

Housing Market Capitalization of Pipeline Risk: Evidence from a Shock to Salience and Awareness

Evan Herrnstadt and Richard L. Sweeney*

March 2024

Abstract

Stated safety concerns are a major impediment to making necessary expansions to the natural gas pipeline network. While revealed willingness to pay to avoid existing natural gas pipelines appears small, it is difficult to know if this reflects true ambivalence or a lack of salience and awareness. We test this latter hypothesis by studying how house prices responded to a deadly 2010 pipeline explosion in San Bruno, CA, which shocked both attention and information. Using a difference-in-differences strategy, we find that properties close to pipelines in the San Francisco area declined by 2 percent following the explosion. The response is larger in the immediate aftermath of the explosion, and among properties closest to the pipeline. However, we see no response among properties similarly exposed in other markets, nor in response to an informational letter sent to households the following year. These results suggest that homebuyers are willing to pay to avoid pipeline risk when the issue has their attention, but that this attention is hard to capture and fleeting.

Keywords: Hedonic; Pipeline; Safety; Information Disclosure

JEL Codes: Q4, Q5, Q51, R21

*Herrnstadt: Congressional Budget Office; Evan.Herrnstadt@cbo.gov. Sweeney: Boston College; sweeneri@bc.edu. This work has been supported by the Sloan Foundation, Harvard Environmental Economics Program, Consortium for Energy Policy Research at Harvard, Belfer Center for Science and International Affairs, and NBER Hydrocarbon Infrastructure and Transportation workshop. We thank Jackie Glasheen and Jean-Francois Gauthier for excellent research assistance. Thanks to Kate Konschnik, Nick Kuminoff, Erzo Luttmer, and participants of various seminars for helpful comments. The analysis and conclusions herein are solely those of the authors and do not represent the view of the U.S. Congressional Budget Office.

1 Introduction

Due to advances in drilling technology, the economically recoverable supply of natural gas in the United States have more than doubled since the turn of the century.¹ In order to fully capture the benefits of this unexpected resource boom, significant increases in and improvements to the existing pipeline network are required. Despite this, according to the regulatory body which oversees these changes, the Federal Energy Regulatory Commission (FERC), new pipelines “are facing unprecedented opposition from local and national groups”.² A major source of this opposition, particularly in densely populated areas, is concern about pipeline safety (Parfomak, 2013, 2016). Efficient infrastructure policy would weigh these safety concerns (and other costs) against the benefits of more transmission.³

Placing a value on the risks imposed by pipelines is challenging. If we consider risk of death alone, natural gas pipelines are extremely safe: over the past two decades, incidents along the United States’ 300,000 mile transmission network have resulted in an average of only 2.3 deaths per year.⁴ However, when they occur, pipeline explosions are horrific.⁵ If individuals are particularly fearful of this risk, a simple benefit transfer using VSL could substantially understate the true disamenity (Slovic, 1987). In theory, a contingent valuation study could elicit valuations which reflect the full extent of individuals’ safety concerns (Carson, 2012). However, in the case of pipelines, where it is clear that no payment will ever actually take place, local groups that are even modestly inconvenienced have an incentive to overstate their willingness to pay.

A revealed preference approach, comparing house prices near to and far from pipelines, has the potential to address both these concerns, but entails other challenges. First, pipelines are not randomly located, so we need quasi-experimental variation to distinguish their effect from that of any other correlated unobservables that also affect home prices (Parmeter and Pope, 2013). A second, less common, challenge arises from the fact that people are generally uninformed about or inattentive to the existing pipeline network. Existing pipelines are hidden underground and not well-marked, and detailed maps were made intentionally difficult to access after the terrorist attacks of September 11, 2001. As a consequence, when Hansen et al. (2006) asked homeowners known to live near pipelines how close they thought they were, 55 percent flatly denied living near one. If people are not mindful of or even able to locate existing pipelines, it will be difficult to infer their true aversion to this disamenity from revealed preference.⁶

In this paper, we study the housing market response to one of the deadliest pipeline incidents in U.S. history. On September 9th, 2010, a 30-inch transmission pipeline owned by Pacific Gas and Electric (PG&E) exploded in a densely populated suburb of San Francisco,

killing eight people. The event generated prolonged media coverage, particularly in the state of California, bringing the issue of pipelines to the forefront of people’s minds. In the weeks that followed, outrage swelled over the lack of pipeline location information. It was revealed that, incredibly, even the local fire chief was unaware of the high pressure pipeline’s presence before it exploded. The following spring, in response to this outrage, PG&E sent letters out to all households living within 2000 feet of a pipeline alerting them to their proximity.

To test whether this shock to pipeline awareness and location information affected people’s revealed preferences for living near pipelines, we look for changes in the hedonic price gradient following these events. We combine data on the universe of housing transactions in California from 1996 to 2012 with a proprietary map containing a snapshot of all natural gas transmission pipelines in the state. Our empirical strategy is difference-in-differences (DD), comparing housing transactions within the transmission pipeline blast zone to those further away within the same census tract. Leveraging the size of our sample to finely control for differential trends in narrow geographic housing markets, we compare the price gradient after the explosion and informational letter to the pre-explosion equilibrium.

We have three main sets of results. First, when we look at PG&E as a whole, we find a noisy decline of roughly 1 percent for properties within 600 feet of a pipeline, which matches the blast radius of the San Bruno explosion. When we restrict attention to the San Francisco area, we find a statistically significant decline of 2 percent. As we discuss in section 2.2, this pattern is consistent with the fact that the San Bruno explosion garnered and generated more prolonged media coverage in the Bay Area. Second, we find that the house price response was larger among properties closest to a pipeline. Properties within 500 feet of a pipeline in the Bay Area decline by 2.5 percent, while properties situated at the other extreme of the range designated at risk by regulators (2000 feet) show no response.

Third, when we allow the treatment effect to vary over time, we see the largest response in the months immediately following the explosion. Properties closest to a pipeline in the Bay Area experience a relative price decline of more than 5 percent in the second quarter after the explosion. This is consistent with the idea that the horrifying images of the event and the extensive coverage in its aftermath thrust the issue of pipeline safety to the forefront of homebuyers minds. However, as time passed and coverage declined, the hedonic price gradient with respect to this issue returned to its pre-explosion state. Importantly, we see no obvious diversion from this trend in response the informational letters. As we discuss below, this may have been due to the fact that the letters were provided to property *owners*, not buyers.

Given the nature of the variation generated by the San Bruno explosion and the reduced-form estimation strategy used, we are not able to recover (or even bound) fully informed,

attentive willingness to pay (WTP) to avoid living near a natural gas pipeline without making additional assumptions.⁷ Borrowing notation from the energy efficiency gap literature (Allcott and Greenstone, 2012), we show that the coefficient on our DD estimator is equal to the product of the change in pipeline awareness and the true, fully attentive and informed, price relationship. After providing evidence that households were very uninformed before the explosion, we consider the implications of an assumption that the post period reflects fully informed preferences in section 6. Under this assumption, we estimate that households within 600 feet of a pipeline are willing to pay \$132 per person per year to remove pipeline risk. Interpreting this response through lens of VSL, this implies that these residents act as if the perceived pipeline risk is one-hundred times larger than the empirical average. This result echoes findings in other settings involving unlikely, but particularly dreadful risks (Slovic, 1987; Gayer et al., 2000).

