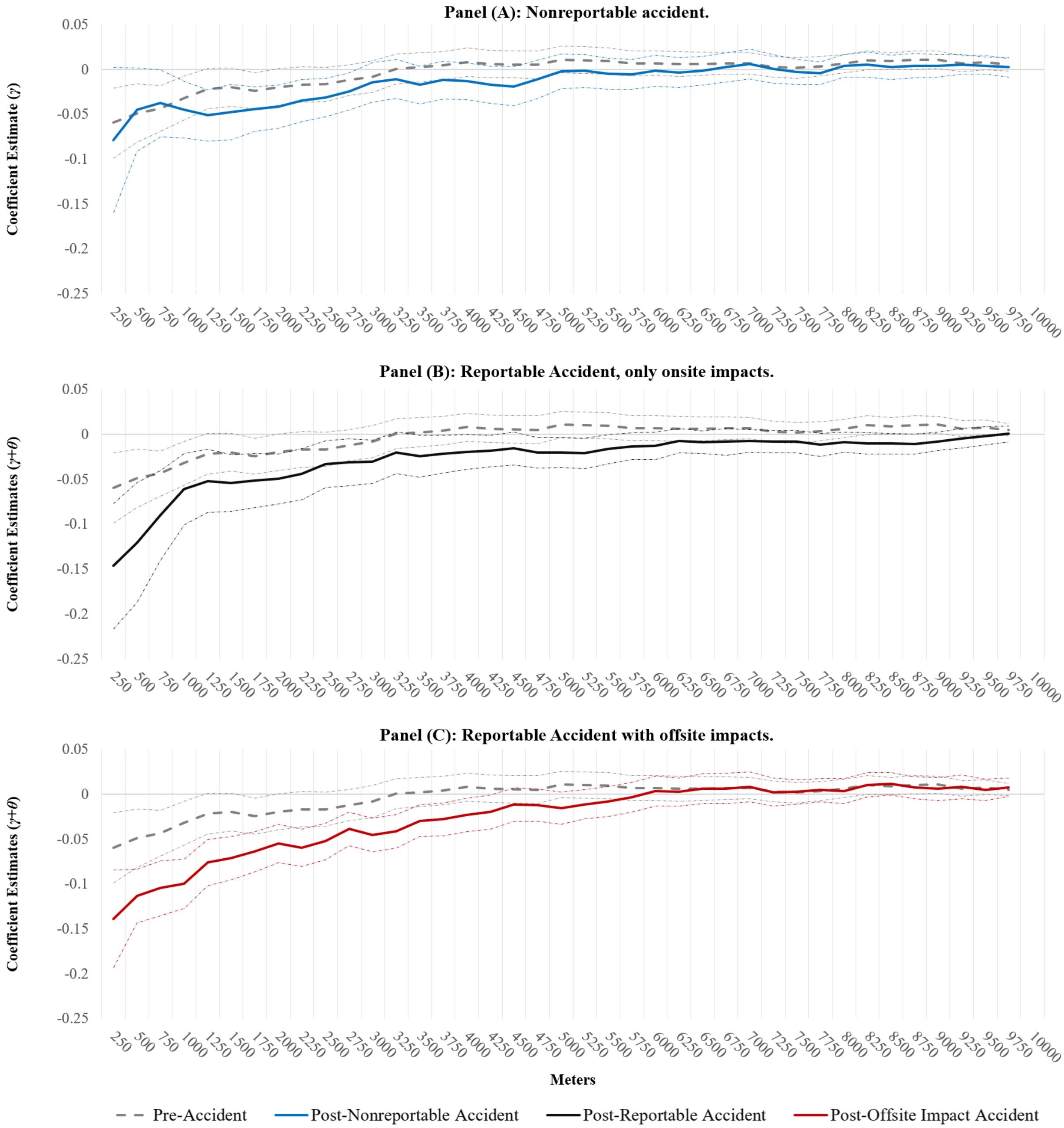
V.B. Estimated price impacts of chemical accidents

We next estimate a series of hedonic price regressions following equation (2). For the first set of models (Model 1) we assume that the price effects of interest are homogenous within the 0 to 5,750 meter treatment zone. A binary scalar denoting homes within 0 to 5,750 m of an RMP facility is used for $\boldsymbol{RMP}_i$. The full hedonic regression results are displayed in Table B.1 of Appendix B. Although not of primary interest, the coefficient estimates corresponding to the house structure and location characteristics are all significant and of the expected sign and magnitude, lending credibility to our results (see Model 1A in Table B.1). House prices increase with lot acres, interior square footage, and the number of stories and bathrooms. House prices decrease with age, following a quadratic relationship. All else constant, prices are higher in areas where the immediate vicinity is more developed, and when the home is near a lake or river. Being located within 500 m of a highway is associated with lower home values.

The ATT estimates following equations (3a) through (3c) are calculated and displayed in Table 3. Model 1A includes year-by-county and quarter-by-county fixed effects, as well as time-invariant census tract fixed effects, but constrains the slope coefficients corresponding to the house and location attributes to be the same over time and across counties. In this initial model we see a negative and marginally significant 1.26% price decline corresponding to the occurrence of a nonreportable chemical accident, although this effect is not robust in subsequent models. The occurrence of a reportable accident that resulted in onsite fatalities, injuries, and/or property damage leads to an average 2.15% decrease to the price of homes within 5.75 km. An even larger decline of 3.27% is experienced by homes within 5.75 km of a chemical accident that impacts offsite populations, property, and/or the environment.

Model 1B includes separate county and year interaction terms with the house and location characteristics, thus allowing the hedonic equilibrium to vary over space and time with respect to these dimensions. The results suggest no statistically significant effects to surrounding home values, on average, due to a nonreportable accident or a reportable accident that only led to onsite impacts. However, Model 1B does suggest a significant 2.25% average decrease in the value of homes within 0 to 5,750 meters of an accident with offsite impacts. This finding is robust to the inclusion of year-by-county interactions with all home and location characteristics in Model 1C, suggesting a 1.91% decrease in home values.

Figure 3. Pre- and post-accident price gradients.



Note: Dotted lines display the 95% confidence intervals.

Table 3. Base model results: Percent change in price due to an accident.

	0-5,750 meters		
	Model 1A	**Model 1B**	**Model 1C**
Nonreportable	-1.2604*	-0.2150	0.1695
	(0.7450)	(0.6320)	(0.5537)
Reportable	-2.1457***	-0.8284	-0.7530
	(0.7966)	(0.6871)	(0.5910)
Offsite Impacts	-3.2726***	-2.2541***	-1.9130***
	(0.6487)	(0.5692)	(0.5982)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R^2	0.737	0.759	0.767

Note: Average percent change in price to homes within 0-5,750 meters of an accident. * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Estimates calculated following equations (3a) through (3c) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression models 1A, 1B, and 1C. Note that 1,804 singleton observations were dropped from the regression model. Full regression results are presented in Table B.1 in Appendix B.

The magnitude of these average price effects could be considered small, but they are averaged over a rather large 5.75 km spatial extent. To investigate how these average price effects vary with distance from the RMP facility, we estimate Model 2, where $\boldsymbol{RMP_i}$ is a vector of indicators denoting whether a facility is within a series of 250-meter incremental bins from a home, starting with 0 to 250 m, and extending out to 5,550 to 5,750 m. The corresponding percent change in price estimates are again calculated following equations 3a through 3c.

The results in Figure 4 are based on Model 2B (a variant of Model 1B).[11] Separate year and county terms are interacted with the house and location attributes to allow the hedonic equilibrium price surface to vary across markets, both temporally and spatially. One could consider pursuing a more flexible model where year-by-county terms are interacted with the house and location characteristics (as we did in Model 1C). However, this was not our preferred model for two reasons. First, the key results are similar across both specifications, but the former models with separate year and county interactions terms are less computationally burdensome to estimate. Second, given the far-extending 5.75 km price effects from offsite impact chemical accidents, it is possible that allowing the slope coefficients to vary flexibly over time for each specific county

[11] See Appendix B Table B.2 for full regression results of Model 2B as well as Models 2A and 2C (the corresponding variants based on Models 1A and 1C).

may absorb some of the price effects of interest. Nonetheless, the offsite impact accident results are robust to these alternative specifications (see Figure B.1 and Figure B. 2 in Appendix B).

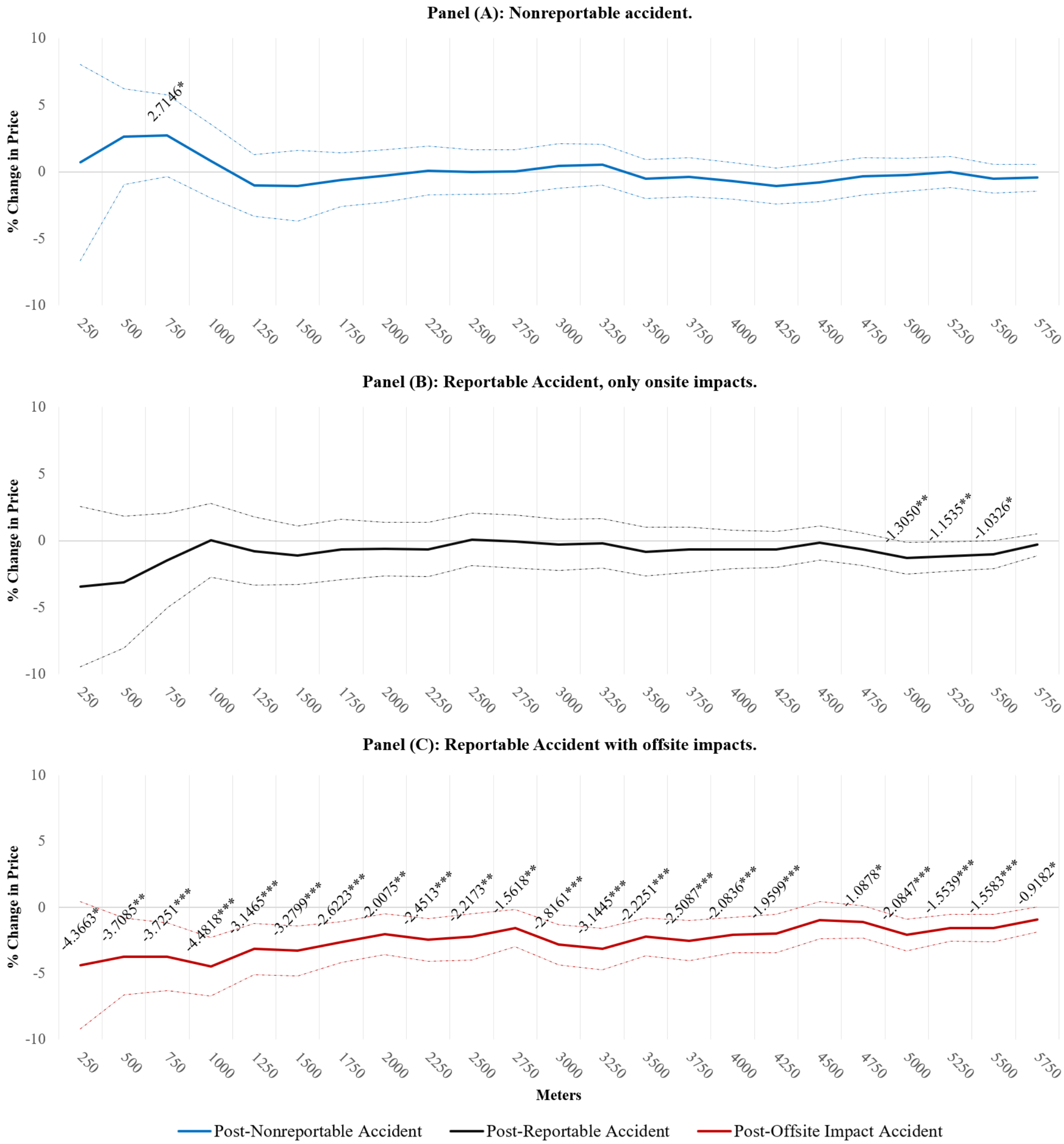
Figure 4 shows noticeable spatial heterogeneity, with the patterns over space meeting two key expectations. First, any negative price effects are only experienced in response to the most severe accidents – i.e., the offsite impact accidents (see Panel (C)). Second, the point estimates suggest that the negative price effects from offsite impact accidents are strongest among the nearest homes, and gradually diminish with distance. Panel (C) in Figure 4 shows that homes nearest an accident with offsite impacts experience a 4.37% decrease in price, on average. These negative price effects generally diminish with distance, but remain significant out to 5,750 meters, where homes experience an average decline of 0.92% after an offsite impact accident.

