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ABSTRACT: Using hedonic property value methods, we examine how chemical accidents at industrial facilities impact home values in surrounding communities. The study focuses on facilities regulated by the U.S. Environmental Protection Agency's (EPA) Risk Management Plan (RMP) program, which is in place to reduce the risk of harm to offsite populations from accidental chemical fires, explosions, and releases of toxic vapors. RMP facility and accident data were linked to residential property transactions in Michigan, Ohio, and Pennsylvania occurring between 2004 and 2014. To facilitate causal inference, alternative quasi-experimental difference-in-differences and triple differences models are estimated, where we compare homes near and far, and before and after, an accident; as well as homes near RMP facilities where an accident did and did not occur. We find that the typical accident does not affect home values, but accidents resulting in offsite injuries, property damage, evacuations, or shelter-in-place orders lead to a 5% to 7% decrease in the value of homes within five kilometers, this translates to an average loss of $12,000 to $17,000 per home. The benefits of the RMP program in avoiding these impacts are particularly relevant from an environmental justice standpoint. We find that proximity to an RMP facility, irrespective of any incidents, is already associated with significantly lower home values. These existing inequities are exacerbated by chemical accidents that impact offsite populations.

KEYWORDS: chemical accident, environmental justice, hedonic, nonmarket valuation, property value, Risk Management Plan

JEL CODES: D63; Q51; Q53

The Property Value Impacts of Industrial Chemical Accidents*

Dennis Guignet,[a] Robin Jenkins,[b] James Belke,[c] and Henry Mason[d]

I. INTRODUCTION

To promote safe industrial activity, the U.S. Environmental Protection Agency (EPA) requires that certain industrial facilities participate in the Risk Management Plan (RMP) program. The purpose of the program is to protect the general public and the environment from accidental chemical releases that can result in toxic clouds, fires, and explosions. While on-site worker safety is regulated under the purview of the U.S. Occupational Safety and Health Administration (OSHA), EPA's RMP program is specifically meant to reduce risks to surrounding populations, living in nearby "fence-line" communities.

The RMP program covers a wide range of industry categories, from large multi-process manufacturing plants such as petroleum refineries and chemical manufacturers, to smaller facilities such as agricultural chemical distributors, water and wastewater treatment systems, and cold storage facilities. In between there are a variety of other specialty chemical manufacturers, energy production facilities, chemical storage terminals and warehouses, natural gas processing plants, and food manufacturers, among others. In total, approximately 12,000 U.S. facilities are currently regulated under the RMP program.[1] EPA estimates that at least 40 million people (or about 12% of the U.S. population), and perhaps as many as 177 million (55%), are at risk of being impacted

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[1] According to EPA's RMP National Database, there were 11,759 active RMP facilities as of July 4, 2021 (Source: EPA Office of Emergency Management).

by an accident at these facilities (U.S. EPA, 2016).[2] From 2004-2013, there was an average of about 150 accidents with reportable impacts each year in the U.S.[3] About 31% of those accidents involved off-site deaths, injuries, property damage, evacuations, sheltering-in-place, or environmental damage (U.S. EPA, 2016).

The RMP program has three primary objectives: accident prevention, damage mitigation, and information provision. The program was authorized in the U.S. Clean Air Act (CAA) Amendments of 1990 as a result of the catastrophic chemical accident that occurred in 1984 in Bhopal, India, as well as other serious chemical accidents in the U.S. during the late 1980s.[4] Section 112(r) of the CAA Amendments created a "general duty" for owners and operators of "stationary sources" holding extremely hazardous substances to identify potential hazards, take steps to prevent releases, and to minimize the consequences of accidental releases that do occur.[5] Section 112(r) also required EPA to develop a list of at least 100 regulated substances for accident prevention[6] and to develop ''reasonable regulations'' requiring facilities with over a threshold quantity of a regulated substance to undertake accident prevention steps and submit a ''risk management plan'' (RMP) to various local, state, and federal planning entities.[7] The final RMP regulation promulgated by EPA in 1996 requires that any stationary source that uses, stores, manufactures, or handles, more than a threshold quantity of one or more of the 140 listed substances must submit an RMP to prevent accidents and minimize any potential damage.[8]

The RMP regulations require regulated facilities to take a number of steps, such as: (i) performing a hazard assessment to estimate the potential effects of an accidental release; (ii) implementing a program to prevent accidental releases of regulated substances, including written safe operating procedures, regular maintenance activities, compliance audits, employee training, and other measures; and (iii) developing an emergency response program requiring specific actions in response to an accidental release in order to minimize the impacts to human health and the environment. The emergency response program includes procedures for informing the public and local agencies responsible for responding to accidental releases, and annual coordination with responders, as well as emergency health care and employee training measures. Owners or operators of regulated facilities must develop and submit a report to EPA that summarizes the facility's RMP. The report must be updated every five years or sooner, if certain changes occur at the facility.

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[2] In the Regulatory Impact Analysis for the "Accidental Release Prevention Requirements" rule, EPA reported that approximately 177 million people would be impacted by a hypothetical worst-case scenario accident 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).

[3] Some facilities reported accidental releases with no "reportable" impacts (i.e., no deaths, injuries, property damage, etc.). Such accidents were not counted in determining the annual average number of accidents (US EPA, 2016).

[4] For example, the Phillips Petroleum Company disaster of 1989 in Pasadena, Texas involved a series of explosions and fire with over 20 worker deaths and over 150 injuries.

[5] 42 U.S.C. § 7412(r)(1)

[6] CAA section 112(r)(3)–(5)

[7] CAA section 112(r)(7)(B)

[8] 61 FR 31668, June 20, 1996

Economic analyses conducted by EPA for recent RMP program rulemakings have omitted estimation of benefits and been limited to presentations of baseline damages (U.S. EPA 2016, 2019). This study fills an important gap by providing valuable information to decision makers assessing the benefits of policies to prevent and mitigate industrial chemical accidents.

Focusing on over 3.6 million single-family home transactions in Michigan, Ohio, and Pennsylvania from 2004-2014, we use hedonic property value methods to examine how chemical accidents at RMP facilities impact nearby residents. To support causal inference, difference-in-differences and triple differences quasi-experimental models are estimated, where we compare homes near and far, and before and after, an accident; as well as homes near RMP facilities where an accident did and did not occur. Although there are local case studies on the property value impacts of similar disamenities (e.g., Carroll et al. 1996; Hansen et al. 2006; Grislain-Letremy and Katossky 2014; and Herrnstadt and Sweeney 2019), to our knowledge this is the first comprehensive broader-scale non-market valuation study on accidents at chemical facilities, and the first specifically on the RMP program.

This study is also unique compared to quasi-experimental hedonic property value studies of other EPA programs involving the cleanup of hazardous chemicals (e.g., Cassidy et al., 2021; Gamper-Rabindran and Timmins, 2013; Guignet et al., 2018; Guignet and Nolte, 2021; Haninger et al., 2017). Relative to lingering environmental contamination at Superfund sites, brownfields, underground storage tank releases, and other types of contaminated industrial sites, the damages addressed by the RMP program are immediate, and perhaps more evident in many cases. These other categories of contamination often involve releases that are not immediately apparent, often entailing, for example, slowly spreading releases into soil or groundwater. In contrast, RMP accidents can involve fires, explosions, immediate shelter-in-place and evacuation orders, first-responder activities, and other overt cues that clearly alert the surrounding community. Certain information about RMP accidents may be more transparent; including the identity of the responsible party, which may be reported by local press.

We find that the typical accident does not affect home values, on average, but accidents resulting in offsite injuries, environmental damage[9], evacuations, or shelter-in-place orders lead to a 5% to 7% decrease in the value of homes within five kilometers. Widespread awareness of accidents resulting in offsite impacts among buyers and sellers in nearby housing markets is more likely relative to accidents resulting only in onsite impacts. Accidents with offsite impacts are generally more severe, and local communities are directly affected.

This finding is important to policy makers. Property value impacts from accidents affecting offsite populations are particularly relevant for EPA's RMP program. EPA's responsibility is primarily to reduce the risk of offsite harms, including to the general public and the environment (US EPA 1996).

RMP program benefits are also important from an environmental justice standpoint. RMP facilities that are larger (indicated by number of workers), that use more regulated chemicals, and that have

[9] Types of environmental damage include fish or animal kills; lawn, shrub, or crop damage; water contamination; etc.

experienced more than one accident, are more likely to be in counties where a greater proportion of the population is Black, and/or where (although the median income is higher) there are higher levels of income inequality (Elliot, et al. 2004). Our data show homes within two kilometers of a single RMP facility, irrespective of any accidents, tend to be 2% to 4% lower in value, all else constant. We also find strong cumulative effects associated with proximity to multiple RMP facilities. For example, being located within one kilometer of three RMP facilities is associated with 13% lower home values. Additional property value declines due to chemical accidents at these facilities further exacerbate existing inequities.

In the next section we review the relevant literature on the property value impacts of similar disamenities involving releases of hazardous chemicals. The data and methods are described in sections III and IV, respectively, followed by the results in section V. We provide concluding remarks in section VI.

II. LITERATURE

Prior research involving RMP facilities includes descriptive analyses of data from the initial wave of RMP submissions covering accident histories from 1994 to 2000. This work identified directions for future research (Kleindorfer, et al., 2003), considered what aspects of an RMP facility best characterized its "hazardousness" (Elliot, et al., 2003), examined the relationship between facilities' propensity for accidents and financial condition, capital structure, regulatory environment, and other characteristics (Kleindorfer et al., 2004), and explored the frequency of RMP chemical accidents and riskiness of RMP facilities in relation to the socioeconomic status of surrounding communities (Elliot et al., 2004). However, to date no study has explored the relationship between RMP facility accidents and surrounding property values.

The economics literature has explored the effect on property values of a wide assortment of environmental disamenities. Grislain-Letrémy and Katossky (2014) provide a targeted review of property price impacts of hazardous industrial facilities, reviewing studies that examined data for one to a handful of affected regions. In general, these studies find that prices increase with distance from the facility and that the magnitude of the price impact varies across regions.

The impact of ambient air pollution on property values has been examined with a variety of property value data and assorted hedonic models.[10] Recently the literature has focused on the distributional impacts of property value appreciation, or on the attenuation of appreciation by labor market impacts. For example, Bento, et al., (2015) examine the effect of the Clean Air Act Amendments of 1990 on tract-level housing values near PM10 air monitors that are in a non-attainment status and likely to be targeted for air quality improvements. They find significant

[10] A broad review of the earlier hedonic property value literature examining ambient air quality is provided in meta-analyses by Smith and Huang (1993; 1995).

appreciation within 5 miles, and insignificant impacts on rents for the same distance. Agarwal, et al. (2019) examine the effect of the NOx Budget Trading Program. House prices increased in areas with low percentages of residents employed in manufacturing but decreased in areas with high percentages, suggesting that negative impacts on labor markets counteract appreciation of housing values. A variety of other studies find that air quality improvements increase housing values (Amini, et al. 2021, Lang 2015, Grainger 2012, Bayer, et al. 2009, Chay and Greenstone 2005).

Many studies of the property value effects of ambient air quality have focused on criteria air pollutants, but Currie, et al. (2015) explore the effect of toxic air pollutants. They examine housing transactions near 1,600 industrial plant openings and closings for plants that report toxic air emissions to the Toxic Release Inventory (TRI) in five U.S. states. The TRI requires firms to report fugitive emissions including pollutant quantities that are accidentally emitted and those that are routinely and intentionally emitted. They compare house prices before and after plant openings and find that prices within 0.5 miles decrease by 11 percent after a plant opens. House prices do not respond when a plant closes.