This paper also contributes to the empirical literature exploring the impact of imperfect information and inattention on hedonic models. Inattention or imperfect information has been shown to lead to suboptimal purchases in many settings (Chetty et al., 2009). Pope (2011) was one of the first papers to explicitly discuss how asymmetries in buyer and seller information can affect the hedonic price gradient and complicate analysis. A number of other papers have expanded upon this empirically, testing how information disclosure pertaining to toxic releases (Mastromonaco, 2015) or underground storage tanks (Guignet, 2013) are capitalized into home values. At the other extreme, several papers have demonstrated that people appear to *over-react* to recent disasters, then eventually forget about them. For instance, Gallagher (2014) shows that flood insurance takeup spikes immediately after a flood, but decays quickly. Tanaka and Zabel (2018) show a large decrease in housing prices near nuclear plants in the United States in the aftermath of the Fukushima meltdown, but this effect decayed fully within one year.⁸

This paper also contributes to a growing literature on the relationship between house prices and energy infrastructure, such as natural gas wells (Muehlenbachs et al., 2015) and power plants (Davis, 2010). One closely related study, examined housing prices in the aftermath of a gasoline pipeline explosion in Bellingham, WA in 1999, which killed three people (Hansen et al., 2006).⁹ In another closely related study, Boslett (2019) estimates the housing price impact of a large *proposed* natural gas pipeline in Appalachia. They find that houses within three kilometers decline by 9 percent in anticipation of the project. Although our largest quarterly estimates are of similar magnitude, the response in anticipation of a new pipeline likely includes large construction disamenities as well as simple pipeline risk once operational. Using over 800 events, Cheng et al. (2022) estimate that homes prices decline by roughly 5% following a distribution pipeline explosion. While that paper is informative

about the ex post costs of infrastructure hazards, our study is focused on homebuyer's ex ante willingness to pay to avoid those risks.

2 Background

2.1 Natural Gas Pipelines

For all intents and purposes, pipelines are the only real option for transporting natural gas from the wellhead to the end-user.¹⁰ This stands in contrast to crude oil, where pipelines compete with barge and railway shipping. There are three main types of natural gas pipelines: gathering, transmission, and distribution. Gathering pipelines are found in the producing region, and collect gas from the wellhead and ship it a processing plant. Transmission lines then send large quantities of processed natural gas to demand centers. Because of the distance and volume involved, these pipelines are larger in diameter (20-42 inches) and operate at much higher pressure than gathering or distribution lines. Once the gas has reached its destination, the gas is depressurized. Some gas will be delivered directly to industrial customers or electricity generation facilities. Residential, commercial, and some industrial users are serviced by distribution pipelines. These pipes are much smaller in diameter and operate at low pressure.

This paper focuses on transmission pipelines, which carry large quantities of gas at very high pressure. There are over 300,000 miles of natural gas transmission lines in the United States, but recent upstream and downstream shocks have prompted a wave of expansion requests. Due to the advent of hydraulic fracturing and horizontal drilling, annual U.S. natural gas production increased by 50 percent over the past decade, with much of the increase coming from new geographic regions rather than existing conventional basins.¹¹ On the demand side, retiring coal-fired and nuclear power plants are increasingly being replaced by natural gas generators, further stressing the existing pipeline network. In response to these developments, thousands of miles of new and expanded natural gas transmission pipelines have been proposed. The Department of Energy projects that \$42 billion will be spent on expanding natural gas pipeline infrastructure during 2015-2030 ([United States Department of Energy, 2015](#)).

Interstate natural gas pipelines are regulated by the Federal Energy Regulatory Commission (FERC). They are granted power of eminent domain, but must meet the requirements for a Certificate of Public Need. The approval process typically involves an environmental impact statement or assessment, a public comment period, and public meetings. This process, along with easement negotiations, will inform local residents about the construction

plans, future existence of the pipeline, and may prompt further information acquisition.

The information available and attention given to pipelines during the siting process declines considerably once they are in operation. As a recent review on the subject concluded, “Americans often pay little attention at all to the nation’s energy infrastructure until they face a nearby pipeline leak, rail accident, or other natural or man-made disaster” (Klass and Meinhardt, 2014). Part of this is because pipelines are not well marked unless necessary. Further, obtaining information on pipeline location was made more difficult by the advent of the Critical Energy Infrastructure Information (CEII) designation following 9/11. Although FERC revised its rules in 2006 to exclude purely locational information from the CEII designation, the only publicly available source of information on transmission pipeline location remains the National Pipeline Mapping System (NPMS). This website does not allow one to download spatial data, view more than one county at a time, or resolve the location of pipelines beyond a 500 foot tolerance. The only individuals allowed to access the database directly are government employees (who may access pipeline data under their jurisdiction) or pipeline operating companies (who may access data about their own pipelines).

2.2 The San Bruno Explosion and Aftermath

On September 9, 2010, a segment of 30-inch diameter PG&E transmission pipeline 132 exploded in the middle of the Crestmoor neighborhood in San Bruno, CA. Eight people were killed, 38 homes were destroyed, and an additional 70 homes had major or minor damage as a result of the explosion and fire.¹² The explosion occurred when an electrical glitch led to an increase in pressure, which blew open an existing welding flaw. In the aftermath of this disaster, PG&E was fined \$1.6 billion by the California Public Utilities Commission, paid out over \$565 million in civil settlements, and was eventually found guilty of six criminal counts in federal court.¹³

Media coverage of the disaster was widespread, and often focused on the existence of pipelines running locally along major roads or through neighborhoods.¹⁴ Shortly after the incident, PG&E was pressured to release a list outlining the 100 pipeline segments of highest priority for maintenance and monitoring. Although this list was generated using a number of criteria, the press coverage dubbed these segments the 100 “riskiest” pipeline segments, generating further publicity for the location of natural gas transmission pipelines throughout Northern California. In November 2010, one community in Northern Sacramento even closed an elementary school mid-year after discovering that it was near PG&E pipelines and natural gas storage tanks.¹⁵

The spike in attention suggested by these anecdotes about media coverage are backed

up by Google search activity. We collected Google Trends data on searches for stories that Google has determined are related to the San Bruno pipeline explosion. Figure 1 displays search activity for this set of stories over time, relative to the overall level of search activity in the geographic area.¹⁶ All three major California markets saw substantial search activity, though LA was less affected. New York City also shows some activity, suggesting that, while this was a major national news story, it got disproportionate attention in California. Although we cannot observe absolute search activity, in Appendix Figure A.3 we compare the San Bruno explosion search rate to that for stories related to the Major League Baseball World Series, which was won by the San Francisco Giants in October 2010. Searches related to San Bruno were roughly 20% of the peak search activity related to the Giants’ Series win, suggesting that pipeline-related coverage and information acquisition were substantial.

[Figure 1 about here.]

By Spring 2011, regulatory pressure led PG&E to send letters to customers living within 2000 feet of a natural gas transmission pipeline. These letters (presented in Appendix Figure A.2) noted the tragic nature of the San Bruno explosion, informed the resident that they lived within 2000 feet of a pipeline, provided a link to their online pipeline location map and the National Pipeline Mapping System (NPMS), and outlined some of the new safety measures that PG&E was implementing. The letter did not give residents any detailed information about their specific distance to the pipeline, or the location of that nearest pipeline. According to the local real estate community, this letter could be considered “knowledge of material fact”, which technically requires the homeowner to disclose this information to any potential buyer.¹⁷ An important detail is that if a transmission pipeline is near – but not actually encroaching – the property, there is otherwise no requirement to disclose this information to a potential buyer.¹⁸ We discuss the implications of this disclosure ambiguity in Section 6.

3 Data

To study the impact of the San Bruno events, we combine data on housing transactions with a map of pipeline locations. We purchased detailed GIS shapefiles of pipeline infrastructure from S&P Global Platts, a private firm that specializes in data related to energy and other heavy industry. These maps provide us with a snapshot of all natural gas pipelines in the state of California, as of October 2015. We observe the owner of the pipeline segment, and (in some cases) the parent pipeline’s name and the segment’s diameter. As our policy questions and treatments relate to transmission pipelines, we take measures to pare the pipeline map

down to segments that are most likely used for transmission purposes.¹⁹ Although we cannot independently verify this, Platts claims that these maps are highly accurate, coding all but two segments in the shapefile as being within 40 feet (78% of all pipeline segments in the sample) or within 165 feet.