V.C. Cumulative price effects and attenuation over time

To assess how home prices respond to the occurrence of multiple accidents, we estimate Model 3B (a variant of Model 1B) following equation (4). The regression model results are presented in Table B.3 of Appendix B. The slope coefficients corresponding to the number of *additional* non-reportable, reportable, and offsite impact accidents are all statistically insignificant. A Wald test confirms that these three coefficients are also jointly insignificant (p=0.5063), as is the sum of the three accident count coefficients (p=0.3549). Overall, the results suggest that accidents subsequent to the first, even if they yield offsite impacts, do not on average have statistically significant impacts on surrounding home values. A possible explanation is that a first accident involving offsite impacts such as, for example, an evacuation event, leads to price declines and a partial turnover in the neighborhood to households with less risk aversion. New residents may choose to accept the risk in exchange for a discounted house price because they cannot afford otherwise. Thus, the risks become capitalized in home prices after the first offsite impact accident, and subsequent accidents do not further depress home values. A different explanation is that household transactions occurring near multiple accident sites may be in relatively heavily industrialized areas in which house prices are already discounted to reflect perceived heightened risks of an industrial accident.

Overall, the inferred percentage change in prices is similar to those estimated from previous models (see Table B.4 in Appendix B). Nonreportable accidents and those yielding only onsite reportable impacts result in no significant effect on surrounding home prices, on average, but homes within 5.75 km of one and even two offsite impact accidents see statistically significant declines in price – between a 1.5% and 2.0% decrease.

Figure 4. Model 2B results: Percent change in price due to an accident, by 250-meter bins.



Note: Dotted lines display the 95% confidence intervals. Estimates calculated following equations (3a) through (3c) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 2B (n=10,426,638; adjusted R2=0.761), which includes separate year-by-housing attribute and county-by-housing attribute terms. Note that 1,804 singleton observations were dropped from the regression model.

To examine whether the decline in home values due to an offsite impact accident are long-lasting or attenuate over time, we estimate Model 4B (for full results, see Table B.5 in Appendix B), which is a variant of Model 1B based on equation (5). The estimated percent change in price due to an offsite impact accident is allowed to vary for each year after the accident. As shown in in Figure B.3, the estimates are generally negative, ranging from -2.06% to a statistical zero. A Wald test fails to reject the null hypothesis that the negative effects from an offsite impact accident are equal for the first 15 years after an accident (p=0.2896), suggesting that the negative price effects persist for at least this 15-year duration. A marginally significant 1.78% appreciation corresponding to 15 to 16 years after an accident is then estimated. This is the last year we are able to observe in our 16-year study period, and so more data are needed to confirm whether the adverse price effects attenuate at this time, on average, or if this appreciation is just an artifact of the available data.

V.D. Assessing the Parallel Trend Assumption

A causal interpretation of our results hinges on the parallel trends assumption. In a well-defined DID quasi-experiment the trajectory of the outcome variable experienced by the treated group in the absence of treatment must be the same as that of the assumed control group in the post-treatment period (Angrist and Pischke, 2009). We do not observe the true counterfactual (i.e., the treated group absent the treatment), but we can observe the pretreatment trends and compare the treated and control groups. If house prices for the two groups follow similar trends before the occurrence of a chemical accident, then it is more reasonable to assume those trajectories would have remained similar in the absence of the treatment event.

We conduct an event study by estimating a variant of Model 1B and equation (2), but where interaction terms are included to allow the RMP and accident coefficients of interest to vary by year *s* relative to the date of the accident (*s* = 0).

$$\text{(8)} \qquad ln(p_{ijmts}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \sum_{s=-16}^{-1}\{\delta_s pre_{is} + \rho_s(pre_{is} \times RMP_i)\}$$

$$+ \sum_{s=0}^{15}\{\delta_s post_{is} + \rho_s(post_{is} \times RMP_i) + (post_{is} \times RMP_i \times \boldsymbol{acc}_{it})\boldsymbol{\theta_s}\}$$

$$+\boldsymbol{\tau}_{mt} + v_{jm} + \varepsilon_{ijmt}$$

Throughout our analysis we find robust evidence of adverse effects on home values due to offsite impact accidents. Thus, these accidents are the focus of the event study graph in Figure 5. To allow for a percent change in price interpretation, estimates of ρ_s and $\boldsymbol{\theta_s}$ from equation (8) are transformed following equations similar to (3a) and (3c).

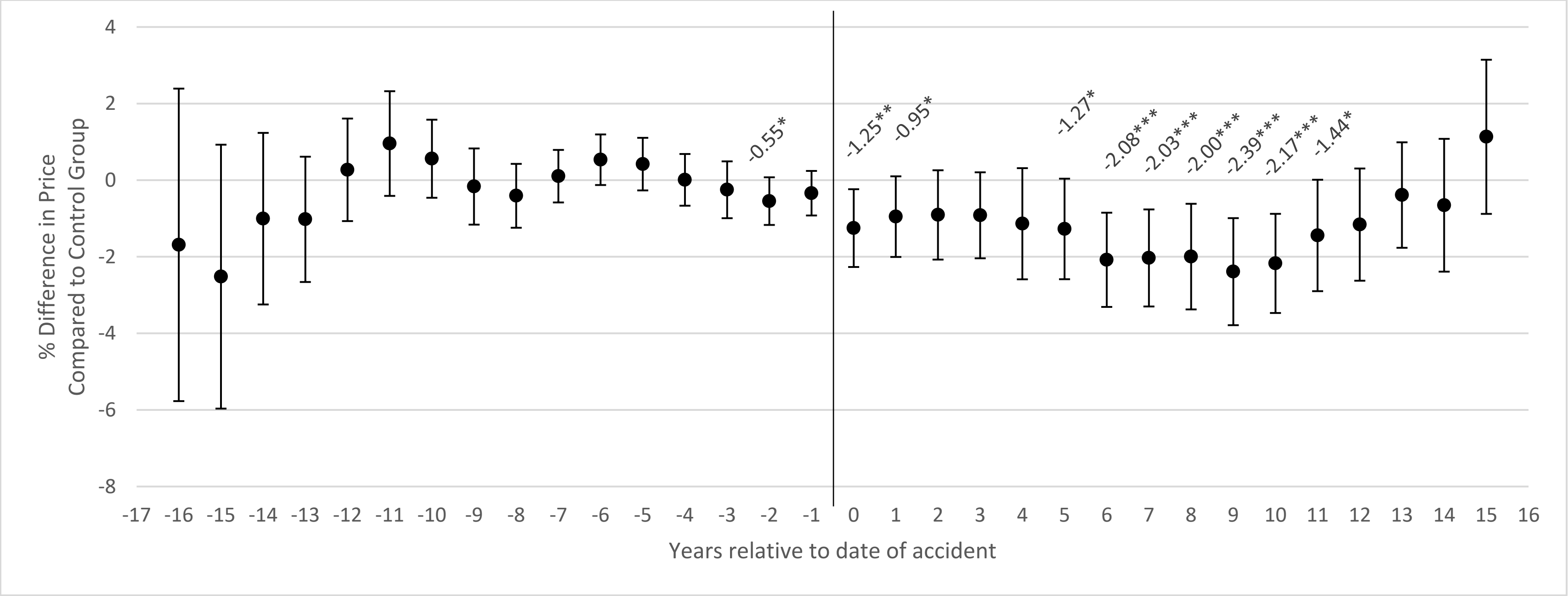
The ρ_s coefficients reflect the incremental price difference between the treated group (homes within 0 to 5,750 meters of an RMP accident site) and the control group (homes located 5,750 to 10,000 meters from the site). Ideally, ρ_s would be equal for all $s < 0$. In other words, given the ideal counterfactual group the event study graph would visually show that any differences in the pre-treatment periods are constant (i.e., the trends are parallel). As can be seen on the left side of Figure 5, the pre-treatment differences in a given year prior to an accident are generally similar, are not statistically different from zero, and do not demonstrate any clear pattern of differences that would violate the parallel trends assumption. A Wald test fails to reject the null hypothesis that the percent change in price estimates in the pre-treatment periods are equal (p = 0.2562), suggesting that the pre-treatment trends between the treated and control groups are parallel. Acknowledging that with any non-classical experimental framework, caution is warranted when making causal inference, this event study supports the parallel trends assumption, and bolsters our interpretation that offsite impact accidents caused an average 2% to 3% decline in the value of homes within 5.75 km.

VI. WELFARE IMPLICATIONS

Based on the different versions of Model 1, we estimate that homes within 5.75 km of an offsite impact accident experience a decline in value ranging from 1.91% to 3.27%. Our middle estimate (from Model 1B) suggests a 2.25% decline. We can calculate the average capitalization effect after an offsite impact accident as $\Delta p^{off} = \bar{p}_1^{off}\left(\frac{\%\Delta p^{off}}{1+\%\Delta p^{off}}\right)$, where $\bar{p}_1^{off} = \$232{,}187$ is the average transaction price after an offsite impact accident and among homes within 0 to 5.75 km, and $\%\Delta p^{off} = -2.25\%$ is estimated from Model 1B following equation (3c). This suggests an average loss in value of \$5,354 per home. Multiplying this by the 7,383,200 single-family residences within 5.75 km of at least one of the 661 RMP sites where an offsite impact accident takes place during our 2004 to 2019 study period suggests a total loss in housing stock value of over \$39.5 billion.

As described in section IV.D, Banzhaf (2021) proposes an adjustment to the more conventional DID hedonic price regression model, where the hedonic price surface is allowed to temporally vary with respect to all dimensions. We carry out such an adjustment here in order to facilitate a more formal welfare comparison. A variant of Model 1B is estimated following equation (6). Then, similar to equation (3c), the percent change in prices for an offsite impact accident is calculated for each year during our study period. The estimated percent change in prices by year are shown in black in Figure 6. In this model the price effects of an offsite impact accident are allowed to vary freely from year to year. The results suggest that a welfare calculation is highly sensitive to the assumed ex post year. If we choose 2019 (the last year of our study period) as the ex post year, for example, the welfare loss to residents from an offsite impact accident is not statistically significant. In contrast, the results would be quite different in a different ex post year, such as 2016 or 2017, for example. A Wald test rejects the null hypothesis that these estimates are statistically equal for each year from 2004 to 2019 (p=0.0053), but at the same time there is no clear monotonic trend over time.

Figure 5. Event study of the percent difference in price from an offsite impact accident: Based on variant of Model 1B.



Note: Graph shows the percent difference in price estimates among the 0 to 5.75 km treated group relative to the 5.75 to 10 km control group, by year relative to the date of accident.

The key question is whether these year-to-year fluctuations are just noise, or do they reflect true changes in the hedonic equilibrium with respect to these RMP accident dimensions. We estimate a variant of Model 1B where the RMP and accident coefficients are constrained to only vary linearly over time. Such a model allows for temporal variation in the hedonic price surface, as required for Banzhaf's (2021) welfare bounding interpretation, while at the same time minimizing noise leading to year-to-year fluctuations. More specifically, the estimated model is:

$$\text{(9)} \quad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \rho RMP_i + \rho_t(RMP_i \times trend_t) + \delta post_{it}$$
$$+\delta_t(post_{it} \times trend_t) + \gamma(RMP_i \times post_{it}) + \gamma_t(RMP_i \times post_{it} \times trend_t)$$
$$+(RMP_i \times post_{it} \times \boldsymbol{acc}_{it})\boldsymbol{\theta} + (RMP_i \times post_{it} \times \boldsymbol{acc}_{it} \times trend_t)\boldsymbol{\theta_t}$$
$$+\boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

where $trend_t$ is a time trend variable with 0=2004, 1=2005, …, 15=2019. The blue line fitted in Figure 6 shows the linear trend of the percent change in price resulting from an offsite impact accident for each ex post year $\tilde{t}$, which are calculated as:

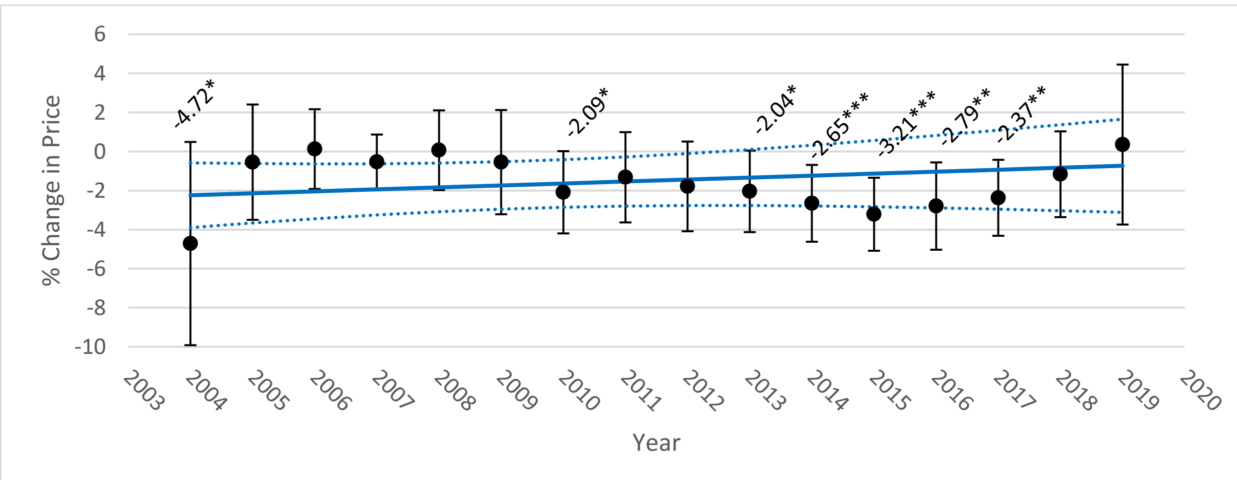
$$\text{(10)} \quad \%\Delta p_{\tilde{t}}^{off} = \left\{exp\left(\gamma + (\gamma_t \times trend_{\tilde{t}}) + \theta^{[rep]} + \left(\theta_t^{[rep]} \times trend_{\tilde{t}}\right) + \theta^{[off]}\right.\right.$$
$$\left.\left. + \left(\theta_t^{[off]} \times trend_{\tilde{t}}\right)\right) - 1\right\} \times 100$$

where $trend_{\tilde{t}}$ is the corresponding value of the time trend variable for year $\tilde{t}$, and the superscripts in brackets denote the elements corresponding to reportable and offsite impact accidents in the respective coefficient vectors $\boldsymbol{\theta}$ and $\boldsymbol{\theta_t}$.