Research on how property values change in response to infrequent, accidental emissions events is relatively uncommon, and mainly limited to a few geographically focused case studies. Flower and Ragas (1994) studied house prices in Louisiana that were located near two petrochemical refineries. They found that being close to one refinery with a large buffer zone was associated with higher property values, except during a one-year period following a tank explosion. For the second refinery, home prices declined with proximity. Carroll et al. (1996) studied property prices in neighborhoods surrounding a chemical facility in Nevada before and after a 1988 explosion. They found a 17.6% decline in property values in the two closest towns following the explosion. These towns were located approximately 3.5 miles from the plant. An announcement regarding closure of the facility was associated with a 38% rebound in home prices, suggesting that proximity to the plant suppressed home values prior to the explosion.

Pipelines are not as visible to nearby residents as chemical facilities. For homeowners near pipelines, post-accident property values may decline by more than they would if accident risks were already capitalized into home values, as one would suspect for properties near more visible RMP facilities. Cheng, et al. (2021) conduct a nationwide property value analysis of how accidents at natural gas distribution pipelines impact nearby home values. Using a difference-in-difference approach comparing pre- and post-incident transactions, their preliminary results suggest that the value of homes within 1 km decline by 7.4% compared to a control group of houses 1-2km from an explosion. Liao, et al. (2022) examine properties near and distant from pipelines in a major city in Taiwan before and after a catastrophic series of gas pipeline explosions, as well as soon after the release of a map disclosing pipeline locations for the first-time. Following both treatments, treated properties (within 1.3 km of any hazardous pipeline) were 2.6% lower in value than homes farther away. Hansen et al. (2006) studied home sales located within a mile of two pipelines to estimate the impacts of a 1999 fuel pipeline explosion in Bellingham, Washington. Following that event, property prices were significantly lower, with the effect diminishing over time and by distance, from a 4.6% decline for a property 50 feet from the pipeline to 0.2% at 1,000 feet away.

Herrnstadt and Sweeney (2019) studied how property values responded to the combination of a 2010 pipeline explosion in San Bruno, California, and a subsequent mail notification to all households living within 2000 feet of any natural gas pipeline. Using a difference-in-differences approach comparing transactions within 2000 feet from a pipeline to those between 2000 and 4000 feet before and after the explosion and mailed notifications, they found no impact on prices. The result is confirmed by a triple differences comparison against properties near pipelines managed by other California utilities. Possibly, the information disclosure did not cause nearby homeowners to revise their perceived risks; the observed risk of death from a pipeline explosion in California is relatively low at only 0.053 deaths per million people annually (Hernstadt and Sweeney 2019).

Less dramatic releases at industrial and commercial facilities that result in lingering contamination can also affect property values. Guignet et al. (2018) examine property value changes around high-profile releases from underground storage tanks (USTs) at retail gas stations. Using difference-in-differences hedonic equations and an internal meta-analysis, they find that homes within 3 km depreciate an average of 6% after a release. Guignet and Nolte (2021) conduct a nationwide property value study of hazardous waste treatment, storage, and disposal facilities (TSDFs) in need of remediation. Although they do not necessarily interpret it as causal, they find evidence that home values within 750 meters of a TSDF decrease up to 5% after the discovery of contamination and initiation of a cleanup investigation. Both studies find causal evidence that home values rebound by 6% to 7% after the contamination is cleaned up.

Chemical releases and accidents at RMP facilities differ from those studied by Guignet et al. (2018) and Guignet and Nolte (2021) because RMP accidents involve fires, explosions, and releases of toxic plumes into the air, which although sometimes severe, rarely result in lingering environmental contamination. RMP accidents are distinct release events, which make them more perceivable to surrounding residents. In cases involving an immediate threat, residents are notified by first-responders, or indirectly informed by visual cues and local press. (Information about RMP accidents is also made available to the public through reports to EPA.[11]) In contrast, releases of hazardous substances from USTs and TSDFs often pollute the land, groundwater, or surface water. The release events may happen years before they are discovered, and there is an element of uncertainty to nearby property owners as to when and if a cleanup will occur. To our knowledge,

[11] Accidents must be reported to EPA within 6 months of their occurrence. Once reported, the information is publicly available though not easily accessible. Non-governmental organizations have occasionally obtained and republished the accident information in a more publicly accessible format. For example, see OMB Watch, Press Release, October 29, 2009 at https://firstamendmentcoalition.org/2009/10/omb-watch-posts-details-of-risks-posed-by-u-s-chemical-facilities/ or Reynolds Journalism Institute, "Houston Chronicle, RJI partner to keep chemical company data site available for journalists," June 12, 2019 at https://rjionline.org/news/houston-chronicle-rji-partner-to-keep-chemical-company-data-site-available-for-journalists/ .

the current study is the first comprehensive, broader-scale non-market valuation study on accidents at chemical facilities that result in fugitive air emissions, and the first specifically on the RMP program.

III. DATA

The analysis focuses on home sales and RMP sites in Michigan, Ohio, and Pennsylvania from 2004 through 2014. Two datasets are combined to examine how RMP facilities and accidents affect home values in the surrounding communities. The first dataset contains all RMP facilities and chemical accidents covered by EPA's RMP program. The RMP facilities and accidents are then spatially and temporally linked to transaction data of single-family homes obtained through Zillow's ZTRAX program. Both datasets are discussed in detail below. Additional data were obtained from a variety of sources to calculate distances between homes and local amenities/dismenities, such as major roads, large lakes, and Superfund sites.

III.A. RMP Facilities and Accidents

Beginning with the initial RMP submissions in 1999, EPA maintains a national database of all RMPs submitted to the Agency by the regulated facilities. All RMP submissions are required to include a facility's five-year history of accidental releases from regulated processes that resulted in deaths, injuries, significant property damage on site, or known offsite deaths, injuries, evacuations, sheltering in place, property damage, or environmental damage.[12] RMPs are required to be updated and resubmitted at least every five years, so the RMP national database contains a continuous record of accidents from regulated facilities spanning from mid-1994 (five years prior to initial submissions) to the present.

Our analysis focuses on the 1,578 RMP facilities in Michigan, Ohio, and Pennsylvania (see Figure 1). These data were pulled from the national database by the EPA's Office of Emergency Management (OEM) in June of 2018. The RMP facilities are involved in an array of different industrial activities (as described in section I). Geographic coordinates are provided by the facilities themselves, and most often refer to the facility centroid (42%) or plant entrance (16%). In the remaining cases the coordinates correspond to some other point on the property (e.g., a storage tank, administrative building, processing or treatment units, and so on.).

During our 2004-2014 study period, 209 accidents involving at least one RMP-regulated chemical occurred at 124 of these facilities. Between 13 and 27 separate chemical accidents occurred in any given year (see Figure A1 in the Appendix). Among the facilities where an accident occurred, most had just a single accident (81), but some facilities had two (24), three (10), four (5), five (2), and

[12] See 40 CFR 68.42.

six accidents (1) during our study period. At the upper end, one facility in Schuylkill County, PA reported 14 separate accidents.

Descriptive statistics for the 209 accidents are provided in Table 1. Most accidents (183 or 88%) involved the release of just a single chemical, with the mean number of chemicals released being 1.2. However, at 26 (12.4%) of the accidents multiple chemicals were released. Sixty-four percent of accidents involved a gas or vapor release, and 38% of the incidents involved a liquid spill and evaporation of the chemical. Although not as common, chemical fires and explosions are observed at 9% and 2% of the accidents, respectively. About 4% of the accidents involved an uncontrolled chemical reaction. Environmental damage (e.g., fish or animal kills, defoliation of trees, and water contamination) occurred in about 5% of the accidents. In about half the cases (48%) first responders were notified and deployed.

Two accidents each resulted in one on-site mortality, and one accident led to the death of two individuals. On-site injuries occurred at 79 (37.8%) of the accidents. Among the 40 accidents where onsite property damage was reported, the average amount of damage was estimated at $3.4 million.

The typical accident did not directly impact offsite populations, but in a quarter of the accidents (51 cases or 24.4%) there were direct impacts to individuals located offsite. No offsite mortalities occurred, but offsite injuries requiring hospitalization or other medical treatments were experienced at 19 of the accidents, with the number of people injured ranging from one to 25 individuals. Damage to offsite properties was reported in 8 cases, with the average amount of damage valued at approximately $175,000. Among the 23 cases involving evacuations of nearby communities, on average about 130 people were evacuated. Anywhere from 20 to over 4,500 people located offsite were ordered to shelter-in-place in 13 of the incidents.

III.B. Residential Property Transactions

The initial analysis focuses on the 3,686,984 single-family home transactions that were within 25 km of at least one RMP site.[13] The average home sold for a price of $159,217 (2019$), had a lot size of 0.28 acres, was 1.5 stories, 52 years in age, and had 2.3 bedrooms, 1.7 bathrooms, and was 3,100 square feet in size. Values for lot acreage, number of stories, number of bathrooms, interior square footage, and age was missing for about 12.9% to 16.7% of the sample, as indicated by the companion missing value indicators. In our subsequent regression models the missing values are coded as zero, and the corresponding missing indicator variables are included as independent variables. Locational variables are included in the regression models to account for any within

[13] Outlier transactions where the real sales price was less than $10,000 or greater than $1 million, where lot size was greater than 1.3 acres (90th percentile), where the number of stories was greater than three (99th percentile), the interior square footage was less than the lowest or greater than the highest percentiles (807 sqft. and 10,048 sqft., respectively), the number of bedrooms was greater than seven, the number of bathrooms was greater than six, or when the census tract identifiers were missing, are dropped. We also excluded likely non-arms-length sales where a token nominal price of $1 was listed, or where different parcels had the exact same coordinates, as recommended by Nolte et al. (2021).

tract price variation due to proximity to local amenities and disamenities. Distance from each home to the nearest primary road, Superfund site listed on the National Priorities List (NPL), and large lake were all calculated within a Geographic Information System (GIS).

There are a substantial number of sales within each of the one-kilometer distance bins around an RMP facility. This number steadily increases, starting with over 210k transactions within 0-1 km of a site, all the way out to over 2.3 million transactions within 24-25 km of an RMP site (see Figure A2 in the Appendix).

Narrowing the focus to transactions with an accident in close proximity, the numbers remain large. Even within the nearest distance bin of 0-1 km, there are 9,657 and 9,289 home sales observed before and after an accident respectively. Among the post-accident transactions, 2,944 are within 0-1 km of an accident that did involve offsite impacts, and 6,345 sales are within 0-1 km of an accident that had no offsite impacts. The number of identifying transactions in each incremental bin before and after an accident increases sharply as distance increases (see Figure A3 in the Appendix). These transactions serve as the treatment and control groups in our quasi-experimental framework.

IV. METHODS

IV.A. The Spatial Difference-in-differences and Triple Differences Approach

The usefulness of the spatial DID approach for causal inference in hedonic pricing studies was made clear through early applications by Davis (2004) and Linden and Rockoff (2008). The approach remains at the forefront of hedonic pricing methods (Guignet and Lee, 2021), and has been applied in numerous studies measuring environmental impacts on home values, including analyses of contaminated site cleanups (Haninger et al., 2017; Guignet et al., 2018;), aquatic vegetation and invasive species (Guignet et al., 2017; Horsch and Lewis, 2009), flood and hurricane risks (Atreya et al., 2013; Bin and Landry, 2013), and unconventional shale gas extraction (Muehlenbachs et al., 2015).