We combine this pipeline map with information on all housing transactions in the state of California from January 1996 - June 2012. The data come from DataQuick (now a part of CoreLogic), a firm that aggregates and produces housing data from markets across the United States. In addition to information on the parties and transaction price, the data contain information on the exact street address and accompanying geolocation, and housing characteristics such as year built, square footage, number of rooms, number of bathrooms, the presence of a pool, and the presence of a garage. The housing characteristics are observed once – they are the most recent assessment at the time the data were collected for our purposes. Similar data have been used in many hedonic applications (e.g., [Muehlenbachs et al., 2015](#)).

3.1 Sample construction

We take a number of steps to ensure that our dataset contains only valid, arms-length transactions that involving new residents. We drop any transactions that are flagged as non-arms length transfers, are non-residential properties, mobile homes, and those whose addresses could not be mapped to a valid latitude and longitude. In each year, we drop transactions with prices in the top and bottom one percent. Finally, we drop properties that sell more than five times in our 16-year dataset, properties with more than five bedrooms or bathrooms, transactions in which the buyer appeared to be a corporate entity, and transactions that took place less than one year since the previous sale. Our main DD specification restricts the sample to counties that are unambiguously serviced by PG&E, excluding any homes within 1 kilometer of the site of the San Bruno explosion.²⁰

Table 1 reports the number of transactions by time period and distance group after making these sample restrictions. Comparing the sum of the first two columns to the third column, we can see that there are roughly 40% more transactions within 2000 feet of a pipeline than there are between 2000 and 4000 feet away, and this proportion is stable across treatment periods. In our main empirical specification, we restrict comparisons to properties sold within the same census tract within the same period (or quarter). Columns 4 and 5 in Table 1, labeled “mixed”, report the number of sales in our two primary treatment groups (properties between 0 and 600 feet and between 600 and 2000 feet from a pipeline) that occur in a census tract where we also observe the sale of at least one property sold in our control

group (homes between 2000 and 4000 feet from a pipeline) in the same sample period. This demonstrates that, although pipelines are ubiquitous in California, they are spaced such that there is real heterogeneity in exposure to pipeline risk in most communities.

[Table 1 about here.]

3.2 Descriptive statistics

Like the rest of the United States, California’s housing market experienced a sharp correction in late 2008. Figure 2 plots the average house price by month for houses near and far away from pipelines in PGE’s territory. Our identifying events occur in the immediate aftermath of that crash. In Section 4, we discuss strategies to address related potential threats to identification associated with this pattern.

[Figure 2 about here.]

Although the two price series in Figure 2 look remarkably similar, a fundamental concern with using house price differentials to infer latent preferences for avoiding pipelines is that pipelines are not located randomly. Figure 3 plots histograms of covariates for houses 0-2000 and 2000-4000 feet from the nearest pipeline. The overall distribution of these variables is generally quite similar across the two bins, with substantial overlap. Table 2 formalizes this by regressing each covariate on distance bin dummies and census tract fixed effects using OLS. Houses within 600-2000 feet of a pipeline are generally more similar than houses within 600 feet. Houses near pipelines tend to be slightly smaller less likely to have a pool or garage, and were more likely to be sold under some measure of foreclosure distress. While these differences are statistically significant, they are small in magnitude relative to the sample means. Nevertheless, we control for any differences in observable house characteristics explicitly and with property fixed effects below.

[Figure 3 about here.]

[Table 2 about here.]

4 Empirical strategy

Our starting point is the hedonic pricing equation relating house prices to pipeline proximity,

$$\ln P_{it} = \alpha Close_i + X_{it}\delta + \epsilon_{it} \tag{1}$$

where P_{it} is the sale price of house i with characteristics X at time t , and $Close_i$ is an indicator for whether the household is close to a natural gas pipeline. In a thick housing market where buyers and sellers are fully informed about all amenities, [Rosen \(1974\)](#) provides a framework to relate α to willingness to pay to avoid pipeline risk.

Two important challenges limit our ability to estimate α , even under the assumptions of [Rosen \(1974\)](#). First, pipelines could be spatially correlated with other omitted factors that also effect home values. In our sample, the natural gas transmission pipeline network had been fixed for decades, precluding the use of panel variation in pipeline proximity to identify housing price changes. Second, as discussed above, home buyers are generally unaware of pipeline proximity. As such, even absent the first concern, estimating equation 1 would produce an attenuated estimate of informed preferences ([Pope, 2008](#)).

We address these challenges by estimating the following difference-in-differences equation,

$$\ln P_{it} = \beta_{Pre}Close_i + \beta_{Post}Close_i \times Post_t + X_{it}\delta + \eta_c + \mu_t + \epsilon_{it} \quad (2)$$

where $Post_t$ indicates that the sale happened after 9/9/2010, the date of the San Bruno explosion. 30-day “month” of sample dummy variables μ_t are constructed such that they perfectly partition the pre- and post- San Bruno periods. η_c is a geographic fixed effect for the property’s census tract, which is a relatively homogeneous geographic unit containing an average of 4000 residents.

As written, the term β_{Pre} in equation 2 includes both of the biases discussed above. Borrowing notation from the energy efficiency gap literature ([Allcott and Greenstone, 2012](#)), let $\gamma \in [0, 1]$ capture the extent to which home buyers are not aware of or attentive to pipeline proximity prior to San Bruno. Then $\beta_{Pre} = \gamma_{Pre}\alpha$, and $\beta_{Post} = (\gamma_{Post} - \gamma_{Pre})\alpha$ reflects the change in the hedonic price gradient induced by a change in awareness following San Bruno.²¹ Our estimate of β_{Pre} will be biased by the presence of any omitted factors z that are a spatially correlated with pipelines and also effect home prices, $\hat{\beta}_{Pre} = \gamma_{Pre}\alpha + \sum_{z \in Z} \delta_z \frac{Cov(z, \tilde{Close})}{Var(Close)}$. However, if we assume that this bias term is constant across the pre and post periods, then our estimate of β_{Post} will be consistent.

In our primary specification, we consider two possible definitions of $Close_i$. According to the official pipeline accident report, the explosion damaged properties up to 600 feet away ([National Transportation Safety Board, 2011](#)). We thus define one treatment group “bin” as properties within 600 feet of any pipeline. As described in section 2.2, in the aftermath of San Bruno, California regulators mandated that PGE inform all residents living with 2000 feet of a pipeline of their proximity. We thus define a second (distinct) treatment bin to be all properties between 600 and 2000 feet. Consistent estimation of β_{Post} in equation 2 comes

from the parallel trends assumption that, absent San Bruno, the average price differences between houses in these two groups and control houses within the same census tract would have been the same during the pre and post period. To lend credibility to this assumption we restrict the sample to properties within 4000 feet of a natural gas pipeline. The control group is thus houses between 2000 and 4000 feet from a pipeline.

We also take several steps to account for the fact that the explosion occurred not long after an unprecedented housing crash. Although our sample begins in 1996, we define the baseline period in equation 2 to be one year prior to the explosion. We also flexibly control for foreclosure activity by including indicators for measures of distressed sale events, as in [Guren \(2018\)](#). Finally, we attempt to control for any latent systematic local trends in the housing market during this time by including fine space-time fixed effects: tract-specific treatment period dummies or tract-specific quarter of sample dummies. This approach allows census tracts to flexibly differ in their recoveries from the crash.

5 Results

We begin by estimating equation 2 using the universe of home purchases within 4000 feet of a pipeline in PG&E’s territory (top panel, Table 3). In column 1, we just include census tract fixed effects and month of sample fixed effects. The coefficient Bin600_Post indicates that the average price of homes within 600 feet of a pipeline were 0.8% *higher*, relative to properties between 2000 and 4000 feet within the same census tract, than they were in the baseline period. The coefficient Bin2000_Post indicates that the difference in prices between 600 and 2000 feet and homes between 2000 and 4000 feet was unchanged in the post period. Although the standard errors are quite small, both estimates are statistically indistinguishable from zero. The model in column 2 restricts comparisons to houses sold in the same census tract in the same sample period, and column 3 restricts comparisons to sales in the same census tract during the same 90 day sample “quarter”. The estimates in both of these models are precise zeros.