A Wald test fails to reject the null hypothesis that the sum of the trend slope coefficients is equal to zero – i.e., H0: $\gamma_t + \theta_t^{[rep]} + \theta_t^{[off]} = 0$ (p=0.3528). The trend slope coefficients are also jointly insignificant (p=0.1417). Together, these results suggest that the equilibrium hedonic price surface with respect to RMP accidents is constant over time. Under that assumption we can interpret the aforementioned capitalization effects from Model 1B as an upper bound of the ex post loss in welfare to residents living within 5.75 km of an RMP accident that resulted in offsite deaths, injuries, property or environmental damage, and/or the evacuation and sheltering-in-place of surrounding populations. The average facility where an offsite impact accident occurred has 11,170 single-family homes within 5.75 km. Multiplying this by the $5,354 loss per household suggests an average welfare loss to surrounding communities of $59.809 million. The median number of single-family homes within 5.75 km of an offsite impact accident site is 4,646, suggesting a median loss of $24.877 million. Considering all 7,383,200 single-family homes around the 661 RMP sites that experienced at least one offsite impact accident, the ex post social cost to the surrounding communities is substantial, suggesting a total loss of $39.533 billion.

Following Banzhaf's (2021) theoretical framework, and our assumption that the hedonic price surface is constant over time with respect chemical accidents, then the formal interpretation is that these results represent an upper bound of the ex post welfare loss to nearby residents. However, our estimated per home price impacts of 2% to 3% are fairly small, and Banzhaf established that the bounding estimates approach the true value for small changes, with the upper bound approximating the true value as the environmental shock approaches a marginal change. Furthermore, our estimates only account for residents living in single-family homes, and therefore disregard impacts to residents living in other types of housing (e.g., multi-family apartment buildings and condos, townhomes, etc.) and impacts to businesses and others in the community.[12] Empirically speaking, it is ambiguous whether our estimates are a lower or upper bound of the ex post external costs imposed on surrounding communities due to offsite impact accidents. Finally, additional work is needed to formalize an ex ante welfare interpretation of the results from DID hedonic applications. Banzhaf (2021) suggests that movement along the ex ante price surface may, in our context, provide a lower bound of the loss in welfare to nearby residents.

Figure 6. Percent change in price estimates from offsite impact accidents by year: Based on variants of Model 1B.



Note: Black dots are the percent change in price estimates from a variant of Model 1B following equation (6). The error bars represent the 95% confidence intervals. The solid blue line represents the percent change in price estimates from a more restrictive linear version of the model following equation (9), and are then calculated as per equation (10). The dotted blue line represents the 95% confidence interval. All estimates are derived using the “nlcom” command in Stata 17/MP.

VII. CONCLUSION

Our analysis of industrial chemical accidents across the contiguous U.S. reveals mixed evidence as to whether accidents resulting in minimal impacts, or where the impacts (e.g., injuries, deaths, and property damage) were confined to the industrial property itself, affect home values, with estimated losses ranging from 0% to 2%. However, we find robust, causal evidence that accidents yielding direct impacts to the surrounding community significantly affect home prices. Such accidents resulted in health impacts to nearby residents, offsite property damage and

[12] Welfare losses may also be experienced by individuals who do not reside in the nearby community; for example, by the employees at the facility, the facility owners, the emergency responders, people who visit the community, and so on.

environmental degradation, and/or people being evacuated or sheltered-in-place to avoid harm. Although the average capitalization effect of 2% to 3% is somewhat small in magnitude, this effect extends 5.75 km from the industrial facility, which is quite far compared to studies of similar disamenities. Past literature generally found stronger local impacts, extending only a few hundred meters and up to 3 km (e.g., Gamper-Rabindran and Timmins, 2013; Guignet et al., 2018; Guignet and Nolte, 2021; Haninger et al., 2017; Muehlenbachs et al., 2015). We find that the adverse price effects from these most severe chemical accidents persist for at least 15 years on average, and possibly longer. Further analysis and data covering a longer study period are needed.

We do not find evidence that losses in value are systematically greater among homes that experience multiple offsite impact accidents. Perhaps the first accident led home values to fully capitalize risks, and additional accidents did not yield new information to update residents' perceptions. It is also possible that less risk averse residents, who might face pressing priorities and financial constraints, moved in after the first accident; or that multiple accidents occur in communities hosting multiple industrial facilities and perceived baseline risk is already built in to home values. Further research should explore the socioeconomic characteristics of communities experiencing multiple accidents.

We adapt the procedure proposed by Banzhaf (2021) to estimate a formal upper bound of the ex-post loss in welfare to residents living within 5.75 km of an offsite impact accident. We find that such welfare calculations are extremely sensitive to the assumed ex post year. A model that restricts the accident impacts to vary linearly over time suggests that the price effects of accidents are constant. Assuming that the price effects of accidents are constant over our study period allows for a welfare interpretation of the estimated capitalization effects. The formal interpretation is that the estimated effects represent a theoretical upper bound of the ex post welfare loss, yet the smaller the incremental impact, the closer the estimates are to a true loss. Our estimate of an average 2% to 3% price change is fairly small, suggesting the estimates are close to the true losses to residents living near an offsite impact accident. Additionally, our estimates only account for residents living in single-family homes, and therefore disregard impacts to residents living in other types of housing, as well as impacts to businesses and others in the community.

Our preferred model specification suggests an average loss of about $5,350 per household. Considering the 7,383,200 single-family homes within 5.75 km of one of the 661 offsite impact accident sites across the contiguous U.S., this implies a social cost to these nearby residents of $39.5 billion. This translates to an average loss of $59.8 million for each site where an offsite impact accident occurs. It is clear that the external costs to fence line communities of these most severe industrial chemical accidents are substantial and critical to account for in benefit-cost analyses used to inform policy and management decisions. This includes the recently proposed "Safer Communities by Chemical Accident Prevention" rule (US EPA 2022a), which is intended to further protect communities and the local environment. Among the criticisms of this proposal was the lack of estimates of social benefits alongside significant estimates of costs (InsideEPA 2022).

This study demonstrates that large-scale nationwide benefits analyses are critical to inform equally as extensive federal policy. Such analyses would be difficult without a widely available, and fairly accurate and consistent dataset like Zillow's ZTRAX database. These data allowed us to analyze home prices around almost the entire population of chemical accidents reported to the RMP program. Prior to the availability of the ZTRAX data, studies on similar EPA programs and disamenities were limited mainly to local-scale case studies (e.g., Michaels and Smith, 1990; Kohlhase, 1991; Flower and Ragas, 1994; Kiel, 1995; Carroll et al., 1996; Kiel and Zabel, 2001; Hansen et al., 2006; Zabel and Guignet, 2012; Guignet, 2013; Liao et al., 2022). Any studies attempting nationwide coverage were often spotty in nature (e.g, Kiel and Williams, 2007; Guignet et al., 2018), or were forced to use spatially and temporally coarse data (e.g., Gamper-Rabindran and Timmins, 2013; Greenstone and Gallagher, 2008).

There are three additional important benefits of using large-scale datasets like that provided by Zillow's ZTRAX program. First, identifying the impacts of environmental commodities on house prices is of primary interest to environmental economists, but such attributes often yield a relatively small contribution to the overall price of a home. Such is the case here, where we estimate a 2% to 3% average decline in value for each home near an offsite impact accident. While the estimated per home price impacts are close to zero, in aggregate, the effects are huge. There is substantial difficulty in statistically distinguishing these price impacts from zero, especially considering the numerous other, often spatially correlated, location attributes that affect house prices. Although the overall sample size may be reasonable, smaller case studies focused on a municipality, county, or even a state or multi-state region, may not have a large enough number of identifying observations to precisely estimate such effects. Our results showing a 2% to 3% decrease in nearby home prices is estimated with remarkable precision. A smaller case study resulting in similar point estimates could well dismiss the findings as null because they would be less precise and potentially statistically insignificant. In addition, there is likely heterogeneity in the price impacts across markets, and estimates from smaller case studies may not be representative of the nationwide effects.

Second, stacked spatial DID study designs like ours and countless others in the literature rely on spatially and temporally dispersed sub-experiments for statistical identification.[13] In our context, a causal interpretation hinges on the assumption that any unobserved influences on house prices are not correlated with the location *and* timing of an accident. The plausibility of such an assumption increases as we observe higher numbers of accidents at different locations and periods in time. Spatially and temporally extensive datasets like ZTRAX facilitate the inclusion of high numbers of treatment events and locations, and therefore reduce endogeneity concerns related to spatially correlated confounders.

A final advantage of large-scale datasets like ZTRAX is that the large number of identifying observations allows researchers to examine treatment heterogeneity in more detail. In our context, this enables several useful directions, including heterogeneity with respect to accident severity, distance, and time. Although we find statistically significant price effects extending out to 5.75 km, we are able to examine heterogeneity in those price impacts with respect to distance from the disamenity at a fine 250-meter bin resolution. We also examine how price impacts evolve over

[13] See Parmeter and Pope (2013) and Guignet and Lee (2021) for reviews.

time, based on one-year bins denoting time since the accident. “Slicing” the data into finer groups based on space and time like this would not be possible without the large number of identifying observations due to the extensive study area and time period afforded by the ZTRAX data.

In that same vein, our welfare analysis following Banzhaf (2021) relies squarely on our ability to model separate treatment effects by year. Identifying year-by-year treatment effects and inferring bounding welfare estimates from first-stage hedonic models is novel, and to our knowledge has only been investigated in two other studies – the original proposal by Banzhaf (2021) and an application to hazardous waste site cleanups by Guignet and Nolte (2021). Estimating formal welfare effects would be difficult in many applications without a large-scale dataset containing a high number of identifying observations.

A formal welfare interpretation is necessary for including estimates from hedonic property value studies in benefit-cost analyses and to inform efficient policy decisions. The estimates from our analysis will help inform decision makers regarding future policies directed at reducing the probability of accidents at chemical facilities, and at RMP facilities in particular. To fully, and quantitatively, incorporate these estimates into regulatory analysis, however, further research is needed on how different regulatory requirements (e.g., third party audits, or employee “stop work” provisions) impact the probability of accidents.

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ONLINE APPENDIX

Two online appendices are included. Appendix A presents the data cleaning and formatting procedures, followed by supplemental descriptive statistics. Appendix B provides full hedonic property value regression results for models reported in the main paper, as well as supplemental results as a sensitivity analysis.

Appendix A. Data formatting details and supplemental data statistics

The hedonic analysis focuses on a total of 10,428,442 full property[14], arms-length transactions of single-family homes from 2004 through 2019, where the home is within 10 km of one or more of the RMP facility accidents. When estimating the hedonic price regression models, 1,804 singleton observations were dropped due to the inclusion of numerous spatiotemporal fixed effects. Therefore, a sample size of 10,426,638 sales is reported in the regression results tables.

The transaction and assessor data for all available states in the contiguous U.S. were obtained through Zillow's ZTRAX program. For this analysis we use the October 2021 release of the data (downloaded on 19 May 2022). We do not rely on the geographic coordinates provided by ZTRAX. Price impacts associated with RMP facility accidents can be local in nature, and so the highest level of spatial precision possible is desired. At the same time, there are documented concerns regarding the accuracy of the geographic coordinates provided directly in ZTRAX, including missing data, mislocated data, and undocumented spatial variation in the geographic coordinate datums (Nolte et al., 2021). We therefore relied on geo-located parcel boundary polygons, which we obtained partially from open-access data sources and partially from Regrid (www.regrid.com) through their "Data with Purpose" program. We used unique parcel identifiers (assessor parcel numbers) to link these parcel boundary data to parcel records in the ZTRAX tax assessor database using county and town-specific deductive string pattern matching and geographic quality controls (Nolte, 2020). The Euclidean distance from the centroid of each residential parcel in ZTRAX to each RMP accident site is calculated.