The DID strategy is intuitive in mimicking a classical experimental design. Consider the stylized illustration in Figure 2. The top row represents homes in a community near an RMP facility where a chemical accident occurs. The bottom row represents homes in a community near an RMP facility where an accident does not occur. The left column denotes the time period before an accident, and the right column denotes the time period after an accident. Each outer circle represents homes farther from an accident than homes represented by each inner circle.

The price effect of interest is experienced by homes in group B. These are homes in close proximity to an RMP facility after an accident occurs (i.e., the treated group, post-treatment). A simple cross-sectional comparison of homes near an RMP site with an accident to those near a site without an accident provides a first difference estimate of how the accident impacts home values, i.e., B-B'. However, the RMP facilities and surrounding communities where accidents tend to occur or not occur may be systematically different for unobserved reasons, which would confound such a first difference estimate.

Our cross-area DID estimate addresses this by exploiting temporal variation in when accidents occur. This second differencing comes from comparing the change in home values before and after the accident occurs *(B-A)*, to the change in home values during this same time period around the counterfactual RMP site *(B'-A')*. Our cross-area DID estimates are represented as *(B-A)-(B'-A')*. Such estimates, however, could be biased if the trends in the neighborhoods where contamination does and does not occur also differ systematically over time.

We can frame an alternative within-area DID estimate that uses homes in the same community, but that are far enough away from the RMP site as to not be impacted by the accident, as the counterfactual. In doing so, broader neighborhood-specific trends can be differenced out. Our within-area DID estimate can be expressed as *(B-A)-(D-C)*. This is the same as the conventional spatial DID strategy implemented in preceding hedonic studies (e.g., Linden and Rockoff, 2008; Haninger et al., 2017; Muehlenbachs et al., 2015). Nonetheless, such estimates could be biased if the trends in homes value near versus far from an RMP facility are systematically different for unobserved reasons.

Our triple differences estimate addresses that latter possibility by accounting for both layers of controls and differencing out broader neighborhood trends *and* systematic differences between homes that are near versus far from an RMP site. Our triple differences estimate in this stylized illustration is represented as: *{(B-A)-(B'-A')} - {(D-C)-(D'-C')}*.

IV.B. Hedonic Property Value Model

Our DID and triple differences approaches are couched within a hedonic regression framework, where the dependent variable is the natural log of the price of home *i*, in neighborhood *j*, in housing market *m* (i.e., county), at time *t* (p_{ijmt}). More formally:

$$\text{(1)} \qquad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \mathbb{1}(\boldsymbol{RMP}_{ijm} > 0)\boldsymbol{\rho} + \boldsymbol{RMP}_{ijm}\boldsymbol{\varphi} + \boldsymbol{pre}_{ijmt}\boldsymbol{\gamma}^{pre}$$

$$+\boldsymbol{post}_{ijmt}\boldsymbol{\gamma}^{post} + (\boldsymbol{post}_{ijmt} \times \boldsymbol{off}_{ijmt})\boldsymbol{\theta}^{post} + \boldsymbol{\tau}_{mt} + \upsilon_{jm} + \varepsilon_{ijmt}$$

We control for house and neighborhood characteristics $(\boldsymbol{x}_{ijmt})$, such as the age of the home, interior square footage, lot size, the number of bathrooms and bedrooms, and distance to primary roads, Superfund sites, and large lakes. As reflected by the subscript on the $\boldsymbol{\beta}_{mt}$ coefficient, the hedonic price surface with respect to these attributes is allowed to vary by housing market (i.e., county) and year. Although not explicitly represented for notational ease, this is implemented by including *county* × *year* interaction terms with all elements of $\boldsymbol{x}_{ijmt}$. We are assuming a single hedonic price surface across the tri-state area when estimating equation (1), but these interaction terms allow the equilibrium price surface to vary across markets and over time in these dimensions. Individual county-by-year and county-by-quarter fixed effects $(\boldsymbol{\tau}_{mt})$ are included to capture broader market-specific trends and seasonal effects. Spatial fixed effects at the neighborhood (i.e., census tract) level are also included (υ_{jm}) to account for all time-invariant factors associated with a specific location. ε_{ijmt} is a normally distributed disturbance term, which we allow to be correlated for all transactions within the same county.

The parameters of direct interest are $\boldsymbol{\rho}$, $\boldsymbol{\varphi}$, $\boldsymbol{\gamma}^{pre}$, $\boldsymbol{\gamma}^{post}$ and $\boldsymbol{\theta}^{post}$. The vector $\boldsymbol{RMP}_{ijm}$ denotes the number of RMP sites within each one-kilometer incremental bin around a home (e.g., 0-1km, 1-2km, and so on), and $\mathbb{1}(\boldsymbol{RMP}_{ijm} > 0)$ is a vector of indicator variables denoting the presence of at least one RMP facility in each one-kilometer bin. Estimates of $\boldsymbol{\rho}$ and $\boldsymbol{\varphi}$ are used to estimate the price-distance gradient associated with proximity to RMP facilities, irrespective of any chemical accidents that may occur. The variable $\boldsymbol{pre}_{ijmt}$ is a vector of indicator variables denoting the presence of an RMP accident in each one-kilometer distance bin around a home, but where the accident had not yet occurred as of the time of the sale. The variable $\boldsymbol{post}_{ijmt}$ denotes the presence of an accident in each one-kilometer bin that had occurred as of the time of sale. The coefficient vectors $\boldsymbol{\gamma}^{pre}$ and $\boldsymbol{\gamma}^{post}$ reflect the incremental difference in home values around an RMP site where an accident will eventually occur or has occurred, respectively, relative to similar homes near an RMP site where an accident does not occur during our timeframe. These parameters by themselves reflect the cross-sectional first difference estimates described in section IV.A.

To investigate heterogeneity in the impact of RMP accidents on home values depending on whether there were offsite accident impacts, we include an additional binary interaction term $\boldsymbol{post}_{ijmt} \times \boldsymbol{off}_{ijmt}$. The corresponding coefficient $\boldsymbol{\theta}^{post}$ captures the incremental effect of an accident when there are direct impacts to the surrounding community; specifically, injuries to offsite populations, offsite environmental damage, or if populations located offsite were evacuated or ordered to shelter-in-place.

In our most flexible models, proximity to RMP sites and accidents are measured using one-kilometer incremental bins, but for the main regression models, as informed by initial data diagnostics (described in section V.B), broader bins are assumed for the treated (i.e., 0-5km) and control groups (i.e., 7-10km).

Let *d* denote a treated group distance bin (e.g., 0-5km). The cross-area DID estimates of the percent change in property price due to an accident are calculated as:

(2) $$DD_{[d]} = \left\{\exp\left(\gamma_{[d]}^{post} - \gamma_{[d]}^{pre}\right) - 1\right\} \times 100$$

This cross-area DID estimate can be interpreted as a weighted average of the Average Treatment Effect on the Treated. It reflects the average percent change in price among homes located in distance bin *d* from a typical RMP accident that did not result in direct offsite impacts, relative to before the accident occurred. In contrast, the DID estimate of the percent change in price from an accident where there are direct offsite impacts can be calculated as:

(3) $$DD_{[d]}^{Offsite} = \left\{\exp\left(\gamma_{[d]}^{post} + \theta_{[d]}^{post} - \gamma_{[d]}^{pre}\right) - 1\right\} \times 100$$

The triple differences and within-area DID estimates require that we further difference out the change in home values in the farther control group distance bin. Among homes located in distance bin *d*, estimates of the triple differences treatment effect from a typical accident that yields no direct offsite impacts and from an accident that does lead to offsite impacts are calculated, respectively, as:

$$(4) \qquad D3_{[d]} = \left\{\exp\left(\left[\gamma_{[d]}^{post} - \gamma_{[d]}^{pre}\right] - \left[\gamma_{[ctrl]}^{post} - \gamma_{[ctrl]}^{pre}\right]\right) - 1\right\} \times 100$$

$$(5) \qquad D3_{[d]}^{Offsite} = \left\{\exp\left(\left[\gamma_{[d]}^{post} + \theta_{[d]}^{post} - \gamma_{[d]}^{pre}\right] - \left[\gamma_{[ctrl]}^{post} + \theta_{[ctrl]}^{post} - \gamma_{[ctrl]}^{pre}\right]\right) - 1\right\} \times 100$$

where $\gamma_{[ctrl]}^{pre}$ and $\gamma_{[ctrl]}^{post}$ are the coefficients corresponding to the farther control group distance bin (which we later assume to be 7-10km, see section V.B for details).

In our more focused analysis of just homes within ten kilometers of an RMP accident, we drop all home transactions that are only near an RMP site where no accident occurs. However, due to the sometimes-clustered nature of RMP sites, we must still control for the presence and number of nearby RMP facilities. Therefore, the within-area DID estimates are also calculated following equations (4) and (5). Although the calculations are the same, dropping that initial control group of homes near an RMP where no accident occurs degrades a triple differences interpretation.

IV.C. Coarsened Exact Matching

To examine the robustness of our results, in later models we perform a pre-regression matching exercise that prunes and re-weights observations so that the defined treatment and control groups have more balanced distributions in terms of the observed attributes. More specifically, we use coarsened exact matching (CEM) techniques (Blackwell et al., 2009; Iacus et al., 2012). The CEM approach first divides the continuous attribute space for the relevant variables into discrete bins. Then home transactions that fall within the same set of discrete attribute bins (i.e., have the same value for *all* "coarsened" attributes) are matched. Homes are matched based on coarsened variables of the number of bathrooms, age, interior square footage, lot acreage, and distance to a primary road.[14] In addition, we match homes in the treated and control groups only if they are in the same county and sold in the same year. Transactions in the control group are dropped from the matched sample if there are no transactions in the treated group that occurred in the same county and year, and vice versa.

The CEM algorithm assigns weights to the treated and control group observations. A weight of one is given to all treated home sales that could be matched to at least one control home sale. A treated observation can potentially be matched to more than one control observation, and one control observation can be matched to more than one treated observation, and so all maintained control home sales are given a positive weight that may be less than, equal to, or greater than one. Despite its advantages in flexibly matching observations to make the treated and control groups

[14] Three coarsened attribute values are defined for each variable, where the cutoffs are roughly based on the 25th and 75th percentiles for each attribute. The coarsened acres variable is divided into four values, using the 25th, 50th, and 75th percentiles as cutoffs. An additional "missing" category is included for each of the coarsened variables, when applicable.

simultaneously more comparable across numerous dimensions, the CEM procedure has been used in only a few other hedonic property value studies (Groves and Rogers, 2011; Guignet et al., 2018; Guignet and Nolte, 2021; Qiu et al., 2017).

V. RESULTS

V.A. Proximity to RMP Sites

Before examining the impacts of a chemical accident on house prices, we first wish to understand the baseline association between house prices and proximity to an RMP site, irrespective of an accident. To do so, we estimate the percent change in price as a function of distance to the site using the results from Model 1 (shown in Table A1 in the Appendix). Following the estimates from Equation (1), the percent change in price associated with one, two, or three RMP sites within distance bin *d* of a home is calculated as:

$$(6) \qquad \%\Delta p_{[d]}^{RMP} = \left\{\exp\left(\rho_{[d]} + \left(\varphi_{[d]} \times RMP_{[d]}\right)\right) - 1\right\} \times 100$$

Figure 4 illustrates the results and suggests that homes within 0-1 km of a single RMP site tend to be 4.4% lower in value, all else constant. This negative association is relative to homes 24-25 km from a single site and extends to two kilometers, with a 1.9% depreciation associated with being within 1-2 km of a single site. Although we do not claim this as a causal estimate, especially since RMP facilities may be located in areas that host multiple industrial uses, it does suggest that homes nearest an RMP site tend to be lower in value due to disamenities associated with the site itself and/or due to the surrounding neighborhood. After two kilometers we see statistically insignificant negative, or even small positive price effects associated with proximity to an RMP site, ranging from -0.4% to 1.1%.