[Table 3 about here.]

These models remove potential confounders in the post period by estimating the average difference in sales price between properties near and far from pipelines within tract in the year prior to the explosion. However, one concern is that the sample of properties within these groups could be changing over time. In columns 4 through 6, we repeat these specifications but include property fixed effects. By construction, this limits the sample to properties sold at least twice between 1996 and 2012, removing nearly than half of the data. In the tract-period and tract-quarter models, the point estimates are negative for the closest properties; however, those estimates are quite noisy.

As was discussed in section 2, coverage of San Bruno was more extensive in the Bay Area. Motivated by this, the bottom panel of Table 3 repeats these models on a sample limited to the Bay Area.²² In columns 1 through 3, we see little response among the closest properties. Properties in the 600 to 2000 foot group decline by a statistically significant amount on the order of 1%, however the model with tract-quarter fixed effects is imprecise. Once we include property fixed effects, this unexpected ordering of responses across distance bins is reversed. We estimate a statistically significant decline of about 2% amount properties within 600 feet, and a statistically insignificant decline of 0.75% among properties between 600 and 2000 feet.

5.1 Narrower treatment groups

In the previous regressions, the spatial delineation of treatment groups was determined by two natural notions of the pipeline risk, the blast radius of San Bruno and the threshold

below which the regulator required PGE to inform residents about pipelines. However, given that the event shocked attention to and awareness of pipelines, it is possible that the *response* to San Bruno could follow a different pattern. For example, while pipelines are hidden underground, it is possible that households very close to them are still able to observe their presence, perhaps through rights of way. In this case, although they are at higher risk, the prices on these houses would adjust less because they were already informed.

To explore this heterogeneity, we replace the 600 and 2000 foot bin definitions with four evenly spaced 500-foot wide distance bins. Table 4 repeats the property fixed effect models for PG&E and the Bay Area, after imposing these narrow 500 foot property bins. The estimates based on PG&E’s entire service area are again quite imprecise. For example, while the point estimates are negative for the properties between 0 and 500 feet and 500 and 1000 feet from the pipeline, the standard errors are nearly as large.

[Table 4 about here.]

However, once we restrict attention to the Bay Area, we find statistically significant effects for the properties closest to the pipeline. The average price difference between properties less than 500 feet from a pipeline and properties more than 2000 feet away is roughly 2.5% lower than it was prior to San Bruno, and this difference is statistically significant at the 5 percent level. Moving to the next distance bin, the point estimates increase by nearly 1%. Although not significant at conventional levels, the point estimates suggest a non-trivial response in economic terms even in this intermediate risk range. The point estimates continues to decline as we look further away from the pipeline, with the point estimate on properties between 1500 and 2000 feet away being essentially zero; however, once again the standard errors are too large to draw strong conclusions.²³

5.2 Time varying effects

The previous models estimate an average price response over the 21-month period from the San Bruno explosion until the end of our sample. As our empirical strategy leverages a shock to awareness and attentiveness to pipelines, we might expect the effect to decline over time. Conversely, PGE did not send mailers out to households within 2000 feet until the spring. So it is possible that the housing market did not respond much initially, but did when provided with the letters. To investigate this empirically, we replace the $Post_t$ definition in equation 2 with indicators for 90 day quarters q post San Bruno (Qtr_t^q). The term $Qtr_t^{q=-1}$ is omitted, so that the estimates on all other quarters reflect the difference in the pipeline house price

gradient relative to this quarter. This specification can be written as:

$$\ln P_{it} = \sum_q \beta_{Qtr}^q Close_i \times Qtr_t^q + X_{it}\delta + \eta_{cq} + \mu_t + \epsilon_{it} \quad (3)$$

where we include tract-quarter fixed effects η_{cq} as well, such that the estimator plots out the quarterly change in the average within-tract price gradient.

Figure 4 presents the estimates for the Bay Area.²⁴ The model includes property fixed effects and tract-quarter fixed effects, and thus is a quarterly version of column 6 in Table 3. The estimated differences in sales price in each quarter are all estimated relative to the difference in price between properties near and far from a pipeline during the 90 day period immediately preceding the San Bruno explosion (quarter -1).

For both treatment bins, we do not see any obvious pre-trends, as the confidence intervals for the first five quarters in each figure comfortably contain zero. We also see no response in the first post period quarter (quarter 0). This is perhaps rationalized by the fact that many sales recorded during this quarter were already initiated prior to the explosion. However, in the following quarter, between 90 and 180 days after San Bruno, we find a large, statistically significant reduction of more than 5% in the 600 foot group.

The second, gray, vertical line corresponds to the approximate date that PG&E began mailing letters to households within 2000 feet.²⁵ The estimates for the 600 foot group are quite noisy during this time, but they do not suggest any large price response to the letter. In the right panel, the quarterly estimates pre and post explosion look remarkably similar, suggesting no response on average among properties between 600 and 2000 feet from a pipeline. As these coefficients are estimated off of a smaller effective sample, they are noisy and so it is difficult to rule out modest, short-lived effects for this group.

[Figure 4 about here.]

Estimating the quarterly model with 500 foot distance bins yields similar patterns (Figure 5). In the closest two distance groups, we find a large and statistically significant decline in relative prices in the period 90 to 180 days after the explosion. These effects gradually dissipate over time, with no obvious additional decline after these properties were sent letters informing them of their proximity. For properties between 1000 and 2000 feet from a pipeline, the figures are flat.

[Figure 5 about here.]

6 Discussion

As was discussed in section 4, our treatment effect is the product of the *change* in attentiveness from the pre to the post period, $(\gamma_{Post} - \gamma_{Pre})$ and true willingness to pay. In this section, we discuss what we might learn about the latter term if we make assumptions about the former. Intuitively, if consumers were already perfectly informed about and attentive to pipeline risk prior to San Bruno, and if the explosion did not change people’s beliefs about the probability of an explosion, then we would expect to see little change in the price gradient after the explosion, even if willingness to pay to avoid pipeline risk was large.²⁶ The background evidence presented above suggests γ_{Pre} was well below one prior to the explosion. Coverage lamenting lack of information was ubiquitous, and even first responders were uninformed about pipeline locations. Moreover, the PG&E letter mailing was prompted precisely because awareness was so low. Thus, it seems reasonable to assume that γ_{Pre} was close to zero.

Taking a stand on the level of γ after the explosion is more difficult. This was a major national news story, garnering days of coverage on nightly news programs, and coverage persisted much longer in California. As the Google search data shows, many of those living in Northern California also turned to the internet for information on pipelines at a rate never seen before. While we cannot relate this directly to the number of homebuyers affected, let alone their priors, it seems reasonable to assume that this bump in attention was considerable. In the time varying treatment effect models, we consistently found that the largest response occurred in the second quarter.

Turning to the informational letter, this intervention constitutes arguably the most direct informational treatment we could imagine implementing at scale. PG&E compiled a list of all residents living within a relatively large area around each of its pipelines. It then sent millions of residents a concise letter invoking the still salient tragedy of San Bruno, alerting them of their situation, and directing them to a website for more information. Despite this, we fail to find any evidence that they these letter caused a meaningful shift in the hedonic price gradient.

Like all mailers, we have no way of knowing how many of these letters were opened and internalized. An additional possible explanation for their lack of impact is that the letters were only given to property owners, not buyers. As was discussed above, there is conflicting information over whether this was a legally material fact that should be disclosed when closing. Regardless of the literal letter of the law, we doubt that this disclosure often happened in practice. Given this, the lack of response to is consistent with earlier disclosure work by [Pope \(2011\)](#), which focused on disclosure laws explicitly mandating disclosure to

potential buyers.