Our data cleaning and formatting starts with the 15,184,233 full property transactions of single-family homes, where the homes are located within 10 km of at least one RMP accident. Single-family homes were identified as those for which the land use code in the ZTRAX assessor database was RR000, RR101, RR102, or RR999. Transactions with missing nominal sales price or with token values of \$1, \$100, or \$1,000 are eliminated, leaving a sample of 15,153,958. Transaction prices are converted to 2021\$ USD based on the Bureau of Labor Statistics annual US city average "All Urban Consumers" consumer price index (CPI).[15]

Outlier observations with a real price less than \$15,000 or greater than \$1,000,000 are eliminated, as are transactions of homes with lot sizes less than 0.05 acres or greater than 2 acres, leaving a sample of 13,567,656 home transactions. These outlier cutoffs fall squarely between the lowest and highest 1st and 5th percentiles; for example, the \$15,000 value is between the lowest 1st and 5th percentiles of the price distribution. Homes with less than one story or greater than three stories,

[14] Partial sales (i.e., transactions where just a portion of a parcel is sold) are disregarded.

[15] Bureau of Labor Statistics (BLS), https://www.bls.gov/cpi/tables/supplemental-files/historical-cpi-u-202206.pdf, accessed 31 July 2022.

less than 750 square feet or greater than 15,000 square feet, and/or less than one full bathroom or greater than 4.5 bathrooms, were also eliminated, leaving a sample of 13,066,840 home sales. These outlier cutoffs correspond approximately to the highest and lowest percentiles.

The age of the home at the time of a transaction was calculated as the difference between the year of transaction and the effective year built variable in the ZTRAX assessor database. Sales where the effective year built variable was missing (566,334) or where the calculated age was negative (357,559) were recoded with an age of zero, and a companion missing age dummy was included. Among transactions where the age of the home is not missing, we drop 87,953 sales where the home age was greater than 120 years (which closely corresponds to the 99th percentile of 118 years).

The sample at this point entailed 12,860,064 unique single-family home transactions. It is with this "cleaned" sample that the usual hedonic analysis might proceed. However, Nolte et al. (2021) took great care in going above and beyond the usual hedonic property value study data protocols to more confidently identify arms-length transactions in the ZTRAX data. Following the criteria developed by Nolte et al. (2021), we drop an additional 2,431,622 sales (18.91% of the sample) where there is low-confidence that the observations reflect an arms-length transaction. To accomplish this we created an aggregated transaction filter that represents the lowest level of confidence determined across all individual filter items, shown in Table A.1. Sales were dropped when the aggregated filter had a value of zero, meaning at least one of the individual filters was designated as "low confidence" following Nolte et al. (2021). As shown in Table A.1, Nolte et al.'s (2021) efforts to identify how transaction contract types are used differently across states contributed the most to this additional data cleaning step, which ultimately provided a final dataset that is more confidently focused on arms-length transactions (see Table A.1).

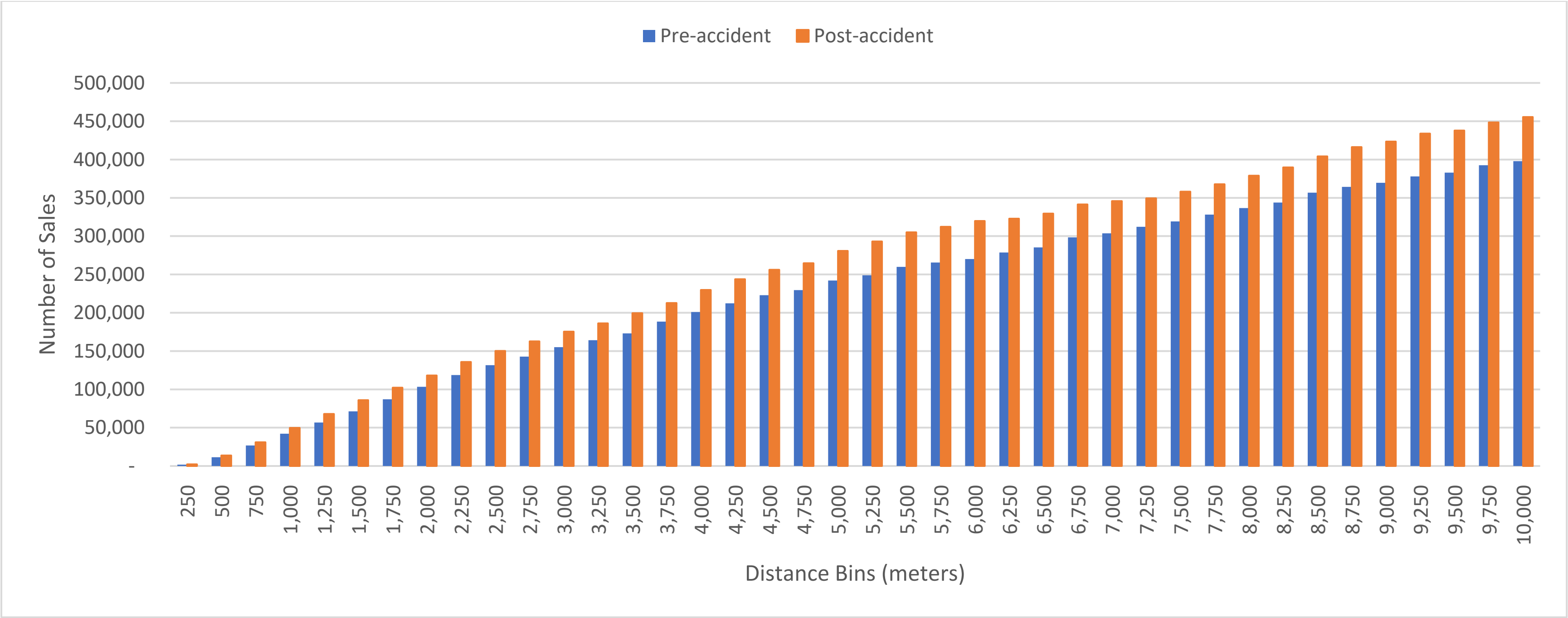
The hedonic analysis in the main paper focuses on the final sample of 10,428,442 full, arms-length transactions of single-family homes. Descriptive statistics and additional details of this sample are presented in section III.B of the main text.

Table A.1. Comparison of sample to data filters developed by Nolte et al. (2021).

	Confidence that arms-length sale		
Transaction Filter	High (=2)	Medium (=1)	Low (=0)
Aggregated filter: Min of individual filters	**62.34%**	**18.75%**	**18.91%**
Similarity between buyer and seller names	96.85%	1.23%	1.92%
Intra-family transaction flag in ZTRAX	98.38%	0%	1.62%
Public buyer and/or seller	99.42%	0.09%	0.49%
Type of transaction contract	84.04%	2.82%	13.14%
Type of mortgage loan	98.80%	0.46%	0.74%
Source of sales price value	81.72%	16.07%	2.21%

Note: Percentage of n=12,860,064 home transactions categorized as high, medium, or low confidence that they reflect an arms-length transaction. Transactions designated as "low confidence" under the aggregated filter are dropped from the final sample. Additional details can be found at https://placeslab.org/ztrax (accessed 15 September 2022), and are further described by Nolte et al. (2021).

Figure A.1. Number of Pre- and Post-Accident Transactions.



Appendix B. Supplemental analysis results.

Table B.1. Base models: Full hedonic property value regression results.

	Model 1A	Model 1B	Model 1C
RMP 0-5750 m†	0.0018	-0.0023	-0.0036
	(0.0044)	(0.0035)	(0.0033)
Post-accident†	0.0110*	0.0102*	0.0093*
	(0.0062)	(0.0055)	(0.0050)
Post-accident × 0-5750 m†	-0.0127*	-0.0022	0.0017
	(0.0075)	(0.0063)	(0.0055)
Post-Reportable Accident × 0-5750 m†	-0.0090	-0.0062	-0.0093
	(0.0102)	(0.0087)	(0.0077)
Post-Offsite Impact Accident × 0-5750 m†	-0.0116	-0.0145*	-0.0118*
	(0.0088)	(0.0080)	(0.0071)
ln(acres)	0.1210***		
	(0.0048)		
Missing: Acres†	-0.3316***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0654***		
	(0.0171)		
Bathrooms	0.0754***		
	(0.0067)		
Missing: Bathrooms†	0.1966***		
	(0.0244)		
ln(interior sqft)	0.4200***		
	(0.0153)		
Missing: Interior sqft	3.4506***		
	(0.1370)		
Age (years)	-0.0066***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8707***		
	(0.0344)		

% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0244***		
	(0.0018)		
Lake w/in 500m†	0.0456***		
	(0.0047)		
River w/in 250m†	0.0313***		
	(0.0087)		
Constant	9.0290***	12.1677***	12.1681***
	(0.1156)	(0.0039)	(0.0037)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Table B.2. Hedonic property value regression results with incremental 250-meter bins.

	Model 2A	**Model 2B**	**Model 2C**
RMP†			
0-250m	-0.0908***	-0.0867***	-0.0943***
	(0.0187)	(0.0185)	(0.0187)
250-500m	-0.0759***	-0.0693***	-0.0706***
	(0.0144)	(0.0130)	(0.0139)
500-750m	-0.0683***	-0.0617***	-0.0625***
	(0.0117)	(0.0105)	(0.0104)
750-1000m	-0.0534***	-0.0506***	-0.0498***
	(0.0110)	(0.0095)	(0.0092)
1000-1250m	-0.0390***	-0.0384***	-0.0381***
	(0.0094)	(0.0077)	(0.0076)
1250-1500m	-0.0347***	-0.0323***	-0.0343***
	(0.0084)	(0.0073)	(0.0071)
1500-1750m	-0.0417***	-0.0347***	-0.0374***
	(0.0077)	(0.0068)	(0.0067)

1750-2000m	-0.0364***	-0.0329***	-0.0347***
	(0.0079)	(0.0066)	(0.0064)
2000-2250m	-0.0357***	-0.0329***	-0.0346***
	(0.0072)	(0.0063)	(0.0061)
2250-2500m	-0.0324***	-0.0308***	-0.0317***
	(0.0067)	(0.0056)	(0.0055)
2500-2750m	-0.0271***	-0.0287***	-0.0297***
	(0.0060)	(0.0051)	(0.0049)
2750-3000m	-0.0208***	-0.0235***	-0.0252***
	(0.0062)	(0.0055)	(0.0054)
3000-3250m	-0.0117*	-0.0153***	-0.0178***
	(0.0060)	(0.0050)	(0.0048)
3250-3500m	-0.0082	-0.0115**	-0.0140***
	(0.0056)	(0.0046)	(0.0044)
3500-3750m	-0.0057	-0.0090**	-0.0122***
	(0.0055)	(0.0045)	(0.0043)
3750-4000m	-0.0030	-0.0063	-0.0087**
	(0.0053)	(0.0046)	(0.0044)
4000-4250m	-0.0032	-0.0046	-0.0063
	(0.0052)	(0.0042)	(0.0040)
4250-4500m	-0.0058	-0.0064	-0.0070*
	(0.0048)	(0.0039)	(0.0037)
4500-4750m	-0.0047	-0.0059	-0.0072*
	(0.0047)	(0.0039)	(0.0037)
4750-5000m	0.0034	0.0009	-0.0002
	(0.0047)	(0.0038)	(0.0036)
5000-5250m	0.0025	-0.0003	-0.0016
	(0.0042)	(0.0035)	(0.0032)
5250-5500m	0.0034	0.0019	0.0005
	(0.0040)	(0.0034)	(0.0030)
5500-5750m	0.0007	-0.0013	-0.0026
	(0.0035)	(0.0028)	(0.0027)
Post-accident†	0.0093	0.0095*	0.0087*
	(0.0062)	(0.0055)	(0.0050)
0-250m	-0.0129	0.0071	0.0166