Figure 3 also demonstrates strong cumulative effects associated with proximity to RMP sites. Being within 0-1 km and 1-2 km of two RMP sites is associated with an 8.7% and 3.7% decline in home values, all else constant. And homes within 0-1 km and 1-2 km of three RMP sites tend to be 12.8% and 5.4% lower in value, respectively. Again, we find no statistically significant evidence of a negative association between home prices and proximity to RMP sites beyond two kilometers. However, these negative associations should be considered conservative because the estimates are conditional on census tract-level fixed effects.

All else constant, we find that homes nearest RMP facilities tend to be significantly lower in value, especially in neighborhoods where multiple facilities are present. This is an important finding from an environmental justice standpoint. Any adverse impacts from a chemical accident could further depress the value of this critical financial asset; thus, further reducing the wealth of resident home owners and diminishing landlords' incentives to maintain or improve the housing stock occupied by renters.

V.B. Determining the Treated and Control Groups

As with any DID application, appropriately determining the treated and control groups is of the utmost importance. Such is particularly true in the case of spatial DID applications, where there is no clear assignment into the treated and control groups. Rather, researchers rely on data diagnostics to determine what observations should fall into the treated or control group categories based on spatial location (usually distance) to the commodity of interest. In such settings, researchers have often relied on an approach by Linden and Rockoff (2008), and later adapted by Haninger et al. (2017), Muehlenbachs et al. (2015), and others. We follow a similar approach by first estimating a regression based on equation (1), where we define proximity to an RMP facility using one-kilometer incremental bins, starting with 0-1km, 1-2km, and going all the way out to 24-25km. The estimated coefficients are then used to flexibly graph the pre- and post-accident price gradients. Expecting the price gradients to be most different nearest the site, we assume the distance at which they converge to be the cutoff between the spatially defined treated and control groups.

For typical accidents, estimates of equation (1) provided no clear evidence of where the spatially defined thresholds between the control and treated group should be. However, accidents that result in offsite impacts are where residents are better informed. For these accidents, the estimated pre- and post-accident price gradients are displayed in Figure 4 (see Model 1 in Table A1 of the Appendix for the full results). All else constant, at closer distances we see that prices are significantly lower after an accident that had offsite impacts. This decrement diminishes with distance but based on the point estimates appears to possibly extend out to about seven kilometers. Therefore, for the main analysis we assume the treated group of homes is within seven kilometers or less of an RMP facility, and examine the price effects of an accident within this distance. As can be seen in the second panel in Figure 3, for all but one of the bins within five kilometers a Wald test rejects the null hypothesis that the pre-accident and post-offsite-accident distance gradients are equal, at the $p \leq 0.10$ level. Subsequent regression analyses focus on a treated group within five kilometers, and disregard sales within 5-7 km due to concerns of potential treatment effect spillover between the assumed treated and control group distance bins.

We limit the control group to homes within 7-10 km of an RMP facility. Figure 4 suggests no systematic difference in prices before or after an accident at these farther distances and the p-values for a Wald test of the null hypotheses that the pre- and post-accident gradients are equal in each bin are all $p \geq 0.40$. In addition, limiting the sample to transactions within 10km draws focus to the neighborhoods nearest to industrial areas, where homes in the treated and control group distance bins are likely more similar in terms of unobserved characteristics.

V.C. Impacts of Chemical Accidents

We estimate a series of hedonic price regressions following equation (1). Each of five models are explained in detail below with full regression results appearing in Table A1 in the Appendix. As per equations (2) through (5), we use the estimated coefficients to derive estimates of the percent change in price due to an accident. All regressions include indicator and count variables denoting the presence of RMP facilities in general, at different distances. To account for differences in the hedonic price surface across markets and time, the regressions include interaction terms between each county-by-year combination and all house and location attributes. County-specific year and quarter indicator variables, and census tract-level fixed effects are also included. Only estimates of the percent change in home prices due to an accident are presented and discussed here.

The estimated percent changes in price due to an accident in Table 3 are based on Model 2, which is estimated using the sample of almost 3.4 million transactions within 10km of an RMP site. This model allows the price effects of an accident to differ for homes in each one-kilometer incremental bin, from 0-1 km out through 6-7 km. The cross-area DID and triple difference estimates for a chemical accident involving no offsite impacts are generally small and statistically insignificant. In the 2-3km bin we even find a counterintuitive statistically significant 2.7% to 4.4% increase in prices. More intuitive results are obtained when focusing on the price effects of accidents that had direct offsite impacts to the surrounding community (i.e., injuries to offsite populations, offsite property damage, or evacuation or shelter-in-place orders). The cross-area DID estimates suggest statistically significant price impacts in each one-kilometer bin within five kilometers, ranging from a 6.2% to 9.7% depreciation. The cross-area DID estimates even suggest a significant 4.3% and 3.9% price decline in the 5-6 km and 6-7 km bins.

Those farther out price effects in the 5-6 km and 6-7 km bins are no longer significant for the triple differences estimates, which better account for broader neighborhood trends. However, the estimated price declines within five kilometers of an accident are fairly robust in the triple differences estimates, ranging from a 4.3% to 7.8% deprecation and being statistically significant in 3 of the 5 bins.

Given the results from our earlier distance gradient diagnostics (see Figure 4) and that we find marginally significant results extending out to five kilometers here, in subsequent models we pool the distance bins together and estimate a single average price effect for all homes within five kilometers of a chemical accident. Model 3 is the same as Model 2, and is estimated using the same sample of transactions, but pools the treatment bins into a single 0-5 km bin. The estimates of the percent change in home prices due to an accident are presented in Table 4. Again, the cross-area DID and triple difference estimates suggest that an accident involving no offsite impacts has no effect on house prices in the surrounding community. The price effects from an accident that resulted in offsite impacts remains robust, with the cross-area DID estimate suggesting a 6.7% average decrease in price to homes within 5km. The more thorough triple differences estimate suggests a marginally significant 4.8% price decline.[15]

The alternative within-area DID estimates are provided by Models 4 and 5 and are presented in Table 5. Model 5 is estimated using the CEM weights and sample, which only includes transactions matched by county, year, and observed (coarsened) house attributes (see section IV.C). These models are estimated using a sample of home transactions that are within 0-5km (the treated group) or 7-10km (the control group) of an RMP site where an accident occurs during the study period.

[15] The percent change in price estimates discussed next are robust to an alternative 0-4km treatment bin, suggesting an average price decrease of 5.3% to 7.4%.

Sales that are only near RMP sites where no accidents occur, or are only within 5-7km of an RMP accident site, are excluded.[16] The CEM algorithm matches similar home sales in the treated (0-5km) and control (7-10km) groups. Home transactions that are not in either group are given a zero weight and excluded from the estimating sample in Model 5. We use the same, but unmatched, sample in Model 4 to cleanly demonstrate the robustness of our results from this matching procedure.

The results of models 4 and 5 again demonstrate that, on average, an accident involving no offsite impacts does not affect surrounding home values, whereas an accident with offsite impacts does. The estimated price effects from accidents with offsite impacts suggest an average 5.4% or 5.7% depreciation in homes values within five kilometers of an accident.

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 do observe the pretreatment trends. If house prices for the treated and control 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 this treatment event.

To assess whether we can interpret the estimated 5% to 7% decline that is experienced among homes within five kilometers of an "offsite" accident as causal, we conduct an event study (Hanna and Olivia, 2010) by estimating a variant of equation (1) and Model 4 that includes annual lead terms $\boldsymbol{pre}_{ijms}$ to denote transactions that occurred *s* years prior to an accident. Similarly, we include the lag terms $\boldsymbol{post}_{ijms}$ and $\boldsymbol{off}_{ijms}$ to denote transactions that occur *s* years after any accident, or after an accident yielding offsite impacts, respectively. The hedonic regression estimated for this event study is:

$$(7) \qquad ln(p_{ijmt}) = \boldsymbol{x}_{ijmt}\boldsymbol{\beta}_{mt} + \mathbb{1}(\boldsymbol{RMP}_{ijm} > 0)\boldsymbol{\rho} + \boldsymbol{RMP}_{ijm}\boldsymbol{\varphi} + \sum_{s=-14}^{-1}\{\boldsymbol{pre}_{ijms}\boldsymbol{\gamma}_{\boldsymbol{s}}^{\boldsymbol{pre}}\}$$

$$+ \sum_{s=0}^{10}\{\boldsymbol{post}_{ijms}\boldsymbol{\gamma}_{\boldsymbol{s}}^{\boldsymbol{post}} + (\boldsymbol{post}_{ijms} \times \boldsymbol{off}_{ijms})\boldsymbol{\theta}_{\boldsymbol{s}}^{\boldsymbol{post}}\} + \boldsymbol{\tau}_{mt} + v_{jm} + \varepsilon_{ijmt}$$

The time component of the lead and lag variables is normalized so that *s*=0 corresponds to the exact day an accident occurred; denoted by the black vertical line in in Figure 5. The estimated lead terms for the 0-5km treated group and 7-10km control group in $\boldsymbol{\gamma}_{\boldsymbol{s}}^{\boldsymbol{pre}}$ are graphed on the left side of Figure 5. Focusing on accidents resulting in offsite impacts, the lag terms $\boldsymbol{\gamma}_{\boldsymbol{s}}^{\boldsymbol{post}} + \boldsymbol{\theta}_{\boldsymbol{s}}^{\boldsymbol{post}}$ are graphed to the right.

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[16] Because homes can be near multiple RMP sites, the corresponding RMP site and accident distance bins are still included as right-hand side variables in the regression models.

The pre-accident coefficients are generally very similar and follow a similar trend, suggesting that the parallel trends assumption is likely valid. There is some divergence in the pre-trends very early in the study period, but we attribute this largely to the small number of transactions observed more than 10 years before an accident. It is mainly after an accident with offsite impacts occurs that we see the price trends between the treated and control groups diverge. Home values within 0-5 km begin to decline compared to homes 7-10 km away. This decrement seems to be largest around 5 to 6 years after an accident, and then prices may start to converge. Confirmation of the parallel trends assumption supports a causal interpretation of the 5% to 7% depreciation among homes within five kilometers of an accident that impacts offsite populations.

VI. CONCLUSION

Accidental chemical releases at industrial facilities can result in toxic clouds, fires, and explosions. These accidents have negative impacts both onsite and off, faced by workers and nearby communities. The U.S. EPA's RMP program is in place to reduce the harm from such events to nearby communities. The program is meant to reduce the risk of chemical accidents and, should one occur, ensure that protocols are in place to minimize damages. The RMP program is truly far-reaching, with almost 12,000 U.S. facilities currently regulated under the program. At least 40 million people (or about 12% of the U.S. population), and perhaps as many as 177 million (55%), are at risk of experiencing impacts from an accidental chemical release, should one occur (U.S. EPA, 2016).