The average sales price in our sample during the post period is \$383,000. If we assume that $\gamma_{Pre} = 0$ and $\gamma_{Post} = 1$, then the 2% decline estimated in the Bay Area (Table B.2) suggests that fully informed and attentive households within 600 feet of a pipeline would be willing to pay \$7,650 to avoid pipeline risk. This one time up front payment gives the household protection from pipeline risk in perpetuity. If we assume a discount rate of 5%, which is the average interest rate on a 30-year fixed rate mortgage in 2010, this would imply an estimate of \$383 per household per year.²⁷ Finally, if we divide by the average California household size of 2.9, this would imply a willingness to pay of \$132 per person per year.

How large is that? Between 1996 and 2015, there were 12 fatalities from natural gas transmission pipeline incidents in California (including San Bruno). In the CoreLogic data, 12% of CA households are within 600 feet of a transmission pipeline, which implies an annual pipeline risk of 0.14 deaths per million people, per year. If we divide our willingness to pay estimate by this “rational” expectations level of pipeline risk, this would imply a VSL of over \$900 million, which is more than one hundred times conventional estimates. One simple explanation is that dying in an explosion is horrific, and people fear that more than other risks. Alternatively, there is a long literature in psychology and behavioral economics demonstrating that people overestimate the likelihood of risks that are uncontrollable, catastrophic, and inequitably distributed (Slovic, 1987; Kahneman et al., eds, 1982). For example, (Gayer et al., 2000) show that households initially over-react to their exposure to cancer risk from Superfund sites, but then temper their aversion once provided information. So one interpretation is that households implicitly believe their probability of dying in a pipeline blast is one hundred times more than the empirical average.²⁸

7 Conclusion

There are more than 7,000 miles of natural gas transmission pipelines currently under consideration in the United States, and industry groups predict that over 20,000 additional miles will be added by 2035.²⁹ While recent natural gas price spikes underscore the benefits of bringing additional supply to market, these benefits need to be balanced against their social costs. In this paper, we focus on one important component of this cost: the small but fundamentally unavoidable chance of a catastrophic explosion. Industry advocates routinely point out that, along the current, vast, natural gas pipeline network, there appears to be little evidence of strong aversion to this risk. However, given that pipelines are hard to observe, it is difficult to know if this reflects true ambivalence or simply a lack of salience and awareness.

In this paper, we attempt to resolve this ambiguity by studying the fallout from the San Bruno disaster, which shocked both salience and information. Using rich housing data, we find that properties nearest to pipelines, in the same market as the explosion, experience a one to two percent decline in sales price in the immediate aftermath of the explosion, consistent with the story that house prices did not fully reflect attentive preferences prior to the event. However, we find that this shock to attention was fleeting, with the house price gradient quickly returning to its pre-period state, in spite of the fact that the regulator forced PG&E to undertake a large informational campaign the following year. This short-lived price response was also quite geographically concentrated, as we observe little response among similarly exposed properties in other areas served by PG&E.

References

- Allcott, Hunt and Michael Greenstone**, “Is There an Energy Efficiency Gap?,” *Journal of Economic Perspectives*, 2012, 26 (1), 3–28.
- Ando, Michihito, Matz Dahlberg, and Gustav Engstrom**, “The risks of nuclear disaster and its impact on housing prices,” *Economics Letters*, 2017, 154, 13 – 16.
- Banzhaf, H Spencer**, “Difference-in-differences hedonics,” *Journal of Political Economy*, 2021, 129 (8), 2385–2414.
- Boslett, Andrew**, “Shale gas transmission and housing prices,” *Resource and Energy Economics*, 2019.
- Brogan, Michael James**, “Evaluating Risk and Natural Gas Pipeline Safety,” *Politics & Policy*, 2017, 45 (4), 657–680.
- Carson, Richard T.**, “Contingent Valuation: A Practical Alternative When Prices Aren’t Available,” *Journal of Economic Perspectives*, 2012, 26 (4), 27–42.
- Cheng, Nieyan, Minghao Li, Pengfei Liu, Qianfeng Luo, Chuan Tang, and Wengdong Zhang**, “Pipeline incidents and property values: a nationwide hedonic analysis,” *Available at SSRN 4116305*, 2022.
- Chetty, Raj, Adam Looney, and Kory Kroft**, “Salience and Taxation: Theory and Evidence,” *American Economic Review*, 2009, 99 (4), 1145–1177.
- Davis, Lucas W.**, “The Effect of Power Plants on Local Housing Values and Rents,” *Review of Economics and Statistics*, 2010, 93 (4), 1391–1402.
- Gallagher, Justin**, “Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States,” *American Economic Journal: Applied Economics*, 2014, 6 (3), 206–33.

- Gayer, Ted, James T Hamilton, and W Kip Viscusi**, “Private values of risk tradeoffs at superfund sites: housing market evidence on learning about risk,” *Review of Economics and Statistics*, 2000, *82* (3), 439–451.
- Guignet, Dennis**, “What do property values really tell us? A hedonic study of underground storage tanks,” *Land Economics*, 2013, *89* (2), 211–226.
- Guren, Adam M.**, “House Price Momentum and Strategic Complementarity,” *Journal of Political Economy*, 2018, *126* (3), 1172–1218.
- Hansen, Julia L., Earl D. Benson, and Daniel A. Hagen**, “Environmental Hazards and Residential Property Values: Evidence from a Major Pipeline Event,” *Land Economics*, 2006, *82* (4), 529–541.
- Iacus, Stefano M, Gary King, and Giuseppe Porro**, “Causal inference without balance checking: Coarsened exact matching,” *Political analysis*, 2012, *20* (1), 1–24.
- International, ICF**, “North American Midstream Infrastructure Through 2035: Leaning into the Headwinds,” 2016.
- Kahneman, Daniel, Paul Slovic, and Amos Tversky, eds**, “Judgment Under Uncertainty: Heuristics and Biases,” 1982.
- Klaiber, H Allen and V Kerry Smith**, “Quasi experiments, hedonic models, and estimating trade-offs for local amenities,” *Land Economics*, 2013, *89* (3), 413–431.
- Klass, Alexandra B. and Danielle Meinhardt**, “Transporting Oil and Gas: U.S. Infrastructure Challenges,” *Iowa Law Review*, 2014, *100*, 947–1054.
- Kuminoff, Nicolai V. and Jaren C. Pope**, “Do ”Capitalization Effects” for Public Goods Reveal the Public’s Willingness to Pay?,” *International Economic Review*, 2014, *55* (4), 1227–1250.
- Mastromonaco, Ralph**, “Do environmental right-to-know laws affect markets? Capitalization of information in the toxic release inventory,” *Journal of Environmental Economics and Management*, 2015, *71*, 54–70.
- Muehlenbachs, Lucija, Elisheba Spiller, and Christopher Timmins**, “The Housing Market Impacts of Shale Gas Development,” *American Economic Review*, 2015, *105* (12), 3633–3659.
- National Transportation Safety Board**, “Pipeline Accident Report: Pacific Gas and Electric Company Natural Gas Transmission Pipeline Rupture and Fire San Bruno, California September 9, 2010,” 2011.
- Parfomak, Paul W.**, “Keeping America’s Pipelines Safe and Secure: Key Issues for Congress,” 2013.
- , “DOT’s Federal Pipeline Safety Program: Background and Key Issues for Congress,” 2016.