	(0.0411)	(0.0372)	(0.0373)
250-500m	0.0087	0.0262	0.0342**
	(0.0219)	(0.0178)	(0.0172)
500-750m	0.0087	0.0268*	0.0309**
	(0.0180)	(0.0152)	(0.0144)
750-1000m	-0.0107	0.0081	0.0081
	(0.0158)	(0.0139)	(0.0130)
1000-1250m	-0.0295**	-0.0102	-0.0084
	(0.0143)	(0.0120)	(0.0114)
1250-1500m	-0.0296*	-0.0106	-0.0054
	(0.0154)	(0.0137)	(0.0129)
1500-1750m	-0.0195*	-0.0058	-0.0004
	(0.0116)	(0.0103)	(0.0099)
1750-2000m	-0.0212*	-0.0030	0.0008
	(0.0116)	(0.0100)	(0.0098)
2000-2250m	-0.0141	0.0010	0.0036
	(0.0105)	(0.0093)	(0.0090)
2250-2500m	-0.0135	-0.0000	0.0022
	(0.0093)	(0.0085)	(0.0078)
2500-2750m	-0.0104	0.0002	0.0030
	(0.0088)	(0.0084)	(0.0077)
2750-3000m	-0.0053	0.0045	0.0078
	(0.0093)	(0.0085)	(0.0079)
3000-3250m	-0.0087	0.0054	0.0081
	(0.0090)	(0.0077)	(0.0075)
3250-3500m	-0.0179**	-0.0052	-0.0012
	(0.0089)	(0.0076)	(0.0070)
3500-3750m	-0.0140	-0.0038	0.0020
	(0.0088)	(0.0075)	(0.0070)
3750-4000m	-0.0170**	-0.0068	-0.0020
	(0.0082)	(0.0070)	(0.0061)
4000-4250m	-0.0204**	-0.0107	-0.0069
	(0.0082)	(0.0070)	(0.0061)
4250-4500m	-0.0192**	-0.0080	-0.0057
	(0.0090)	(0.0074)	(0.0068)
4500-4750m	-0.0119	-0.0031	0.0003
	(0.0083)	(0.0071)	(0.0064)
4750-5000m	-0.0098	-0.0023	0.0008
	(0.0073)	(0.0063)	(0.0055)

5000-5250m	-0.0076	-0.0000	0.0032
	(0.0067)	(0.0059)	(0.0053)
5250-5500m	-0.0111*	-0.0051	-0.0023
	(0.0063)	(0.0056)	(0.0051)
5500-5750m	-0.0091	-0.0044	-0.0025
	(0.0058)	(0.0051)	(0.0046)
Post-Reportable Accident†			
0-250m	-0.0654	-0.0421	-0.0498
	(0.0509)	(0.0462)	(0.0450)
250-500m	-0.0738**	-0.0577*	-0.0661**
	(0.0366)	(0.0313)	(0.0287)
500-750m	-0.0505*	-0.0415*	-0.0468**
	(0.0286)	(0.0238)	(0.0230)
750-1000m	-0.0140	-0.0077	-0.0100
	(0.0228)	(0.0192)	(0.0176)
1000-1250m	0.0020	0.0023	-0.0023
	(0.0204)	(0.0174)	(0.0156)
1250-1500m	-0.0038	-0.0004	-0.0026
	(0.0197)	(0.0171)	(0.0163)
1500-1750m	-0.0044	-0.0008	-0.0023
	(0.0171)	(0.0151)	(0.0149)
1750-2000m	-0.0046	-0.0031	-0.0037
	(0.0156)	(0.0138)	(0.0135)
2000-2250m	-0.0062	-0.0076	-0.0085
	(0.0165)	(0.0144)	(0.0139)
2250-2500m	0.0017	0.0010	0.0001
	(0.0146)	(0.0131)	(0.0122)
2500-2750m	-0.0032	-0.0007	-0.0030
	(0.0142)	(0.0130)	(0.0125)
2750-3000m	-0.0122	-0.0074	-0.0083
	(0.0141)	(0.0127)	(0.0118)
3000-3250m	-0.0057	-0.0074	-0.0064
	(0.0140)	(0.0124)	(0.0120)
3250-3500m	-0.0025	-0.0030	-0.0036
	(0.0140)	(0.0123)	(0.0116)
3500-3750m	-0.0056	-0.0028	-0.0042
	(0.0131)	(0.0112)	(0.0106)
3750-4000m	-0.0016	0.0004	-0.0002
	(0.0121)	(0.0102)	(0.0093)
4000-4250m	0.0033	0.0040	0.0029
	(0.0114)	(0.0093)	(0.0086)
4250-4500m	0.0077	0.0064	0.0057
	(0.0123)	(0.0102)	(0.0099)
4500-4750m	-0.0050	-0.0033	-0.0047

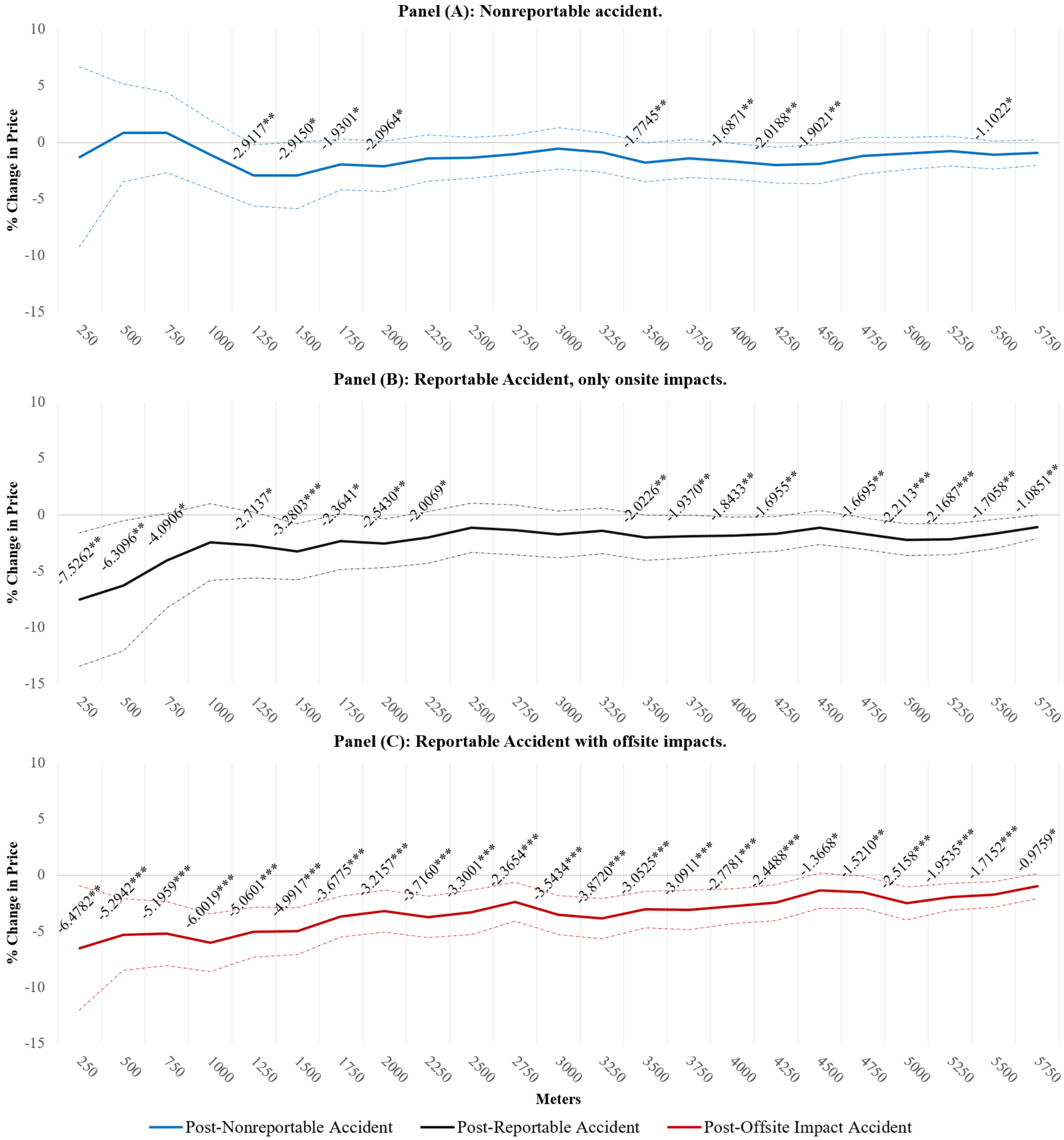
	(0.0111)	(0.0093)	(0.0088)
4750-5000m	-0.0125	-0.0109	-0.0113
	(0.0097)	(0.0080)	(0.0075)
5000-5250m	-0.0143	-0.0116	-0.0123*
	(0.0092)	(0.0078)	(0.0073)
5250-5500m	-0.0061	-0.0053	-0.0055
	(0.0085)	(0.0068)	(0.0062)
5500-5750m	-0.0018	0.0014	0.0009
	(0.0074)	(0.0062)	(0.0057)
Post-Offsite Impact Accident†			
0-250m	0.0113	-0.0097	0.0033
	(0.0434)	(0.0380)	(0.0380)
250-500m	0.0108	-0.0063	0.0006
	(0.0354)	(0.0304)	(0.0278)
500-750m	-0.0116	-0.0232	-0.0155
	(0.0277)	(0.0245)	(0.0231)
750-1000m	-0.0372*	-0.0463**	-0.0397**
	(0.0212)	(0.0181)	(0.0171)
1000-1250m	-0.0244	-0.0241	-0.0173
	(0.0186)	(0.0165)	(0.0151)
1250-1500m	-0.0179	-0.0224	-0.0183
	(0.0168)	(0.0153)	(0.0145)
1500-1750m	-0.0135	-0.0200	-0.0172
	(0.0162)	(0.0148)	(0.0142)
1750-2000m	-0.0069	-0.0141	-0.0125
	(0.0151)	(0.0139)	(0.0132)
2000-2250m	-0.0176	-0.0182	-0.0143
	(0.0145)	(0.0130)	(0.0124)
2250-2500m	-0.0218	-0.0234*	-0.0205*
	(0.0138)	(0.0127)	(0.0122)
2500-2750m	-0.0103	-0.0152	-0.0105
	(0.0136)	(0.0121)	(0.0117)
2750-3000m	-0.0186	-0.0257**	-0.0237**
	(0.0132)	(0.0121)	(0.0116)
3000-3250m	-0.0251*	-0.0300**	-0.0272**
	(0.0134)	(0.0125)	(0.0121)
3250-3500m	-0.0106	-0.0143	-0.0127
	(0.0125)	(0.0116)	(0.0109)
3500-3750m	-0.0118	-0.0188*	-0.0167
	(0.0122)	(0.0113)	(0.0111)
3750-4000m	-0.0096	-0.0146	-0.0143
	(0.0105)	(0.0096)	(0.0093)
4000-4250m	-0.0077	-0.0131	-0.0124
	(0.0111)	(0.0104)	(0.0104)

4250-4500m	-0.0023	-0.0081	-0.0087
	(0.0104)	(0.0095)	(0.0090)
4500-4750m	0.0015	-0.0045	-0.0052
	(0.0095)	(0.0084)	(0.0081)
4750-5000m	-0.0031	-0.0079	-0.0091
	(0.0092)	(0.0075)	(0.0073)
5000-5250m	0.0022	-0.0041	-0.0046
	(0.0082)	(0.0067)	(0.0064)
5250-5500m	-0.0001	-0.0053	-0.0058
	(0.0070)	(0.0060)	(0.0055)
5500-5750m	0.0011	-0.0062	-0.0054
	(0.0063)	(0.0053)	(0.0048)
ln(acres)	0.1203***		
	(0.0048)		
Missing: Acres†	-0.3302***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0653***		
	(0.0171)		
Bathrooms	0.0753***		
	(0.0067)		
Missing: Bathrooms†	0.1962***		
	(0.0244)		
ln(interior sqft)	0.4198***		
	(0.0153)		
Missing: Interior sqft	3.4492***		
	(0.1369)		
Age (years)	-0.0065***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8704***		
	(0.0344)		
% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0238***		
	(0.0018)		
Lake w/in 500m†	0.0458***		
	(0.0047)		
River w/in 250m†	0.0317***		
	(0.0087)		
Constant	9.0375***	12.1750***	12.1753***

	(0.1155)	(0.0041)	(0.0039)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Figure B.1. Model 2A results: Percent change in price due to an accident, by 250-meter bins.



Note: Estimates calculated following equations (3a) through (3c) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 2A, which constrains the slope coefficients for the housing and location attributes to be common across counties and years. Full regression results for model 2A are presented in Appendix B.

Supplemental analysis results.

Table B.1. Base models: Full hedonic property value regression results.