This study examines how chemical accidents at RMP facilities impact the welfare of residents in surrounding communities using hedonic property value methods and an extensive dataset of 3.6 million single-family home transactions in Michigan, Ohio, and Pennsylvania. Our hedonic regression models use a variety of difference-in-differences and triple differences identification strategies, in conjunction with spatial and temporal fixed effects and coarsened exact matching techniques, to estimate the causal impacts of chemical accidents on nearby home values. In general, we have more confidence in the triple differences and within-area DID estimates, compared to the cross-area DID estimates. First, the within-area DID and triple differences estimates better account for local price trends that could otherwise confound the results. Second, the cross-area DID approach is a staggered DID design, and recent literature has raised concerns over the interpretation and appropriateness of DID settings where the treatment event is staggered over time (Goodman-Bacon, 2021; Marcus and Sant'Anna, 2021; Sun and Abraham, 2021). Our within-area DID and triple differences estimates are akin to a stacked DID design (Cengiz et al., 2019; Deshpande and Li, 2019; Fadlon and Nielsen, 2021), which alleviates concerns regarding staggered treatment events (Goodman-Bacon, 2021, Roth et al., 2022). Still, the cross-area DID estimates instill confidence in our primary findings as they yield remarkably similar results, despite relying on an entirely different set of counterfactuals.

The results indicate that the typical RMP accident, where adverse impacts are contained on-site, does not impact surrounding home values. However, for the roughly 25% of incidents in our data in which the chemical accident resulted in injuries to offsite populations, offsite property damage, or necessitated the evacuation or shelter-in-place of individuals located offsite, we find an average 5% to 7% decline in the value of homes within five kilometers of the accident.

This finding is not unexpected as households are likely to be well-informed about accidents with offsite impacts. Such accidents overtly impose real risks and costs to nearby populations. Whereas workers may be compensated thorough wage rates for facing onsite risks, causing chemical firms to internalize at least some of the costs to employees of accidents, the costs of offsite damages are external and borne by nearby homeowners and residents. Our findings illustrate that these external costs are substantial, corresponding to an average loss in home value of $12,000 to $17,000 (see Table 6 for details).

The environmental justice implications are particularly important. We find that proximity to an RMP facility, even in the absence of any accidents, is associated with lower home values. Homes within one kilometer of a single facility tend to be worth over 4% less, all else constant; and homes within 1-2km experience an almost 2% discount. This adverse relationship is particularly noticeable in the presence of multiple facilities. For example, homes within a kilometer of three RMP facilities are more than 12% lower in value, and those within 1-2km are 5% lower. Additional depreciation due to a chemical accident at a nearby facility will exacerbate these baseline inequities. Elliot et al. (2004) find that risk factors associated with RMP accidents (e.g., number of chemicals and employees), and facilities that have more than one accident, are more likely in counties where a greater proportion of the population is Black, and where there are higher levels of income inequality.

The RMP program serves a critical role in minimizing such inequities, and in reducing the risk to populations living in the “fence-line” communities around industrial facilities more generally. The increased occurrence of extreme storms, heat waves, floods, wildfires and other natural disasters due to climate change, makes industrial facilities more vulnerable to experience accidental chemical releases, which emphasizes the importance of the RMP program (Flores, et al. 2021; US Chemical Safety Board, 2017; Chemical Industries Association, 2015). The U.S. has a long-standing, proud industrial tradition, but at the same time it is important to consider the magnitude of the negative externalities imposed by these facilities. This study provides significant insight into the monetized external costs of these industrial chemical accidents.

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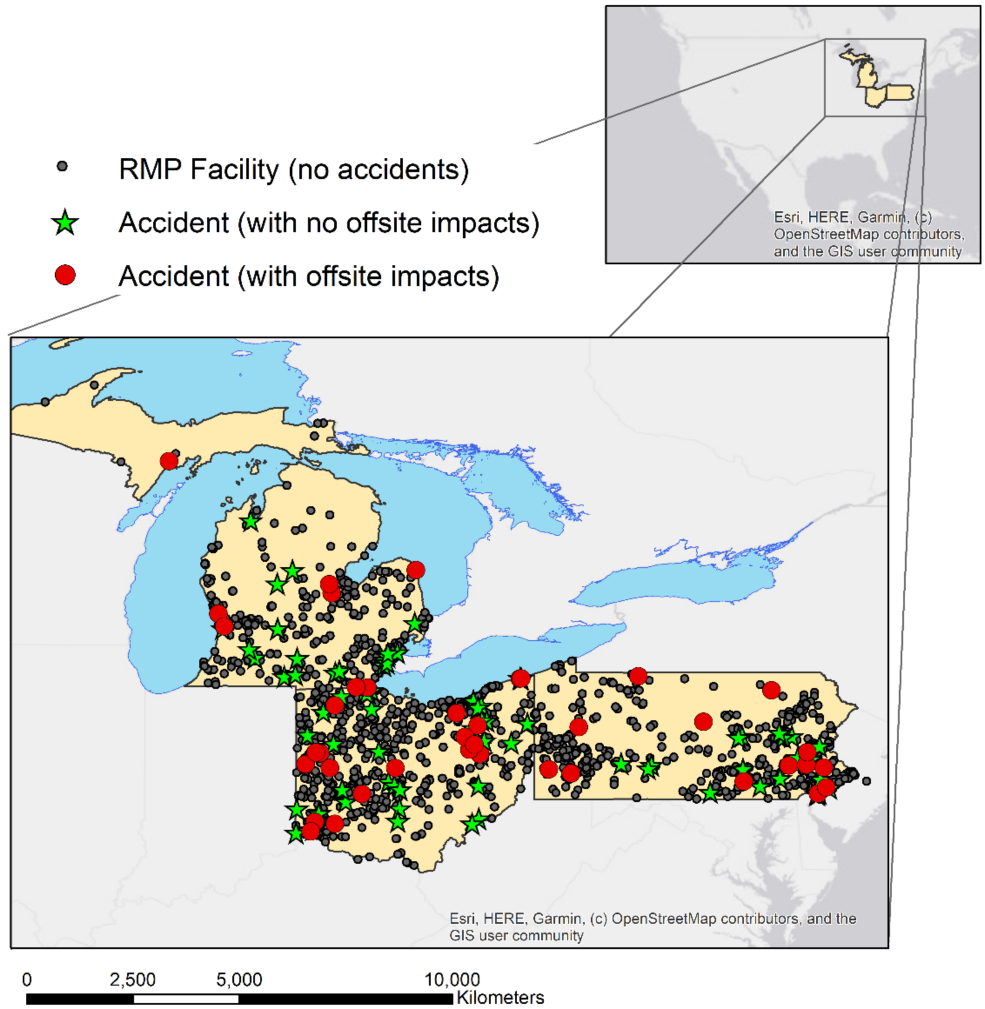
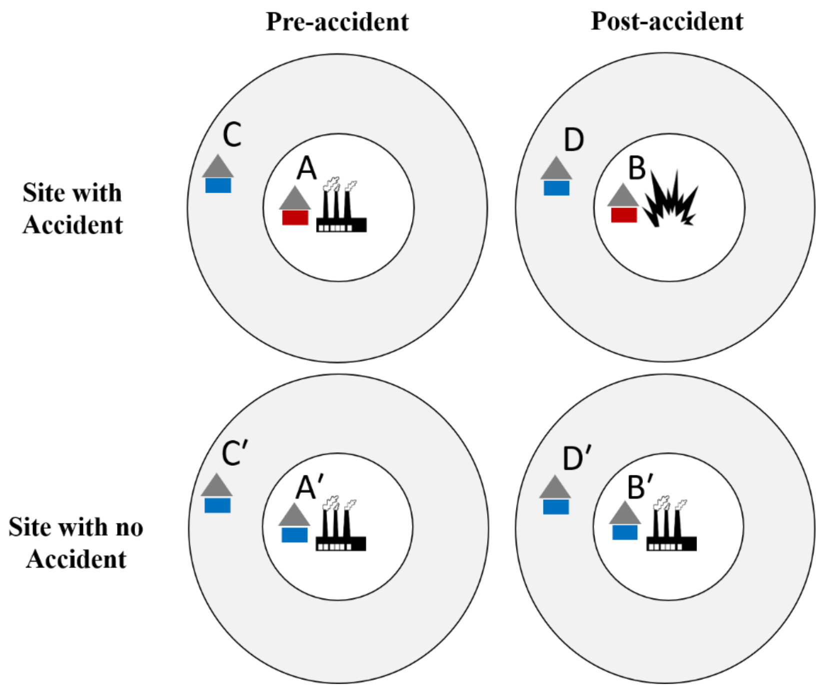
FIGURES AND TABLES

Figure 1. Tri-state Study Area, RMP Facilities, and Chemical Accidents.



Note: Map of tri-state study area includes Michigan, Ohio, and Pennsylvania, U.S.

Figure 2. Conceptual Illustration of Difference-in-Differences and Triple Differences Approaches.



Note: As discussed in section IV.A, based on the above illustration our cross-area DID estimates are represented as *(B-A)-(B'-A')*, the within-area DID estimates are represented as *(B-A)-(D-C)*, and the triple differences estimates are represented as: *{(B-A)-(B'-A')} - {(D-C)-(D'-C')}*.

Figure 3. Price Gradient Associated with Proximity to RMP Sites.