- Parmeter, Christopher F. and Jaren C. Pope**, “Quasi-experiments and hedonic property value methods,” in “Handbook on Experimental Economics and the Environment” 2013.
Personal Communication
- Personal Communication**, 2016.
- Pope, Jaren C.**, “Do Seller Disclosures Affect Property Values? Buyer Information and the Hedonic Model,” *Land Economics*, 2008, 84 (4), 551–572.
- , “Buyer information and the hedonic: The impact of a seller disclosure on the implicit price for airport noise,” *Journal of Urban Economics*, 2011, 63 (2), 498–516.
- Rosen, Sherwin**, “Hedonic prices and implicit markets: product differentiation in pure competition,” *Journal of Political Economy*, 1974, 82 (1), 34–55.
- Slovic, P.**, “Perception of risk,” *Science*, 1987, 236 (4799), 280–285.
- Tanaka, Shinsuke and Jeffrey Zabel**, “Valuing nuclear energy risk: Evidence from the impact of the Fukushima crisis on U.S. house prices,” *Journal of Environmental Economics and Management*, 2018, 88, 411 – 426.
- United States Department of Energy**, “Quadrennial Energy Review: First Installment,” 2015.
- Walsh, Patrick and Preston Mui**, “Contaminated sites and information in hedonic models: An analysis of a NJ property disclosure law,” *Resource and Energy Economics*, 2017, 50, 1–14.

Table 1: Sample observations by time-period and distance to nearest pipeline (feet)

	0-600	600-2000	2000-4000	0-600, mixed	600-2000, mixed
Pre	8,923	20,088	20,848	6,595	17,416
Post-Exp.	6,443	14,217	14,795	4,387	11,792
Post-Letter	8,352	18,472	18,729	5,989	15,827

The “Pre” period includes the 12 months prior to the San Bruno explosion. The explosion period (“Post-Exp”) runs from September 9, 2010 to April 20, 2011 when the PG&E letters were sent. The “Post-Letter” period runs from that date until the end of the sample, June 30, 2012. In columns 4 and 5, “mixed” counts, the sample is restricted to census tracts containing both properties less than 2000 feet from a pipeline and properties further than 2000 feet from a pipeline.

Table 2: Housing transaction summary statistics

	(1) Price	(2) Beds	(3) Baths	(4) Pool	(5) Garage	(6) Sq. Ft.	(7) Distress
Less than 600 ft.	-37327.6*** (776.7)	-0.14*** (0.0030)	-0.084*** (0.0025)	-0.017*** (0.00096)	-0.027*** (0.00097)	-88.0*** (1.87)	0.023*** (0.0016)
600 - 2000 ft.	-20700.3*** (595.3)	-0.067*** (0.0023)	-0.049*** (0.0019)	-0.0077*** (0.00073)	-0.0089*** (0.00074)	-47.7*** (1.43)	0.011*** (0.0012)
Mean: 2000-4000 ft.	469455.0	2.99	2.10	0.097	0.69	1585.1	0.32

Each column is a separate OLS regression of the characteristic listed in the column title on indicators for whether a property is less than 600 feet from a pipeline or between 600 and 2000 feet from a pipeline, and census tract fixed effects. The number of observations in each regression is 924,522.

Table 3: Treatment effects by sample

(a) PGE						
	(1)	(2)	(3)	(4)	(5)	(6)
Bin600_Post	0.0082 (0.0059)	0.0011 (0.0053)	0.0016 (0.0055)	0.0088 (0.0090)	-0.0093 (0.0076)	-0.0090 (0.0082)
Bin2000_Post	0.00095 (0.0040)	-0.00027 (0.0037)	0.000012 (0.0039)	0.0016 (0.0063)	-0.00090 (0.0058)	-0.0014 (0.0066)
Property FE	No	No	No	Yes	Yes	Yes
Tract-Time FE	None	Tract-Period	Tract-Qtr	None	Tract-Period	Tract-Qtr
Observations	924508	924318	914165	509844	509383	476664
R-Squared	0.86	0.87	0.90	0.93	0.95	0.97
(b) Bay Area						
	(1)	(2)	(3)	(4)	(5)	(6)
Bin600_Post	0.0023 (0.0074)	-0.0061 (0.0069)	-0.0042 (0.0072)	0.0072 (0.012)	-0.021** (0.010)	-0.019* (0.011)
Bin2000_Post	-0.011** (0.0052)	-0.0089* (0.0051)	-0.0078 (0.0054)	-0.0050 (0.0080)	-0.0075 (0.0081)	-0.0076 (0.0095)
Property FE	No	No	No	Yes	Yes	Yes
Tract-Time FE	None	Tract-Period	Tract-Qtr	None	Tract-Period	Tract-Qtr
Observations	549395	549315	544260	303723	303511	285415
R-Squared	0.82	0.83	0.87	0.92	0.93	0.96

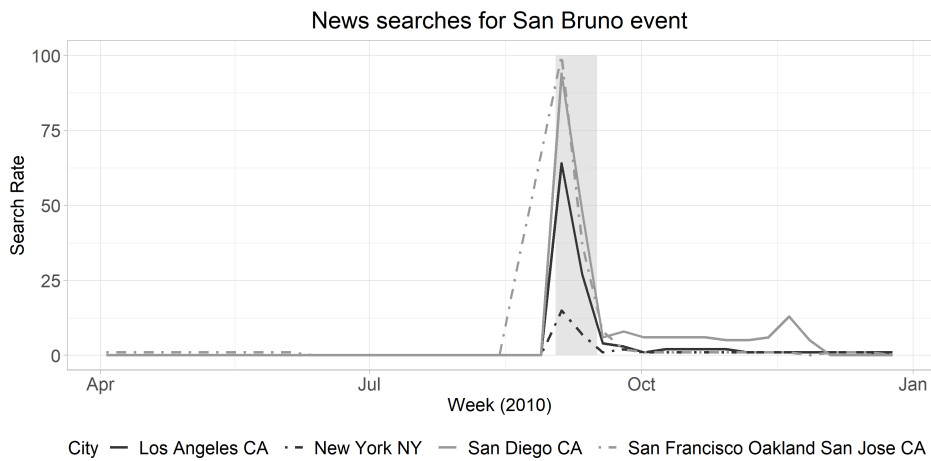
The dependent variable in each regression is log house price. All models contain month of sample dummies, and models without property fixed effects including housing characteristic controls. Standard errors clustered by census tract are reported in parentheses.

Table 4: PGE vs Bay Area, 500 foot bins

	(1)	(2)	(3)	(4)
Bin500_Post	-0.010 (0.0083)	-0.0090 (0.0089)	-0.026** (0.011)	-0.024** (0.012)
Bin1000_Post	-0.0078 (0.0074)	-0.0092 (0.0085)	-0.016 (0.010)	-0.014 (0.012)
Bin1500_Post	-0.0054 (0.0074)	-0.0072 (0.0083)	-0.0050 (0.010)	-0.011 (0.012)
Bin2000_Post	0.0077 (0.0070)	0.0091 (0.0080)	-0.0024 (0.0097)	0.0027 (0.011)
Sample	PGE	PGE	Bay Area	Bay Area
Property FE	Y	Y	Y	Y
Tract-Time FE	Period	Quarter	Period	Quarter
Observations	509383	476664	303511	285415
R-Squared	0.95	0.97	0.93	0.96

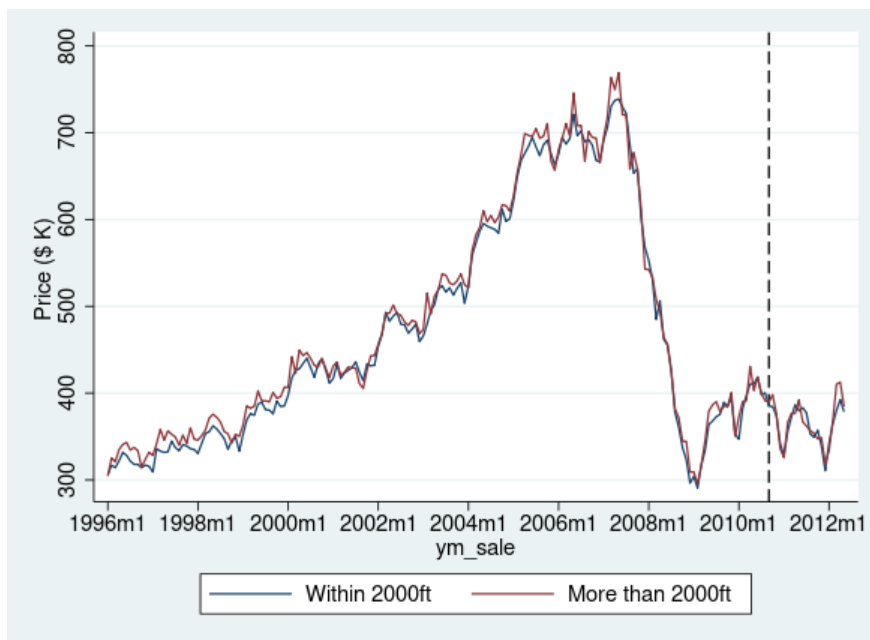
The dependent variable in each regression is log house price. All models contain month of sample dummies, and models without property fixed effects including housing characteristic controls. Standard errors clustered by census tract are reported in parentheses.