	Model 1A	Model 1B	Model 1C

RMP 0-5750 m†	0.0018	-0.0023	-0.0036
	(0.0044)	(0.0035)	(0.0033)
Post-accident†	0.0110*	0.0102*	0.0093*
	(0.0062)	(0.0055)	(0.0050)
Post-accident × 0-5750 m†	-0.0127*	-0.0022	0.0017
	(0.0075)	(0.0063)	(0.0055)
Post-Reportable Accident × 0-5750 m†	-0.0090	-0.0062	-0.0093
	(0.0102)	(0.0087)	(0.0077)
Post-Offsite Impact Accident × 0-5750 m†	-0.0116	-0.0145*	-0.0118*
	(0.0088)	(0.0080)	(0.0071)
ln(acres)	0.1210***		
	(0.0048)		
Missing: Acres†	-0.3316***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0654***		
	(0.0171)		
Bathrooms	0.0754***		
	(0.0067)		
Missing: Bathrooms†	0.1966***		
	(0.0244)		
ln(interior sqft)	0.4200***		
	(0.0153)		
Missing: Interior sqft	3.4506***		
	(0.1370)		
Age (years)	-0.0066***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8707***		
	(0.0344)		
% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0244***		
	(0.0018)		
Lake w/in 500m†	0.0456***		

	(0.0047)		
River w/in 250m†	0.0313***		
	(0.0087)		
Constant	9.0290***	12.1677***	12.1681***
	(0.1156)	(0.0039)	(0.0037)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Table B.2. Hedonic property value regression results with incremental 250-meter bins.

	Model 2A	**Model 2B**	**Model 2C**
RMP†			
0-250m	-0.0908***	-0.0867***	-0.0943***
	(0.0187)	(0.0185)	(0.0187)
250-500m	-0.0759***	-0.0693***	-0.0706***
	(0.0144)	(0.0130)	(0.0139)
500-750m	-0.0683***	-0.0617***	-0.0625***
	(0.0117)	(0.0105)	(0.0104)
750-1000m	-0.0534***	-0.0506***	-0.0498***
	(0.0110)	(0.0095)	(0.0092)
1000-1250m	-0.0390***	-0.0384***	-0.0381***
	(0.0094)	(0.0077)	(0.0076)
1250-1500m	-0.0347***	-0.0323***	-0.0343***
	(0.0084)	(0.0073)	(0.0071)
1500-1750m	-0.0417***	-0.0347***	-0.0374***
	(0.0077)	(0.0068)	(0.0067)
1750-2000m	-0.0364***	-0.0329***	-0.0347***
	(0.0079)	(0.0066)	(0.0064)

2000-2250m	-0.0357***	-0.0329***	-0.0346***
	(0.0072)	(0.0063)	(0.0061)
2250-2500m	-0.0324***	-0.0308***	-0.0317***
	(0.0067)	(0.0056)	(0.0055)
2500-2750m	-0.0271***	-0.0287***	-0.0297***
	(0.0060)	(0.0051)	(0.0049)
2750-3000m	-0.0208***	-0.0235***	-0.0252***
	(0.0062)	(0.0055)	(0.0054)
3000-3250m	-0.0117*	-0.0153***	-0.0178***
	(0.0060)	(0.0050)	(0.0048)
3250-3500m	-0.0082	-0.0115**	-0.0140***
	(0.0056)	(0.0046)	(0.0044)
3500-3750m	-0.0057	-0.0090**	-0.0122***
	(0.0055)	(0.0045)	(0.0043)
3750-4000m	-0.0030	-0.0063	-0.0087**
	(0.0053)	(0.0046)	(0.0044)
4000-4250m	-0.0032	-0.0046	-0.0063
	(0.0052)	(0.0042)	(0.0040)
4250-4500m	-0.0058	-0.0064	-0.0070*
	(0.0048)	(0.0039)	(0.0037)
4500-4750m	-0.0047	-0.0059	-0.0072*
	(0.0047)	(0.0039)	(0.0037)
4750-5000m	0.0034	0.0009	-0.0002
	(0.0047)	(0.0038)	(0.0036)
5000-5250m	0.0025	-0.0003	-0.0016
	(0.0042)	(0.0035)	(0.0032)
5250-5500m	0.0034	0.0019	0.0005
	(0.0040)	(0.0034)	(0.0030)
5500-5750m	0.0007	-0.0013	-0.0026
	(0.0035)	(0.0028)	(0.0027)
Post-accident†	0.0093	0.0095*	0.0087*
	(0.0062)	(0.0055)	(0.0050)
0-250m	-0.0129	0.0071	0.0166
	(0.0411)	(0.0372)	(0.0373)
250-500m	0.0087	0.0262	0.0342**
	(0.0219)	(0.0178)	(0.0172)
500-750m	0.0087	0.0268*	0.0309**
	(0.0180)	(0.0152)	(0.0144)
750-1000m	-0.0107	0.0081	0.0081

	(0.0158)	(0.0139)	(0.0130)
1000-1250m	-0.0295**	-0.0102	-0.0084
	(0.0143)	(0.0120)	(0.0114)
1250-1500m	-0.0296*	-0.0106	-0.0054
	(0.0154)	(0.0137)	(0.0129)
1500-1750m	-0.0195*	-0.0058	-0.0004
	(0.0116)	(0.0103)	(0.0099)
1750-2000m	-0.0212*	-0.0030	0.0008
	(0.0116)	(0.0100)	(0.0098)
2000-2250m	-0.0141	0.0010	0.0036
	(0.0105)	(0.0093)	(0.0090)
2250-2500m	-0.0135	-0.0000	0.0022
	(0.0093)	(0.0085)	(0.0078)
2500-2750m	-0.0104	0.0002	0.0030
	(0.0088)	(0.0084)	(0.0077)
2750-3000m	-0.0053	0.0045	0.0078
	(0.0093)	(0.0085)	(0.0079)
3000-3250m	-0.0087	0.0054	0.0081
	(0.0090)	(0.0077)	(0.0075)
3250-3500m	-0.0179**	-0.0052	-0.0012
	(0.0089)	(0.0076)	(0.0070)
3500-3750m	-0.0140	-0.0038	0.0020
	(0.0088)	(0.0075)	(0.0070)
3750-4000m	-0.0170**	-0.0068	-0.0020
	(0.0082)	(0.0070)	(0.0061)
4000-4250m	-0.0204**	-0.0107	-0.0069
	(0.0082)	(0.0070)	(0.0061)
4250-4500m	-0.0192**	-0.0080	-0.0057
	(0.0090)	(0.0074)	(0.0068)
4500-4750m	-0.0119	-0.0031	0.0003
	(0.0083)	(0.0071)	(0.0064)
4750-5000m	-0.0098	-0.0023	0.0008
	(0.0073)	(0.0063)	(0.0055)
5000-5250m	-0.0076	-0.0000	0.0032
	(0.0067)	(0.0059)	(0.0053)
5250-5500m	-0.0111*	-0.0051	-0.0023
	(0.0063)	(0.0056)	(0.0051)
5500-5750m	-0.0091	-0.0044	-0.0025
	(0.0058)	(0.0051)	(0.0046)
Post-Reportable Accident[†]			
0-250m	-0.0654	-0.0421	-0.0498
	(0.0509)	(0.0462)	(0.0450)
250-500m	-0.0738**	-0.0577*	-0.0661**
	(0.0366)	(0.0313)	(0.0287)

500-750m	-0.0505*	-0.0415*	-0.0468**
	(0.0286)	(0.0238)	(0.0230)
750-1000m	-0.0140	-0.0077	-0.0100
	(0.0228)	(0.0192)	(0.0176)
1000-1250m	0.0020	0.0023	-0.0023
	(0.0204)	(0.0174)	(0.0156)
1250-1500m	-0.0038	-0.0004	-0.0026
	(0.0197)	(0.0171)	(0.0163)
1500-1750m	-0.0044	-0.0008	-0.0023
	(0.0171)	(0.0151)	(0.0149)
1750-2000m	-0.0046	-0.0031	-0.0037
	(0.0156)	(0.0138)	(0.0135)
2000-2250m	-0.0062	-0.0076	-0.0085
	(0.0165)	(0.0144)	(0.0139)
2250-2500m	0.0017	0.0010	0.0001
	(0.0146)	(0.0131)	(0.0122)
2500-2750m	-0.0032	-0.0007	-0.0030
	(0.0142)	(0.0130)	(0.0125)
2750-3000m	-0.0122	-0.0074	-0.0083
	(0.0141)	(0.0127)	(0.0118)
3000-3250m	-0.0057	-0.0074	-0.0064
	(0.0140)	(0.0124)	(0.0120)
3250-3500m	-0.0025	-0.0030	-0.0036
	(0.0140)	(0.0123)	(0.0116)
3500-3750m	-0.0056	-0.0028	-0.0042
	(0.0131)	(0.0112)	(0.0106)
3750-4000m	-0.0016	0.0004	-0.0002
	(0.0121)	(0.0102)	(0.0093)
4000-4250m	0.0033	0.0040	0.0029
	(0.0114)	(0.0093)	(0.0086)
4250-4500m	0.0077	0.0064	0.0057
	(0.0123)	(0.0102)	(0.0099)
4500-4750m	-0.0050	-0.0033	-0.0047
	(0.0111)	(0.0093)	(0.0088)
4750-5000m	-0.0125	-0.0109	-0.0113
	(0.0097)	(0.0080)	(0.0075)
5000-5250m	-0.0143	-0.0116	-0.0123*
	(0.0092)	(0.0078)	(0.0073)
5250-5500m	-0.0061	-0.0053	-0.0055
	(0.0085)	(0.0068)	(0.0062)
5500-5750m	-0.0018	0.0014	0.0009
	(0.0074)	(0.0062)	(0.0057)
Post-Offsite Impact Accident†			
0-250m	0.0113	-0.0097	0.0033

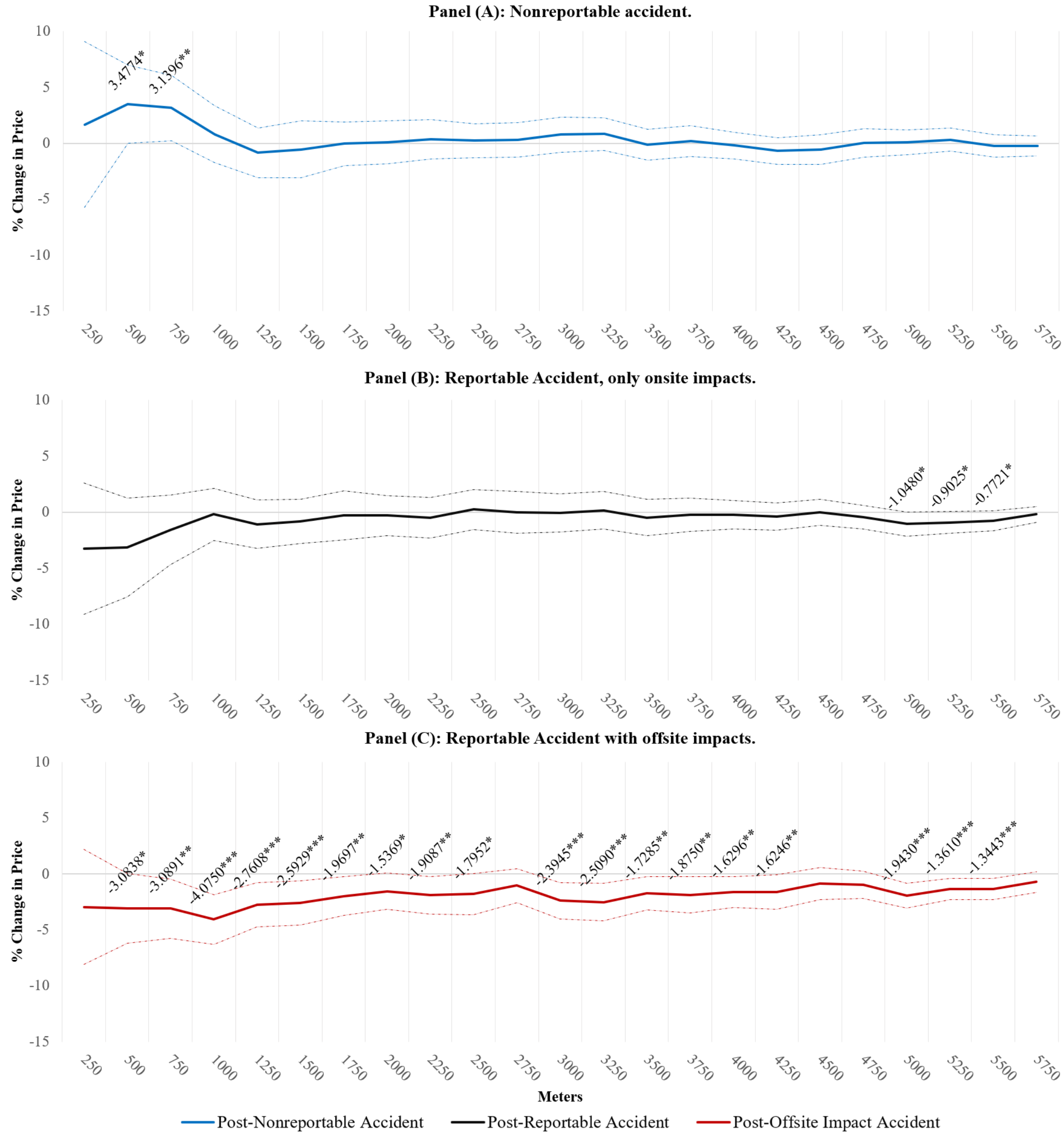
	(0.0434)	(0.0380)	(0.0380)
250-500m	0.0108	-0.0063	0.0006
	(0.0354)	(0.0304)	(0.0278)
500-750m	-0.0116	-0.0232	-0.0155
	(0.0277)	(0.0245)	(0.0231)
750-1000m	-0.0372*	-0.0463**	-0.0397**
	(0.0212)	(0.0181)	(0.0171)
1000-1250m	-0.0244	-0.0241	-0.0173
	(0.0186)	(0.0165)	(0.0151)
1250-1500m	-0.0179	-0.0224	-0.0183
	(0.0168)	(0.0153)	(0.0145)
1500-1750m	-0.0135	-0.0200	-0.0172
	(0.0162)	(0.0148)	(0.0142)
1750-2000m	-0.0069	-0.0141	-0.0125
	(0.0151)	(0.0139)	(0.0132)
2000-2250m	-0.0176	-0.0182	-0.0143
	(0.0145)	(0.0130)	(0.0124)
2250-2500m	-0.0218	-0.0234*	-0.0205*
	(0.0138)	(0.0127)	(0.0122)
2500-2750m	-0.0103	-0.0152	-0.0105
	(0.0136)	(0.0121)	(0.0117)
2750-3000m	-0.0186	-0.0257**	-0.0237**
	(0.0132)	(0.0121)	(0.0116)
3000-3250m	-0.0251*	-0.0300**	-0.0272**
	(0.0134)	(0.0125)	(0.0121)
3250-3500m	-0.0106	-0.0143	-0.0127
	(0.0125)	(0.0116)	(0.0109)
3500-3750m	-0.0118	-0.0188*	-0.0167
	(0.0122)	(0.0113)	(0.0111)
3750-4000m	-0.0096	-0.0146	-0.0143
	(0.0105)	(0.0096)	(0.0093)
4000-4250m	-0.0077	-0.0131	-0.0124
	(0.0111)	(0.0104)	(0.0104)
4250-4500m	-0.0023	-0.0081	-0.0087
	(0.0104)	(0.0095)	(0.0090)
4500-4750m	0.0015	-0.0045	-0.0052
	(0.0095)	(0.0084)	(0.0081)
4750-5000m	-0.0031	-0.0079	-0.0091
	(0.0092)	(0.0075)	(0.0073)
5000-5250m	0.0022	-0.0041	-0.0046
	(0.0082)	(0.0067)	(0.0064)
5250-5500m	-0.0001	-0.0053	-0.0058
	(0.0070)	(0.0060)	(0.0055)
5500-5750m	0.0011	-0.0062	-0.0054