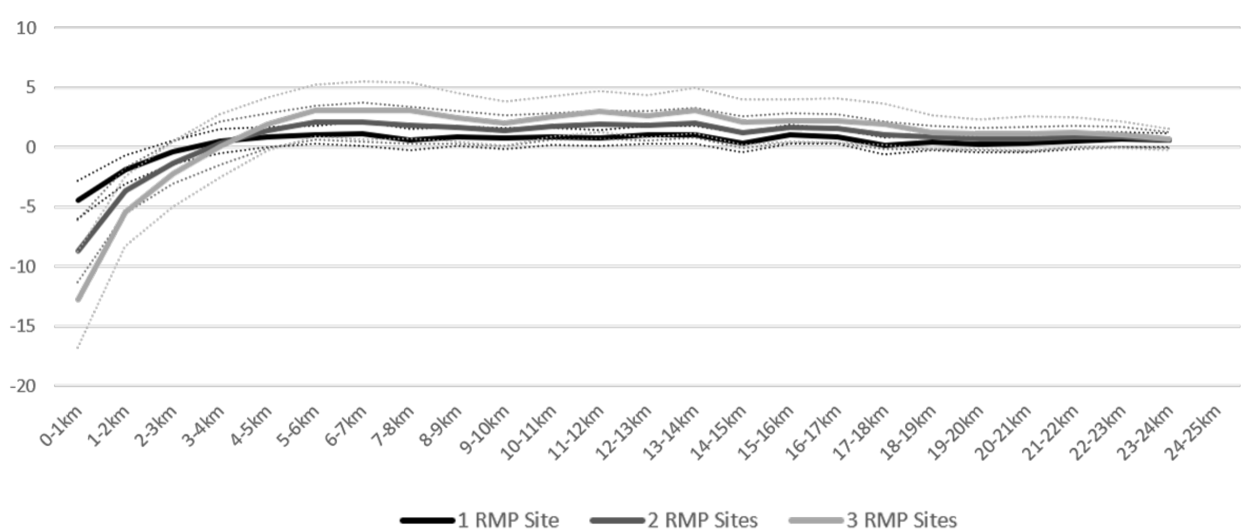
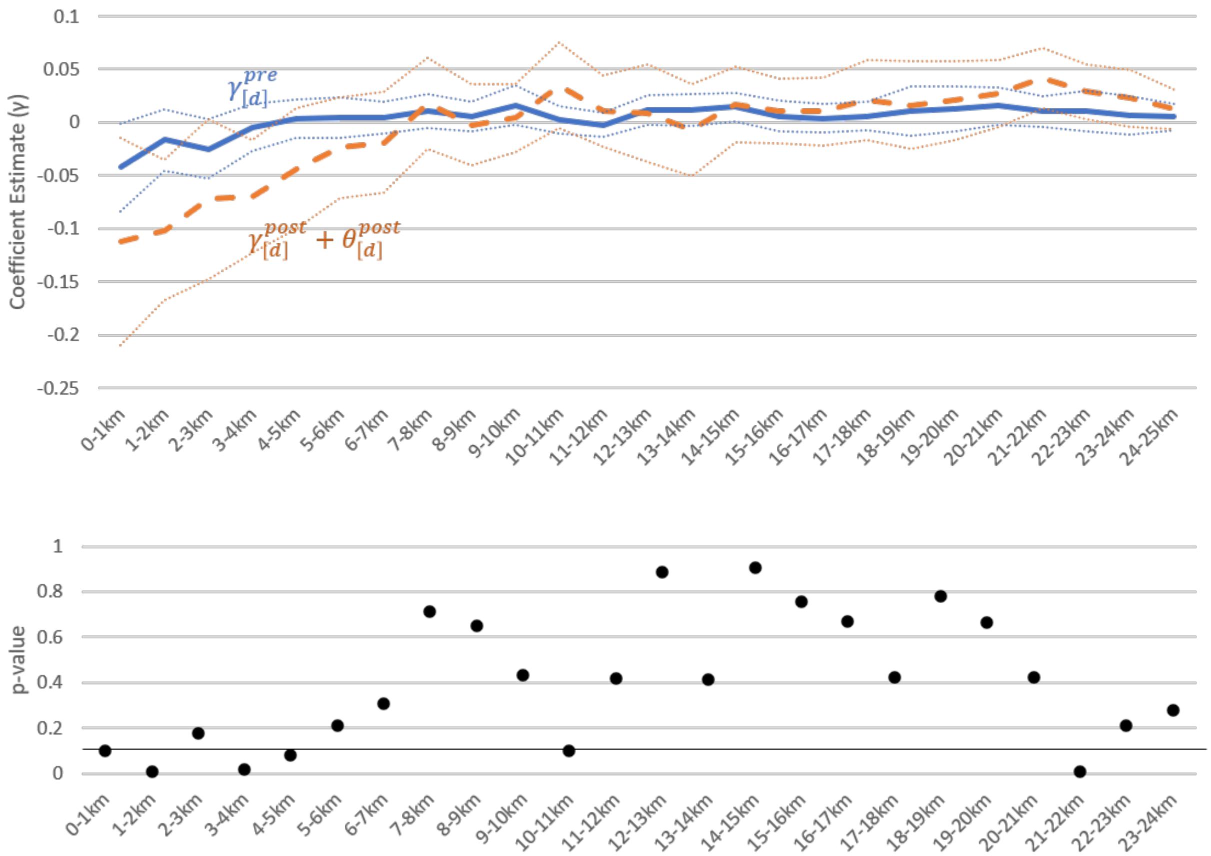
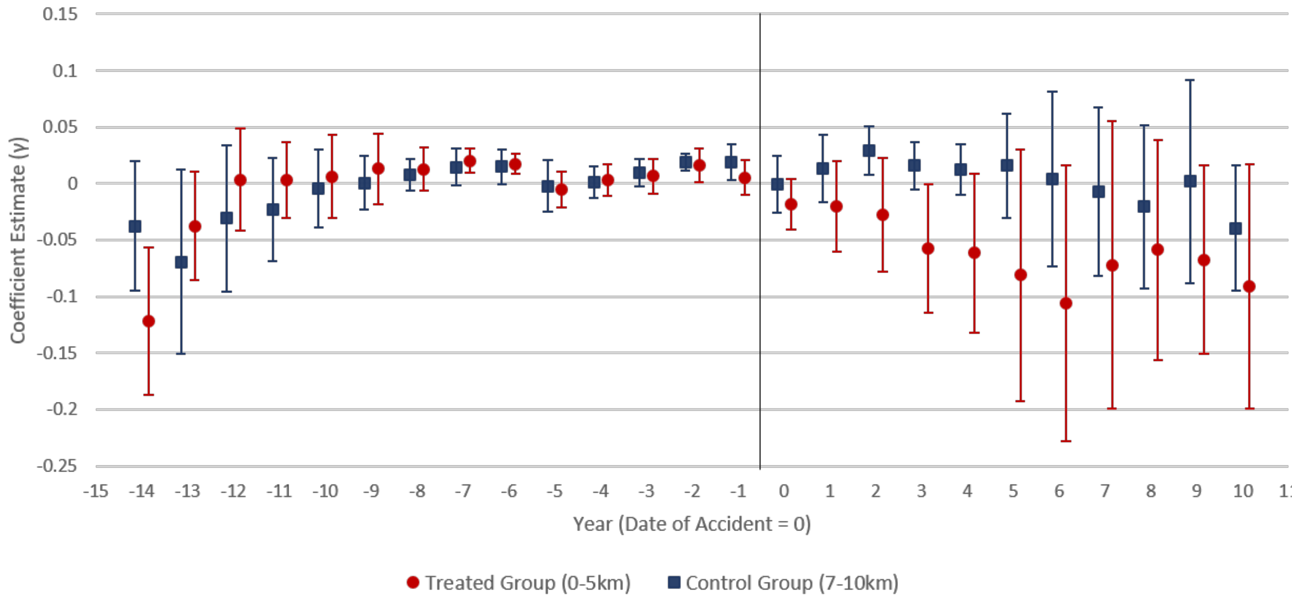


Figure 4. Pre-Accident and Post-Offsite-Accident Price Gradients (top panel); and P-values testing if pre- and post-offsite-accident coefficients are equal (bottom panel).



Note: Top panel shows the pre- and post-accident price gradient, where the latter pertains to accidents with offsite impacts. Coefficient estimates are based on model 1 in Table A1 of the Appendix. The 95% confidence intervals are shown by the dotted lines, with standard errors calculated via the delta method using the "nlcom" command in Stata 17/MP. The lower panel shows the p-values from a Wald test of the null hypothesis that the pre- and post-offsite accident points are equal at distance *d*. For points below the *p=0.10* line we reject the null that the gradients are equal at distance *d*.

Figure 5. Event Study Graph of Price Differentials by Year.



Note: Figure shows estimates based on a variant of Model 4 that includes interaction terms to allow $\boldsymbol{\gamma}^{\boldsymbol{pre}}$, $\boldsymbol{\gamma}^{\boldsymbol{post}}$, and $\boldsymbol{\theta}^{\boldsymbol{post}}$ coefficients to vary by year, relative to the date of the accident. Pre-accident points show estimates of $\boldsymbol{\gamma}^{\boldsymbol{pre}}$, and post-accident points pertain to accidents with offsite impacts, and thus show estimates of $\boldsymbol{\gamma}^{\boldsymbol{post}} + \boldsymbol{\theta}^{\boldsymbol{post}}$.

Table 1. Descriptive Statistics, RMP Accidents from 2004-2014 in MI, OH and PA

Variable	Obs	Mean	Std. dev.	Min	Max
# Chemicals Released	209	1.20	0.82	1	10
Gas release (dummy)	209	0.6411	0.4808	0	1
Spill/evaporation (dummy)	209	0.3828	0.4872	0	1
Fire (dummy)	209	0.0861	0.2812	0	1
Explosion (dummy)	209	0.0191	0.1373	0	1
Reactive Incident (dummy)	209	0.0431	0.2035	0	1
Environmental Damage (dummy)	209	0.0478	0.2140	0	1
First Responders Deployed (dummy)	209	0.4785	0.5007	0	1
Onsite Deaths (# of people)†	3	1.33	0.58	1	2
Onsite Injuries (# of people) †	79	1.76	1.59	1	9
Onsite Property Damage (nominal USD) †	40	3,432,218	12,700,000	100	75,000,000
Offsite Deaths (# of people)	0	-	-	-	-
Offsite Injuries (# of people) †	19	3.68	6.09	1	25
Offsite Environmental Damage (nominal USD) †	8	175,441	258,824	250	750,000
Offsite Evacuated (# of people) †	23	130.13	231.92	1	735
Offsite Shelter-in-Place (# of people) †	13	501.23	1281.36	20	4,677

Notes: There were a total of 209 chemical accidents from 2004-2014, at 124 different RMP facilities.
† Descriptive statistics here reported only for accidents where the respective variable has a nonzero value.

Table 2. Single-Family Home Transactions Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Price (2019$)	3,686,984	159,217	132,272	10,001	999,815
Acres	3,212,836	0.2779	0.2433	2.300E-05	1.3000
Missing: Acres†	3,686,984	0.1286	0.3348	0	1
Stories	3,071,319	1.53	0.51	0.75	3.00
Missing: Stories†	3,686,984	0.1670	0.3730	0	1
Bedrooms	3,686,984	2.30	1.52	0	7
Bathrooms	3,117,285	1.67	0.75	0.5	6
Missing: Bathrooms†	3,686,984	0.1545	0.3614	0	1
Interior square footage	3,164,277	3,107	1,701	807	10,048
Missing: Interior square footage†	3,686,984	0.1418	0.3488	0	1
Age (years)	3,191,921	52.23	31.30	0	232
Missing: Age†	3,686,984	0.1343	0.3409	0	1
Distance to primary road (km)	3,686,984	5.22	6.56	0.00	154.93
Distance to NPL site (km)	3,686,984	13.81	11.94	0.01	104.73
Distance to large lake (km)	3,686,984	11.46	7.89	0.00	59.00

Note: The final sample includes n=3,686,984 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.

Table 3. Percent Change in Price from a Chemical Accident: One-kilometer Treatment Bins.

	Model 2			
	All w/in 10km of RMP Site			
	Cross-area DID No Offsite	Triple Diff No Offsite	Cross-area DID Offsite	Triple Diff Offsite
0 to 1 km	0.8947	2.5222	-8.0546**	-6.1371
	(1.7382)	(2.2555)	(3.8954)	(4.0178)
1 to 2 km	-0.3919	1.2149	-9.7147***	-7.8319**
	(1.7256)	(2.3497)	(2.9725)	(3.1385)
2 to 3 km	2.7383**	4.3955**	-6.4483*	-4.4972
	(1.2743)	(1.7760)	(3.7189)	(4.1000)
3 to 4 km	0.3710	1.9901	-8.0571***	-6.1396**
	(1.5244)	(2.0302)	(2.7377)	(2.8822)
4 to 5 km	-1.1755	0.4186	-6.2371**	-4.2816*
	(1.0383)	(1.2916)	(2.4991)	(2.4100)
5 to 6 km	-0.7101	0.8915	-4.3052**	-2.3095
	(1.1612)	(1.4912)	(2.0302)	(1.9344)
6 to 7 km	-0.7859	0.8145	-3.9428*	-1.9395
	(1.0568)	(0.7657)	(2.1289)	(1.6580)
House and Location Attributes	County × Year			
Year Fixed Effects	County × Year			
Quarter Fixed Effects	County × Quarter			
Tract Fixed Effects	Yes			
Observations	3,359,856			

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Estimates calculated following equations (2)-(5) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 2. Full regression coefficient results presented in Table A1 in Appendix.

Table 4. Percent Change in Price from a Chemical Accident: 0-5km Treatment Bin.