Figure 1: Google search rates



Figures show weekly relative search rates related to the “San Bruno Pipeline Explosion” event as determined by Google algorithm.

Figure 2: California house price trends



Monthly average sales price (thousands of dollars) for properties less than 2000 feet from a pipeline or between 2000 and 4000 feet from a pipeline. The dashed vertical line denotes the San Bruno explosion.

Figure 3: Housing characteristic support by distance from pipeline

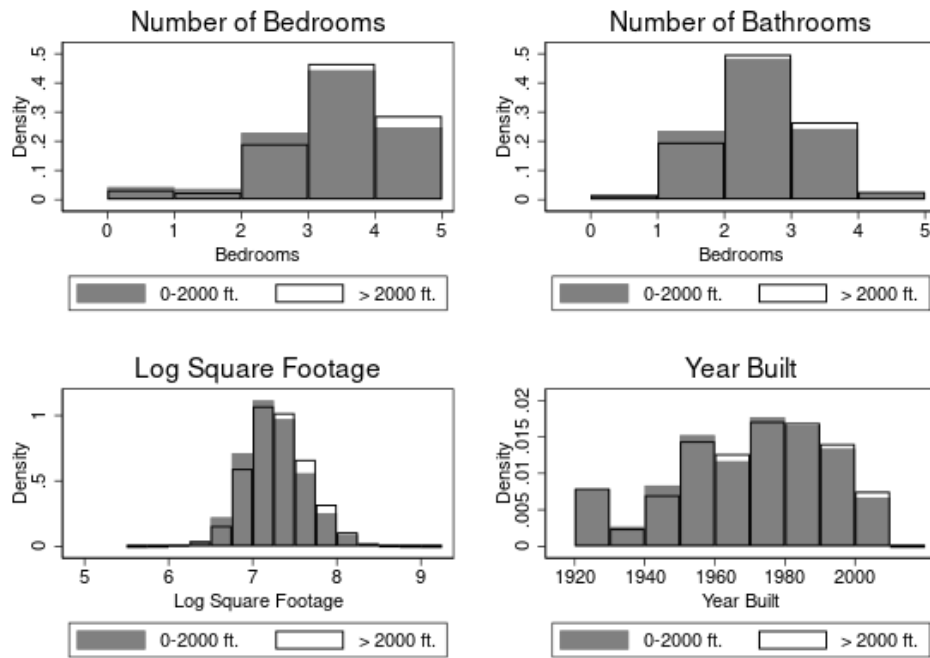
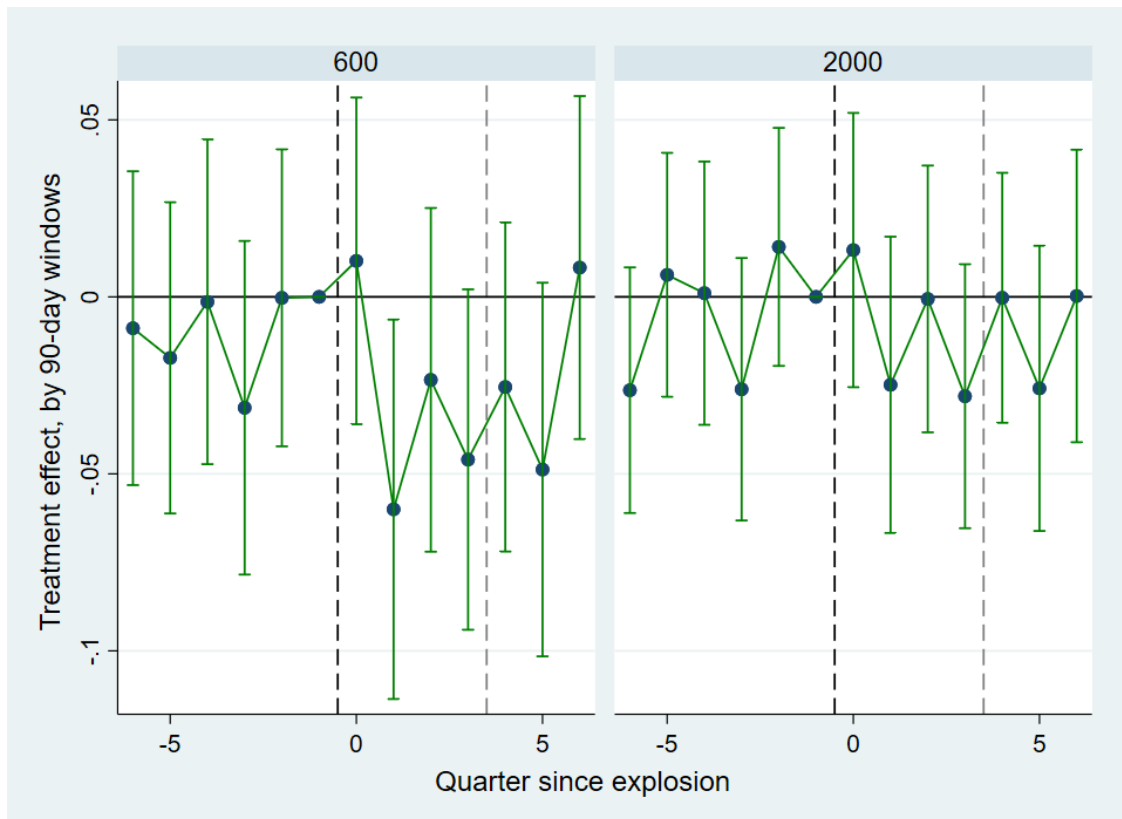
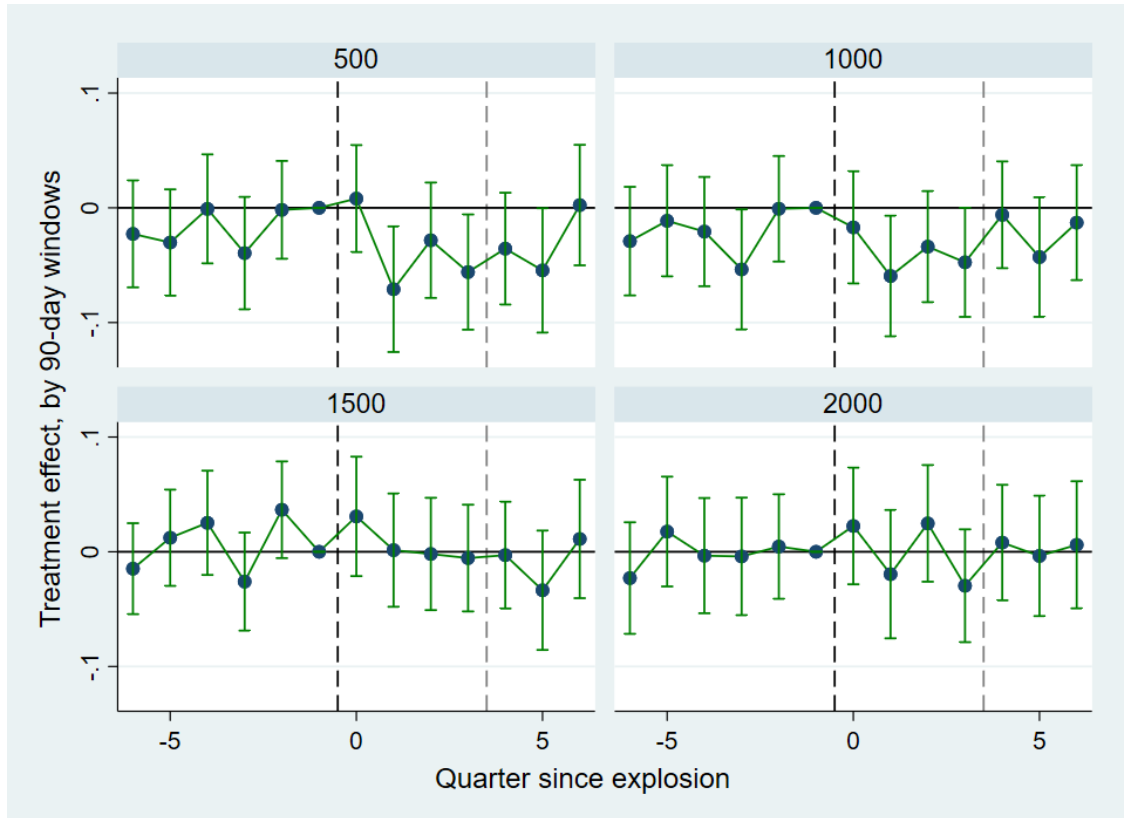