	(0.0063)	(0.0053)	(0.0048)
ln(acres)	0.1203***		
	(0.0048)		
Missing: Acres†	-0.3302***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0653***		
	(0.0171)		
Bathrooms	0.0753***		
	(0.0067)		
Missing: Bathrooms†	0.1962***		
	(0.0244)		
ln(interior sqft)	0.4198***		
	(0.0153)		
Missing: Interior sqft	3.4492***		
	(0.1369)		
Age (years)	-0.0065***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8704***		
	(0.0344)		
% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0238***		
	(0.0018)		
Lake w/in 500m†	0.0458***		
	(0.0047)		
River w/in 250m†	0.0317***		
	(0.0087)		
Constant	9.0375***	12.1750***	12.1753***
	(0.1155)	(0.0041)	(0.0039)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

in Appendix B.

Figure B. 2. Model 2C results: Percent change in price due to an accident, by 250-meter bins.



Note: Estimates calculated following equations (3a) through (3c) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 2C, which includes county-by-year interactions with the housing and location attributes. Full regression results for model 2C are presented in Appendix B. Supplemental analysis results.

Table B.1. Base models: Full hedonic property value regression results.

	Model 1A	Model 1B	Model 1C

RMP 0-5750 m†	0.0018	-0.0023	-0.0036
	(0.0044)	(0.0035)	(0.0033)
Post-accident†	0.0110*	0.0102*	0.0093*
	(0.0062)	(0.0055)	(0.0050)
Post-accident × 0-5750 m†	-0.0127*	-0.0022	0.0017
	(0.0075)	(0.0063)	(0.0055)
Post-Reportable Accident × 0-5750 m†	-0.0090	-0.0062	-0.0093
	(0.0102)	(0.0087)	(0.0077)
Post-Offsite Impact Accident × 0-5750 m†	-0.0116	-0.0145*	-0.0118*
	(0.0088)	(0.0080)	(0.0071)
ln(acres)	0.1210***		
	(0.0048)		
Missing: Acres†	-0.3316***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0654***		
	(0.0171)		
Bathrooms	0.0754***		
	(0.0067)		
Missing: Bathrooms†	0.1966***		
	(0.0244)		
ln(interior sqft)	0.4200***		
	(0.0153)		
Missing: Interior sqft	3.4506***		
	(0.1370)		
Age (years)	-0.0066***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8707***		
	(0.0344)		
% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0244***		
	(0.0018)		

Lake w/in 500m†	0.0456***		
	(0.0047)		
River w/in 250m†	0.0313***		
	(0.0087)		
Constant	9.0290***	12.1677***	12.1681***
	(0.1156)	(0.0039)	(0.0037)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Table B.2. Hedonic property value regression results with incremental 250-meter bins.

	Model 2A	**Model 2B**	**Model 2C**
RMP†			
0-250m	-0.0908***	-0.0867***	-0.0943***
	(0.0187)	(0.0185)	(0.0187)
250-500m	-0.0759***	-0.0693***	-0.0706***
	(0.0144)	(0.0130)	(0.0139)
500-750m	-0.0683***	-0.0617***	-0.0625***
	(0.0117)	(0.0105)	(0.0104)
750-1000m	-0.0534***	-0.0506***	-0.0498***
	(0.0110)	(0.0095)	(0.0092)
1000-1250m	-0.0390***	-0.0384***	-0.0381***
	(0.0094)	(0.0077)	(0.0076)
1250-1500m	-0.0347***	-0.0323***	-0.0343***
	(0.0084)	(0.0073)	(0.0071)
1500-1750m	-0.0417***	-0.0347***	-0.0374***
	(0.0077)	(0.0068)	(0.0067)
1750-2000m	-0.0364***	-0.0329***	-0.0347***

	(0.0079)	(0.0066)	(0.0064)
2000-2250m	-0.0357***	-0.0329***	-0.0346***
	(0.0072)	(0.0063)	(0.0061)
2250-2500m	-0.0324***	-0.0308***	-0.0317***
	(0.0067)	(0.0056)	(0.0055)
2500-2750m	-0.0271***	-0.0287***	-0.0297***
	(0.0060)	(0.0051)	(0.0049)
2750-3000m	-0.0208***	-0.0235***	-0.0252***
	(0.0062)	(0.0055)	(0.0054)
3000-3250m	-0.0117*	-0.0153***	-0.0178***
	(0.0060)	(0.0050)	(0.0048)
3250-3500m	-0.0082	-0.0115**	-0.0140***
	(0.0056)	(0.0046)	(0.0044)
3500-3750m	-0.0057	-0.0090**	-0.0122***
	(0.0055)	(0.0045)	(0.0043)
3750-4000m	-0.0030	-0.0063	-0.0087**
	(0.0053)	(0.0046)	(0.0044)
4000-4250m	-0.0032	-0.0046	-0.0063
	(0.0052)	(0.0042)	(0.0040)
4250-4500m	-0.0058	-0.0064	-0.0070*
	(0.0048)	(0.0039)	(0.0037)
4500-4750m	-0.0047	-0.0059	-0.0072*
	(0.0047)	(0.0039)	(0.0037)
4750-5000m	0.0034	0.0009	-0.0002
	(0.0047)	(0.0038)	(0.0036)
5000-5250m	0.0025	-0.0003	-0.0016
	(0.0042)	(0.0035)	(0.0032)
5250-5500m	0.0034	0.0019	0.0005
	(0.0040)	(0.0034)	(0.0030)
5500-5750m	0.0007	-0.0013	-0.0026
	(0.0035)	(0.0028)	(0.0027)
Post-accident†	0.0093	0.0095*	0.0087*
	(0.0062)	(0.0055)	(0.0050)
0-250m	-0.0129	0.0071	0.0166
	(0.0411)	(0.0372)	(0.0373)
250-500m	0.0087	0.0262	0.0342**
	(0.0219)	(0.0178)	(0.0172)
500-750m	0.0087	0.0268*	0.0309**
	(0.0180)	(0.0152)	(0.0144)

750-1000m	-0.0107	0.0081	0.0081
	(0.0158)	(0.0139)	(0.0130)
1000-1250m	-0.0295**	-0.0102	-0.0084
	(0.0143)	(0.0120)	(0.0114)
1250-1500m	-0.0296*	-0.0106	-0.0054
	(0.0154)	(0.0137)	(0.0129)
1500-1750m	-0.0195*	-0.0058	-0.0004
	(0.0116)	(0.0103)	(0.0099)
1750-2000m	-0.0212*	-0.0030	0.0008
	(0.0116)	(0.0100)	(0.0098)
2000-2250m	-0.0141	0.0010	0.0036
	(0.0105)	(0.0093)	(0.0090)
2250-2500m	-0.0135	-0.0000	0.0022
	(0.0093)	(0.0085)	(0.0078)
2500-2750m	-0.0104	0.0002	0.0030
	(0.0088)	(0.0084)	(0.0077)
2750-3000m	-0.0053	0.0045	0.0078
	(0.0093)	(0.0085)	(0.0079)
3000-3250m	-0.0087	0.0054	0.0081
	(0.0090)	(0.0077)	(0.0075)
3250-3500m	-0.0179**	-0.0052	-0.0012
	(0.0089)	(0.0076)	(0.0070)
3500-3750m	-0.0140	-0.0038	0.0020
	(0.0088)	(0.0075)	(0.0070)
3750-4000m	-0.0170**	-0.0068	-0.0020
	(0.0082)	(0.0070)	(0.0061)
4000-4250m	-0.0204**	-0.0107	-0.0069
	(0.0082)	(0.0070)	(0.0061)
4250-4500m	-0.0192**	-0.0080	-0.0057
	(0.0090)	(0.0074)	(0.0068)
4500-4750m	-0.0119	-0.0031	0.0003
	(0.0083)	(0.0071)	(0.0064)
4750-5000m	-0.0098	-0.0023	0.0008
	(0.0073)	(0.0063)	(0.0055)
5000-5250m	-0.0076	-0.0000	0.0032
	(0.0067)	(0.0059)	(0.0053)
5250-5500m	-0.0111*	-0.0051	-0.0023
	(0.0063)	(0.0056)	(0.0051)
5500-5750m	-0.0091	-0.0044	-0.0025
	(0.0058)	(0.0051)	(0.0046)
Post-Reportable Accident†			
0-250m	-0.0654	-0.0421	-0.0498
	(0.0509)	(0.0462)	(0.0450)
250-500m	-0.0738**	-0.0577*	-0.0661**

	(0.0366)	(0.0313)	(0.0287)
500-750m	-0.0505*	-0.0415*	-0.0468**
	(0.0286)	(0.0238)	(0.0230)
750-1000m	-0.0140	-0.0077	-0.0100
	(0.0228)	(0.0192)	(0.0176)
1000-1250m	0.0020	0.0023	-0.0023
	(0.0204)	(0.0174)	(0.0156)
1250-1500m	-0.0038	-0.0004	-0.0026
	(0.0197)	(0.0171)	(0.0163)
1500-1750m	-0.0044	-0.0008	-0.0023
	(0.0171)	(0.0151)	(0.0149)
1750-2000m	-0.0046	-0.0031	-0.0037
	(0.0156)	(0.0138)	(0.0135)
2000-2250m	-0.0062	-0.0076	-0.0085
	(0.0165)	(0.0144)	(0.0139)
2250-2500m	0.0017	0.0010	0.0001
	(0.0146)	(0.0131)	(0.0122)
2500-2750m	-0.0032	-0.0007	-0.0030
	(0.0142)	(0.0130)	(0.0125)
2750-3000m	-0.0122	-0.0074	-0.0083
	(0.0141)	(0.0127)	(0.0118)
3000-3250m	-0.0057	-0.0074	-0.0064
	(0.0140)	(0.0124)	(0.0120)
3250-3500m	-0.0025	-0.0030	-0.0036
	(0.0140)	(0.0123)	(0.0116)
3500-3750m	-0.0056	-0.0028	-0.0042
	(0.0131)	(0.0112)	(0.0106)
3750-4000m	-0.0016	0.0004	-0.0002
	(0.0121)	(0.0102)	(0.0093)
4000-4250m	0.0033	0.0040	0.0029
	(0.0114)	(0.0093)	(0.0086)
4250-4500m	0.0077	0.0064	0.0057
	(0.0123)	(0.0102)	(0.0099)
4500-4750m	-0.0050	-0.0033	-0.0047
	(0.0111)	(0.0093)	(0.0088)
4750-5000m	-0.0125	-0.0109	-0.0113
	(0.0097)	(0.0080)	(0.0075)
5000-5250m	-0.0143	-0.0116	-0.0123*
	(0.0092)	(0.0078)	(0.0073)
5250-5500m	-0.0061	-0.0053	-0.0055
	(0.0085)	(0.0068)	(0.0062)
5500-5750m	-0.0018	0.0014	0.0009
	(0.0074)	(0.0062)	(0.0057)
Post-Offsite Impact Accident†			