	Model 3 All w/in 10km of RMP Site			
	Cross-area DID No Offsite	Triple Diff No Offsite	Cross-area DID Offsite	Triple Diff Offsite
0 to 5 km	0.5616	2.0803	-6.6905***	-4.8032*
	(1.3883)	(1.7592)	(2.3352)	(2.4678)
House and Location Attributes	County × Year			
Year Fixed Effects	County × Year			
Quarter Fixed Effects	County × Quarter			
Tract Fixed Effects	Yes			
Observations	3,359,856			

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Estimates calculated following equations (2)-(5) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression model 3. Full regression coefficient results presented in Table A1 in Appendix.

Table 5. Within-area DID Estimates of Percent Change in Price from a Chemical Accident: 0-5km Treatment Bin.

	Model 4 0-5km or 7-10km of Accident		Model 5 CEM 0-5km or 7-10km of Accident	
	Within-area DID No Offsite	Within-area DID Offsite	Within-area DID No Offsite	Within-area DID Offsite
0 to 5 km	1.8805	-5.4222**	0.7805	-5.7289*
	(1.6825)	(2.6284)	(1.0844)	(3.0592)
House and Location Attributes	County × Year		County × Year	
Year Fixed Effects	County × Year		County × Year	
Quarter Fixed Effects	County × Quarter		County × Quarter	
Tract Fixed Effects	Yes		Yes	
Observations	1,037,013		893,115	

Note: Dependent variable is ln(price). * p<0.10, ** p<0.05, *** p<0.01. Standard errors in parentheses, clustered at the county level. Estimates calculated following equations (4) and (5) using the "nlcom" command in Stata 17/MP, and are based on the coefficient estimates from the hedonic regression models 4 and 5. Full regression coefficient results presented in Table A1 in Appendix.

Table 6. Average Loss in Home Values due to an Accident with Offsite Impacts (2019$).

	Model 3		Model 4	Model 5
	Cross-area DID	Triple Diff	Within-area DID	Within-area DID
0 to 5 km	-16,949***	-12,168*	-13,736**	-14,513*
	[-28,543 to -5,354]	[-24,421 to 85]	[-26,786 to -686]	[-29,702 to 676]

Note: * p<0.10, ** p<0.05, *** p<0.01. Average implicit price estimates based on percent change in price estimates from models 3 through 5 (in tables 4 and 5), multiplied by the pre-accident average price of $253,327. The 95% confidence intervals are shown in brackets. Estimates and corresponding confidence intervals are calculated using the "nlcom" command in Stata 17/MP.

APPENDIX

Figure A1. Number of RMP Accidents in Michigan, Ohio, and Pennsylvania by Year.

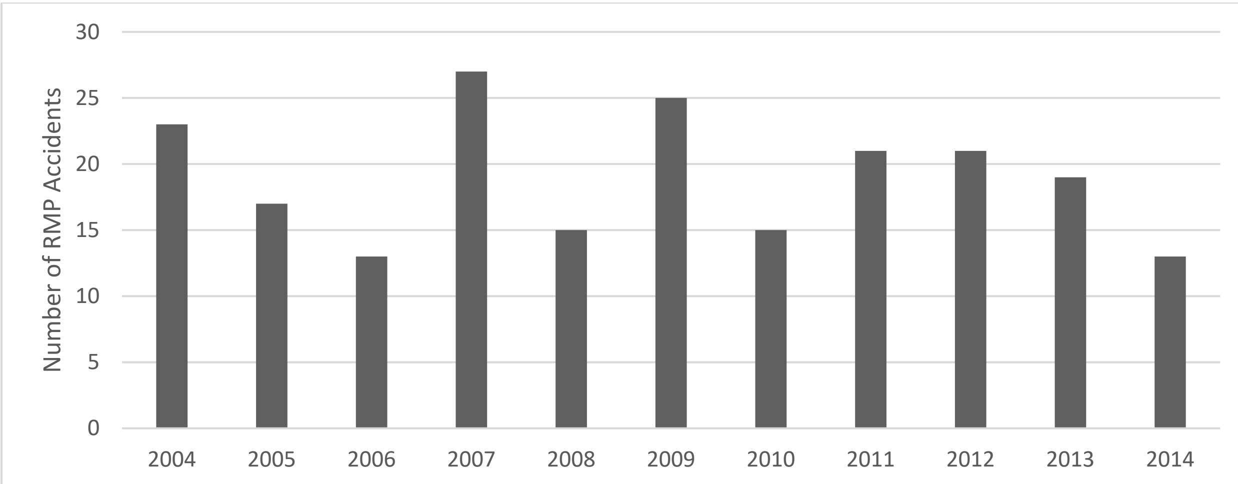


Figure A2. Number of Transactions within each One-Kilometer Distance from an RMP Site

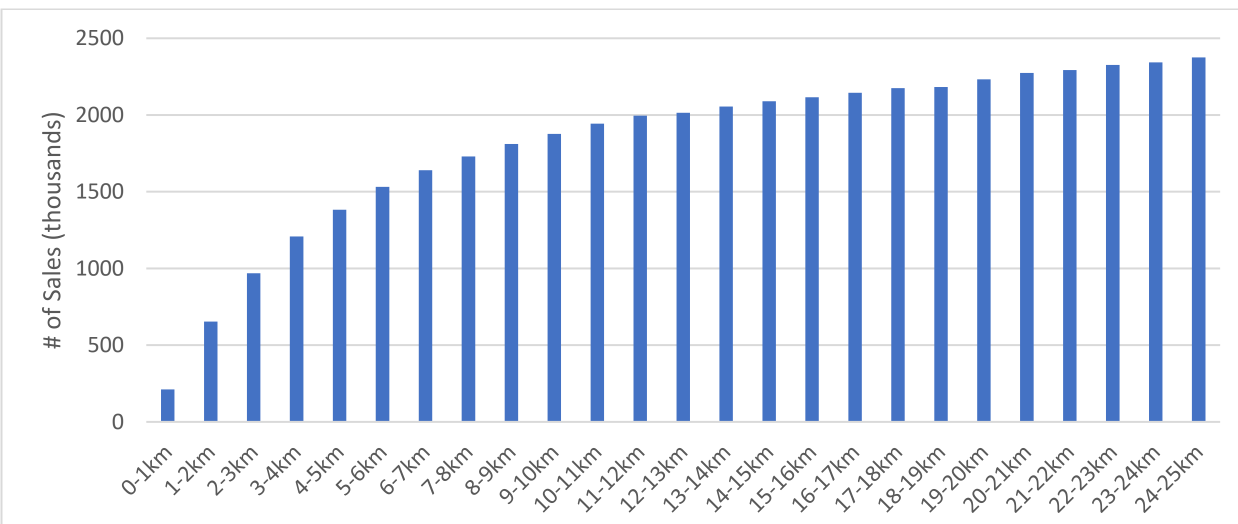


Figure A3. Number of Pre- and Post-Accident Transactions in each One-Kilometer Bin.

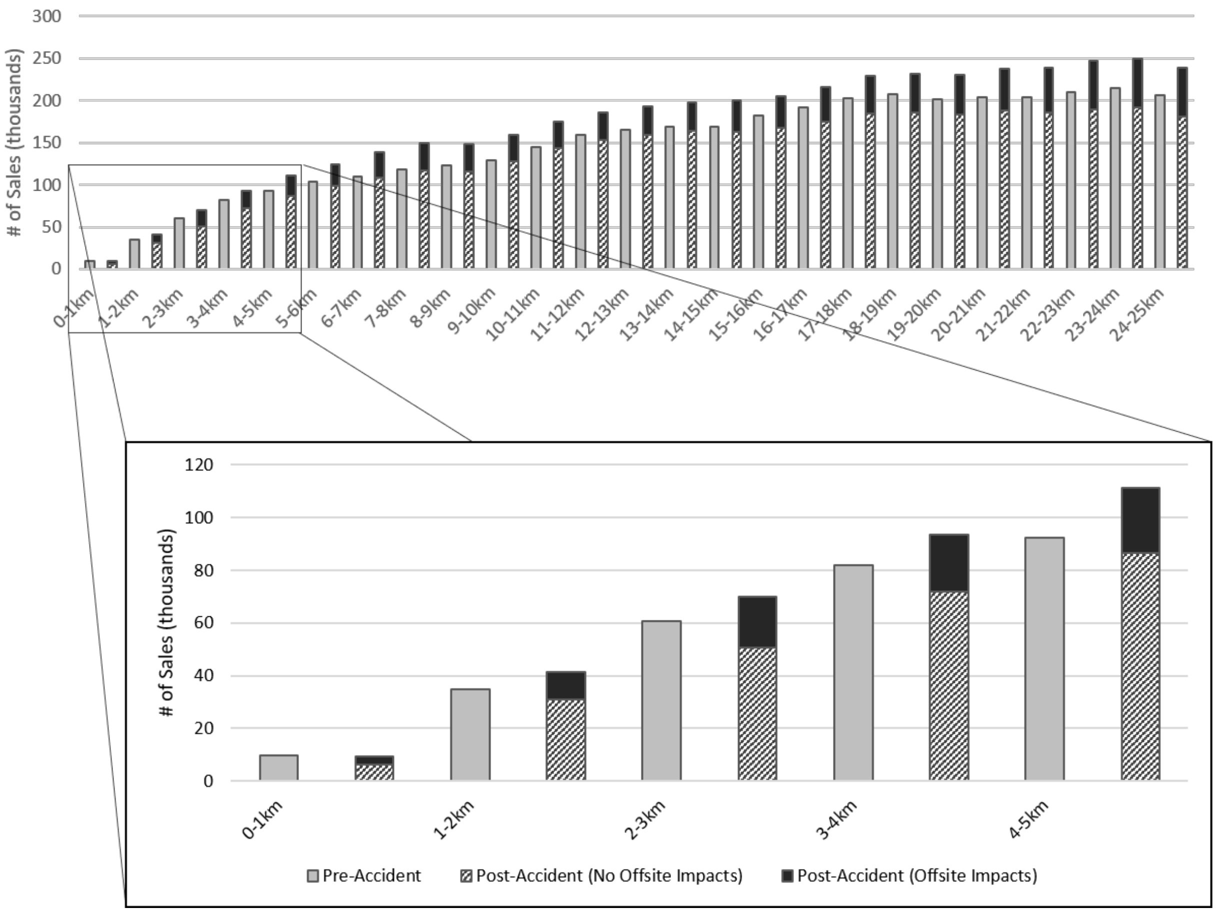


Table A1. Full Hedonic Regression Results.