0-250m	0.0113	-0.0097	0.0033
	(0.0434)	(0.0380)	(0.0380)
250-500m	0.0108	-0.0063	0.0006
	(0.0354)	(0.0304)	(0.0278)
500-750m	-0.0116	-0.0232	-0.0155
	(0.0277)	(0.0245)	(0.0231)
750-1000m	-0.0372*	-0.0463**	-0.0397**
	(0.0212)	(0.0181)	(0.0171)
1000-1250m	-0.0244	-0.0241	-0.0173
	(0.0186)	(0.0165)	(0.0151)
1250-1500m	-0.0179	-0.0224	-0.0183
	(0.0168)	(0.0153)	(0.0145)
1500-1750m	-0.0135	-0.0200	-0.0172
	(0.0162)	(0.0148)	(0.0142)
1750-2000m	-0.0069	-0.0141	-0.0125
	(0.0151)	(0.0139)	(0.0132)
2000-2250m	-0.0176	-0.0182	-0.0143
	(0.0145)	(0.0130)	(0.0124)
2250-2500m	-0.0218	-0.0234*	-0.0205*
	(0.0138)	(0.0127)	(0.0122)
2500-2750m	-0.0103	-0.0152	-0.0105
	(0.0136)	(0.0121)	(0.0117)
2750-3000m	-0.0186	-0.0257**	-0.0237**
	(0.0132)	(0.0121)	(0.0116)
3000-3250m	-0.0251*	-0.0300**	-0.0272**
	(0.0134)	(0.0125)	(0.0121)
3250-3500m	-0.0106	-0.0143	-0.0127
	(0.0125)	(0.0116)	(0.0109)
3500-3750m	-0.0118	-0.0188*	-0.0167
	(0.0122)	(0.0113)	(0.0111)
3750-4000m	-0.0096	-0.0146	-0.0143
	(0.0105)	(0.0096)	(0.0093)
4000-4250m	-0.0077	-0.0131	-0.0124
	(0.0111)	(0.0104)	(0.0104)
4250-4500m	-0.0023	-0.0081	-0.0087
	(0.0104)	(0.0095)	(0.0090)
4500-4750m	0.0015	-0.0045	-0.0052
	(0.0095)	(0.0084)	(0.0081)
4750-5000m	-0.0031	-0.0079	-0.0091
	(0.0092)	(0.0075)	(0.0073)
5000-5250m	0.0022	-0.0041	-0.0046
	(0.0082)	(0.0067)	(0.0064)
5250-5500m	-0.0001	-0.0053	-0.0058
	(0.0070)	(0.0060)	(0.0055)

5500-5750m	0.0011	-0.0062	-0.0054
	(0.0063)	(0.0053)	(0.0048)
ln(acres)	0.1203***		
	(0.0048)		
Missing: Acres†	-0.3302***		
	(0.0286)		
Stories	0.0482***		
	(0.0061)		
Missing: Stories†	0.0653***		
	(0.0171)		
Bathrooms	0.0753***		
	(0.0067)		
Missing: Bathrooms†	0.1962***		
	(0.0244)		
ln(interior sqft)	0.4198***		
	(0.0153)		
Missing: Interior sqft	3.4492***		
	(0.1369)		
Age (years)	-0.0065***		
	(0.0004)		
Age^2	0.0000***		
	(0.0000)		
Missing: Age†	-0.8704***		
	(0.0344)		
% Land Developed w/in 0-500m	0.0009***		
	(0.0001)		
Highway w/in 500m†	-0.0238***		
	(0.0018)		
Lake w/in 500m†	0.0458***		
	(0.0047)		
River w/in 250m†	0.0317***		
	(0.0087)		
Constant	9.0375***	12.1750***	12.1753***
	(0.1155)	(0.0041)	(0.0039)
House attributes	Yes	House × County House × Year	House × County × Year
Year Fixed Effects	Year × County	Year × County	Year × County
Quarter Fixed Effects	Quarter × County	Quarter × County	Quarter × County
Tract Fixed Effects	Yes	Yes	Yes
Observations	10,426,638	10,426,638	10,426,638
Adjusted R-squared	0.737	0.759	0.767

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression models estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

in Appendix B.

Table B.3. Model 3B: Hedonic Regression Examining Price Effects of Multiple Accidents.

	Model 3B
RMP 0-5750 m†	-0.0026
	(0.0034)
# RMP sites 0-5750 m	-0.0006
	(0.0018)
Post-accident†	0.0086*
	(0.0052)
# subsequent accidents	-0.0025
	(0.0016)
Post-accident × 0-5750 m†	-0.0014
	(0.0063)
# subsequent accidents × 0-5750 m	-0.0034
	(0.0028)
Post-Reportable Accident × 0-5750 m†	-0.0047
	(0.0087)
# subsequent post-reportable accidents × 0-5750 m	0.0034
	(0.0053)
Post-Offsite Impact Accident × 0-5750 m†	-0.0139*
	(0.0080)
# subsequent post-offsite impact accidents × 0-5750 m	0.0045
	(0.0075)
Constant	12.1711***
	(0.0038)
House attributes	House × County House × Year
Year Fixed Effects	Year × County
Quarter Fixed Effects	Quarter × County
Tract Fixed Effects	Yes

Observations	10,426,638
Adjusted R-squared	0.759

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression model results of equation (4), and based on a variant of Model 1B. Regression model estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Table B.4. Cumulative price impacts of multiple accidents based on Model 3B.

	Number of Accidents				
	1	**2**	**3**	**4**	**5**
Nonreportable	-0.1395	-0.4768	-0.8129	-1.1479	-1.4817
	(0.6270)	(0.6687)	(0.8075)	(1.0023)	(1.2256)
Reportable	-0.6033	-0.5986	-0.5938	-0.5891	-0.5844
	(0.7027)	(0.8092)	(1.0677)	(1.3960)	(1.7556)
Offsite Impacts	-1.9758***	-1.5339**	-1.0901	-0.6442	-0.1963
	(0.5729)	(0.7410)	(1.1117)	(1.5496)	(2.0145)

Note: * p<0.10, ** p<0.05, *** p<0.01. Estimates calculated following equations similar to (3a) through (3c) using the “nlcom” command in Stata 17/MP, and are based on the coefficient estimates from Model 3B regression results in Table B.3.

Table B.5. Hedonic regression results examining evolution of accident price effects over time.

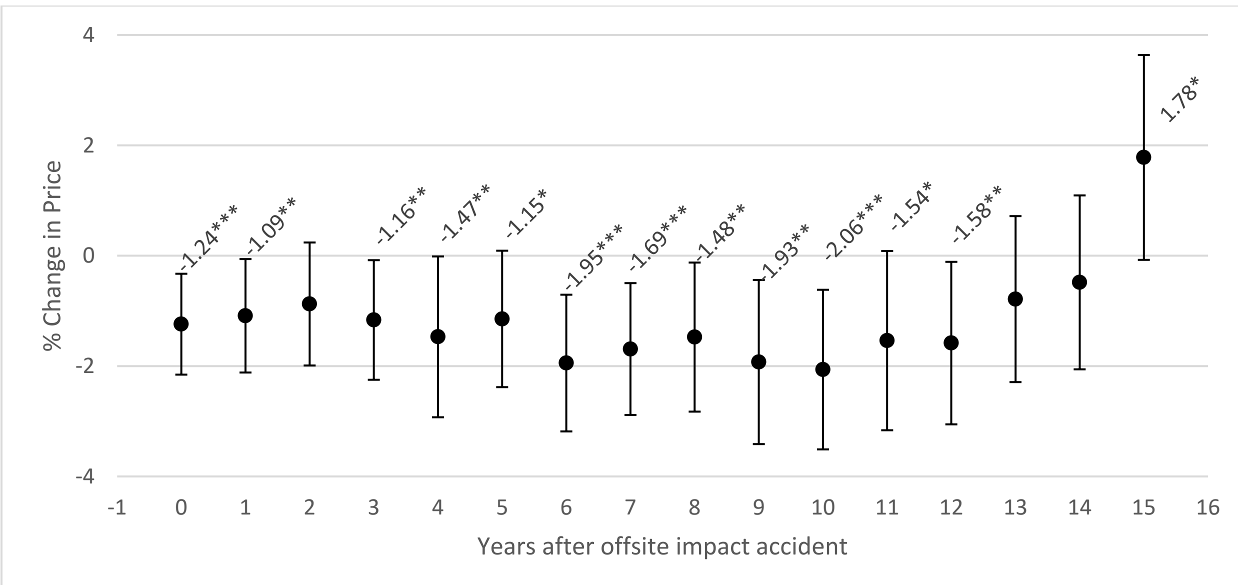
	Model 4B
RMP 0-5750 m†	-0.0035
	(0.0032)
Post-accident†	0.0087
	(0.0054)
Post-accident × 0-5750 m†	
0-1 year	-0.0073
	(0.0058)
1-2 year	0.0005
	(0.0049)
2-3 year	-0.0022
	(0.0049)
3-4 year	-0.0068
	(0.0065)
4-5 year	-0.0059
	(0.0056)
5-6 year	-0.0042
	(0.0051)
6-7 year	-0.0048
	(0.0057)
7-8 year	0.0007
	(0.0062)
8-9 year	-0.0021
	(0.0061)
9-10 year	-0.0032
	(0.0063)
10-11 year	-0.0018
	(0.0058)
11-12 year	-0.0041
	(0.0066)

12-13 year	-0.0028
	(0.0064)
13-14 year	-0.0134
	(0.0086)
14-15 year	-0.0123
	(0.0104)
15-16 year	-0.0075
	(0.0157)
Post-Reportable Accident × 0-5750 m†	
0-1 year	0.0052
	(0.0080)
1-2 year	-0.0078
	(0.0080)
2-3 year	-0.0024
	(0.0081)
3-4 year	-0.0086
	(0.0091)
4-5 year	-0.0099
	(0.0091)
5-6 year	0.0001
	(0.0076)
6-7 year	-0.0023
	(0.0081)
7-8 year	-0.0044
	(0.0082)
8-9 year	0.0061
	(0.0088)
9-10 year	0.0044
	(0.0084)
10-11 year	0.0042
	(0.0091)
11-12 year	-0.0005
	(0.0100)
12-13 year	-0.0019
	(0.0088)
13-14 year	0.0113
	(0.0113)
14-15 year	0.0251
	(0.0171)
15-16 year	0.0267
	(0.0217)
Post-Offsite Impact Accident × 0-5750 m†	
0-1 year	-0.0104*
	(0.0062)

1-2 year	-0.0037
	(0.0085)
2-3 year	-0.0042
	(0.0089)
3-4 year	0.0036
	(0.0086)
4-5 year	0.0010
	(0.0096)
5-6 year	-0.0075
	(0.0086)
6-7 year	-0.0126
	(0.0085)
7-8 year	-0.0134
	(0.0083)
8-9 year	-0.0189**
	(0.0087)
9-10 year	-0.0207**
	(0.0096)
10-11 year	-0.0233**
	(0.0098)
11-12 year	-0.0109
	(0.0102)
12-13 year	-0.0112
	(0.0098)
13-14 year	-0.0058
	(0.0103)
14-15 year	-0.0176
	(0.0147)
15-16 year	-0.0016
	(0.0189)
Constant	12.1690***
	(0.0039)
House attributes	House × County House × Year
Year Fixed Effects	Year × County
Quarter Fixed Effects	Quarter × County
Tract Fixed Effects	Yes
Observations	10,426,638
Adjusted R-squared	0.759

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Regression model results of equation (5), and based on a variant of Model 1B. Regression model estimated using "reghdfe" command in Stata 17/MP. Note that 1,804 singleton observations were dropped from the regression model. Variables denoted with † are binary indicators.

Figure B.3. Percent change in price by year after offsite impact accident: Based on Model 4B.



Note: Estimates calculated following an equation similar to equation (3c) using the “nlcom” command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 4B in Table B.5 in Appendix B.