	Model 1 All w/in 25km of RMP	Model 2 All w/in 10km of RMP	Model 3 All w/in 10km of RMP	Model 4 0-5km or 7-10km of Accident	Model 5 CEM Sample
RMP Site[a]					
0 to 1 km	0.0004	-0.0009	-0.0016	-0.0143	-0.0203
	(0.0110)	(0.0108)	(0.0109)	(0.0174)	(0.0215)
1 to 2 km	-0.0008	-0.0015	-0.0019	0.0115	0.0156
	(0.0072)	(0.0070)	(0.0072)	(0.0113)	(0.0126)
2 to 3 km	0.0052	0.0057	0.0056	-0.0007	0.0001
	(0.0050)	(0.0050)	(0.0051)	(0.0083)	(0.0098)
3 to 4 km	0.0068*	0.0065*	0.0067**	0.0030	-0.0006
	(0.0035)	(0.0034)	(0.0033)	(0.0040)	(0.0057)
4 to 5 km	0.0030	0.0031	0.0030	0.0077*	0.0132*
	(0.0034)	(0.0033)	(0.0033)	(0.0045)	(0.0070)
5 to 6 km	0.0002	0.0002	0.0002	0.0021	0.0054
	(0.0029)	(0.0030)	(0.0029)	(0.0056)	(0.0062)
6 to 7 km	0.0015	0.0009	0.0010	0.0001	-0.0015
	(0.0033)	(0.0033)	(0.0033)	(0.0049)	(0.0062)
7 to 8 km	-0.0057*	-0.0064**	-0.0063**	-0.0089*	-0.0182**
	(0.0031)	(0.0031)	(0.0031)	(0.0045)	(0.0077)
8 to 9 km	0.0009	-0.0005	-0.0004	-0.0020	0.0010
	(0.0030)	(0.0026)	(0.0026)	(0.0047)	(0.0054)
9 to 10 km	0.0011				
	(0.0040)				
10 to 11 km	0.0004				
	(0.0031)				
11 to 12 km	-0.0031				
	(0.0027)				
12 to 13 km	0.0023				
	(0.0027)				
13 to 14 km	0.0005				
	(0.0027)				
14 to 15 km	-0.0048				
	(0.0031)				
15 to 16 km	0.0052				
	(0.0036)				
16 to 17 km	0.0022				
	(0.0030)				
17 to 18 km	-0.0074**				
	(0.0038)				
18 to 19 km	0.0000				
	(0.0031)				

19 to 20 km	-0.0018				
	(0.0027)				
20 to 21 km	-0.0012				
	(0.0032)				
21 to 22 km	0.0013				
	(0.0034)				
22 to 23 km	0.0047				
	(0.0029)				
23 to 24 km	0.0056*				
	(0.0030)				
RMP Site Count					
0 to 1 km	-0.0457***	-0.0526***	-0.0551***	-0.0524***	-0.0494***
	(0.0098)	(0.0097)	(0.0102)	(0.0136)	(0.0177)
1 to 2 km	-0.0183***	-0.0260***	-0.0273***	-0.0400***	-0.0425***
	(0.0062)	(0.0059)	(0.0061)	(0.0103)	(0.0135)
2 to 3 km	-0.0094*	-0.0180***	-0.0187***	-0.0174**	-0.0169
	(0.0055)	(0.0056)	(0.0053)	(0.0086)	(0.0105)
3 to 4 km	-0.0020	-0.0108**	-0.0107***	-0.0126*	-0.0114
	(0.0046)	(0.0042)	(0.0039)	(0.0065)	(0.0077)
4 to 5 km	0.0055	-0.0036	-0.0029	-0.0068	-0.0075
	(0.0037)	(0.0028)	(0.0029)	(0.0049)	(0.0062)
5 to 6 km	0.0101***	0.0012	0.0015	-0.0035	-0.0041
	(0.0039)	(0.0026)	(0.0028)	(0.0055)	(0.0067)
6 to 7 km	0.0096**	0.0007	0.0011	0.0019	0.0046
	(0.0039)	(0.0029)	(0.0030)	(0.0055)	(0.0063)
7 to 8 km	0.0119***	0.0029	0.0030	0.0044	0.0049
	(0.0039)	(0.0030)	(0.0030)	(0.0052)	(0.0069)
8 to 9 km	0.0078**	-0.0017	-0.0016	-0.0018	-0.0007
	(0.0035)	(0.0026)	(0.0026)	(0.0043)	(0.0066)
9 to 10 km	0.0062*	-0.0028*	-0.0027	-0.0035	-0.0032
	(0.0032)	(0.0016)	(0.0016)	(0.0029)	(0.0039)
10 to 11 km	0.0083***				
	(0.0029)				
11 to 12 km	0.0109***				
	(0.0030)				
12 to 13 km	0.0078***				
	(0.0029)				
13 to 14 km	0.0098***				
	(0.0032)				
14 to 15 km	0.0085***				
	(0.0031)				
15 to 16 km	0.0055*				
	(0.0029)				
16 to 17 km	0.0066*				

	(0.0035)	
17 to 18 km	0.0088***	
	(0.0033)	
18 to 19 km	0.0041	
	(0.0025)	
19 to 20 km	0.0042**	
	(0.0018)	
20 to 21 km	0.0041*	
	(0.0023)	
21 to 22 km	0.0036	
	(0.0024)	
22 to 23 km	0.0019	
	(0.0019)	
23 to 24 km	0.0003	
	(0.0015)	
24 to 25 km	0.0008	
	(0.0015)	
Pre-Accident[a]		
0 to 1 km	-0.0423**	-0.0479**
	(0.0210)	(0.0213)
1 to 2 km	-0.0166	-0.0204
	(0.0146)	(0.0148)
2 to 3 km	-0.0251*	-0.0279*
	(0.0142)	(0.0148)
3 to 4 km	-0.0047	-0.0073
	(0.0113)	(0.0113)
4 to 5 km	0.0039	0.0023
	(0.0092)	(0.0095)
5 to 6 km	0.0044	0.0030
	(0.0098)	(0.0102)
6 to 7 km	0.0045	0.0040
	(0.0078)	(0.0076)
7 to 8 km	0.0107	
	(0.0080)	
8 to 9 km	0.0054	
	(0.0073)	
9 to 10 km	0.0162*	
	(0.0094)	
10 to 11 km	0.0024	
	(0.0066)	
11 to 12 km	-0.0022	
	(0.0056)	
12 to 13 km	0.0121*	
	(0.0071)	

13 to 14 km	0.0117				
	(0.0076)				
14 to 15 km	0.0147**				
	(0.0068)				
15 to 16 km	0.0059				
	(0.0073)				
16 to 17 km	0.0040				
	(0.0068)				
17 to 18 km	0.0059				
	(0.0069)				
18 to 19 km	0.0103				
	(0.0119)				
19 to 20 km	0.0127				
	(0.0108)				
20 to 21 km	0.0154*				
	(0.0088)				
21 to 22 km	0.0105				
	(0.0073)				
22 to 23 km	0.0108				
	(0.0097)				
23 to 24 km	0.0067				
	(0.0090)				
24 to 25 km	0.0053				
	(0.0065)				
16 to 25 km					
0 to 5 km			-0.0138	-0.0044	-0.0160**
			(0.0108)	(0.0089)	(0.0067)
5 to 7 km			-0.0015	0.0002	-0.0078
			(0.0066)	(0.0085)	(0.0081)
7 to 10 km		0.0154*	0.0132*	0.0117*	0.0086
		(0.0079)	(0.0076)	(0.0067)	(0.0077)
Post-Accident[a]					
0 to 1 km	-0.0480*	-0.0390			
	(0.0258)	(0.0249)			
1 to 2 km	-0.0342	-0.0244			
	(0.0226)	(0.0220)			
2 to 3 km	-0.0103	-0.0009			
	(0.0153)	(0.0146)			
3 to 4 km	-0.0139	-0.0036			
	(0.0154)	(0.0144)			
4 to 5 km	-0.0197*	-0.0096			
	(0.0107)	(0.0089)			
5 to 6 km	-0.0153	-0.0041			

	(0.0106)	(0.0088)			
6 to 7 km	-0.0166	-0.0039			
	(0.0125)	(0.0089)			
7 to 8 km	-0.0128				
	(0.0117)				
8 to 9 km	-0.0241**				
	(0.0105)				
9 to 10 km	-0.0205*				
	(0.0105)				
10 to 11 km	-0.0225**				
	(0.0103)				
11 to 12 km	-0.0227**				
	(0.0101)				
12 to 13 km	-0.0288**				
	(0.0129)				
13 to 14 km	-0.0268**				
	(0.0111)				
14 to 15 km	-0.0177*				
	(0.0100)				
15 to 16 km	-0.0232**				
	(0.0116)				
16 to 17 km	-0.0164				
	(0.0111)				
17 to 18 km	-0.0159				
	(0.0123)				
18 to 19 km	-0.0209				
	(0.0130)				
19 to 20 km	-0.0195				
	(0.0160)				
20 to 21 km	-0.0186				
	(0.0146)				
21 to 22 km	-0.0156				
	(0.0104)				
22 to 23 km	-0.0147				
	(0.0129)				
23 to 24 km	-0.0139				
	(0.0120)				
24 to 25 km	-0.0021				
	(0.0077)				
16 to 25 km					
0 to 5 km			-0.0082	0.0164*	0.0029
			(0.0093)	(0.0088)	(0.0093)
5 to 7 km			-0.0078	0.0086	0.0043

			(0.0075)	(0.0089)	(0.0075)
7 to 10 km		-0.0006	-0.0018	0.0139	0.0197*
		(0.0083)	(0.0087)	(0.0095)	(0.0115)
Post-Accident × Offsite[a]					
0 to 1 km	-0.0639	-0.0929*			
	(0.0470)	(0.0480)			
1 to 2 km	-0.0673*	-0.0983**			
	(0.0354)	(0.0385)			
2 to 3 km	-0.0622	-0.0937**			
	(0.0383)	(0.0429)			
3 to 4 km	-0.0563*	-0.0877***			
	(0.0321)	(0.0333)			
4 to 5 km	-0.0238	-0.0526*			
	(0.0346)	(0.0317)			
5 to 6 km	-0.0084	-0.0369			
	(0.0287)	(0.0240)			
6 to 7 km	-0.0023	-0.0323			
	(0.0299)	(0.0255)			
7 to 8 km	0.0309				
	(0.0258)				
8 to 9 km	0.0218				
	(0.0241)				
9 to 10 km	0.0247				
	(0.0207)				
10 to 11 km	0.0573**				
	(0.0248)				
11 to 12 km	0.0339*				
	(0.0202)				
12 to 13 km	0.0375				
	(0.0295)				
13 to 14 km	0.0197				
	(0.0281)				
14 to 15 km	0.0348				
	(0.0240)				
15 to 16 km	0.0337				
	(0.0220)				
16 to 17 km	0.0267				
	(0.0210)				
17 to 18 km	0.0368				
	(0.0234)				
18 to 19 km	0.0373				
	(0.0251)				
19 to 20 km	0.0403				
	(0.0260)				

20 to 21 km	0.0457**				
	(0.0232)				
21 to 22 km	0.0573***				
	(0.0197)				
22 to 23 km	0.0438**				
	(0.0210)				
23 to 24 km	0.0367**				
	(0.0184)				
24 to 25 km	0.0145				
	(0.0118)				
0 to 5 km			-0.0748**	-0.0658*	-0.0651
			(0.0303)	(0.0360)	(0.0464)
5 to 7 km			-0.0357	-0.0264	-0.0205
			(0.0235)	(0.0214)	(0.0251)
7 to 10 km		-0.0046	-0.0050	0.0086	0.0017
		(0.0141)	(0.0139)	(0.0168)	(0.0215)
Constant	11.5125***	11.6612***	11.6615***	11.5509***	11.5253***
	(0.0544)	(0.0134)	(0.0135)	(0.0385)	(0.0498)
House and Location Attributes	County × Year	County × Year	County × Year	County × Year	County × Year
Year Fixed Effects	County × Year	County × Year	County × Year	County × Year	County × Year
Quarter Fixed Effects	County × Qtr	County × Qtr	County × Qtr	County × Qtr	County × Qtr
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	3,686,898	3,359,856	3,359,856	1,037,013	893,115
Adj. R-squared	0.664	0.675	0.675	0.689	0.686

Notes: 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. (a) denotes binary indicator variables.