Figure 4: Quarterly Estimates - Bay Area: 0 - 600 ft and 600 - 2000 ft bins



This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and our treatment distance group by quarter of sample fixed effects. The left panel presents the quarterly coefficient on properties between 0 and 600 feet from the pipeline, and the right panel presents the coefficient on properties between 600 and 2000 feet from the pipeline. The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

Figure 5: Quarterly Estimates - Bay Area - 500 ft bins



This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and our treatment distance group by quarter of sample fixed effects. Panels present the quarterly coefficient on properties 0-500 feet (top left), 500-1000 feet (top right), 1000-1500 feet (bottom left), and 1500-2000 feet (bottom right). The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

Appendix A Additional figures

A.1 Background

[Figure A.1 about here.]

[Figure A.2 about here.]

[Figure A.3 about here.]

A.2 Continuous treatment effect

The results in Table 4 suggest that the housing market response to the shock of San Bruno was continuous, with properties closer to pipelines responding more to the explosion than those further away. By grouping properties into discrete bins, we are estimating an average of that gradient over the interval, and potentially masking even larger responses. One option to address this would be to make the distance groups even smaller. However, this would not be an efficient use of the data, as each narrow group's estimate would not be informed by relevant transactions just outside the bin. As an alternative, we replace the binary $Close_i$ groups definition in equation 2 with basis functions from a cubic spline in distance to the pipeline. We place knots at 500 foot intervals starting from zero out to 2000 feet. Properties between 2000 and 4000 feet only appear in the intercept. We then interact these basis functions with the $Post_t$ indicator, and repeat the property fixed effect specifications.

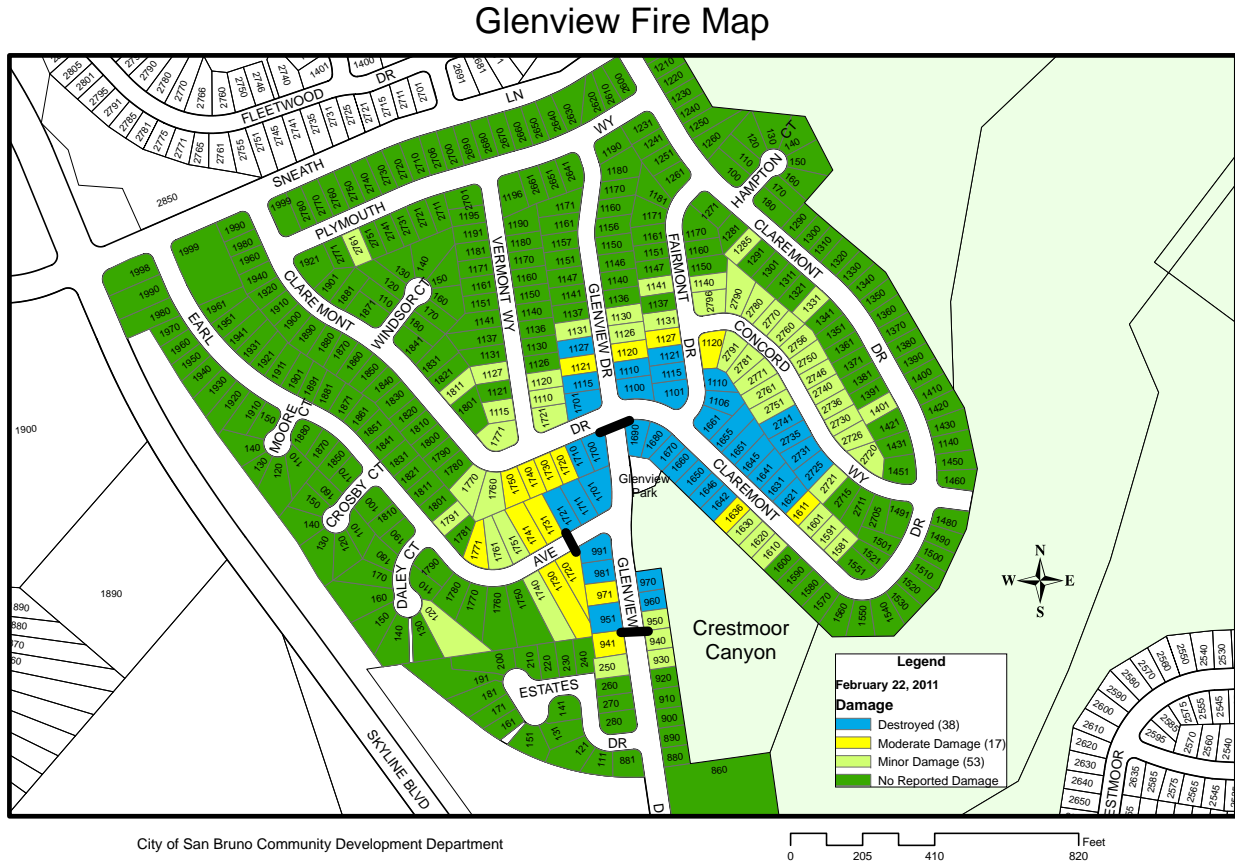
Figure A.4 presents the estimated response function and associated 95% confidence interval. As expected, these results suggest that the discrete bins masked meaningful heterogeneity. In all four models, the estimated price response is largest for properties right on top of a pipeline. In PGE the estimate at this point is roughly 2%, and this is statistically distinguishable from zero at the 10 percent level. In the Bay Area the estimated response zero feet from a pipeline is between 3% and 4%. The response for properties more than 500 feet from a pipeline appears fairly constant all the way out to around 1200 feet, at which point it converges back to properties more than 2000 feet away.

[Figure A.4 about here.]

In section 5.2, we allowed the discrete distance bin effects in the Bay Area to vary by quarter. Here we repeat that exercise for the cubic spline model. In Figure A.5, each panel presents the estimated value at the knot placed at the point indicated in the caption. As in the preceding section, these models demonstrate the continuous nature of the response. The largest decline across all four panels comes at the knot placed directly on top of a pipeline, in the period 90 to 180 days following San Bruno. The estimated 10% decline is economically quite large, and of similar magnitude to the estimates in (Boslett, 2019). However, this effect quickly dissipates, with the estimated price gradient at this point returning to its pre-period levels by the end of the sample.

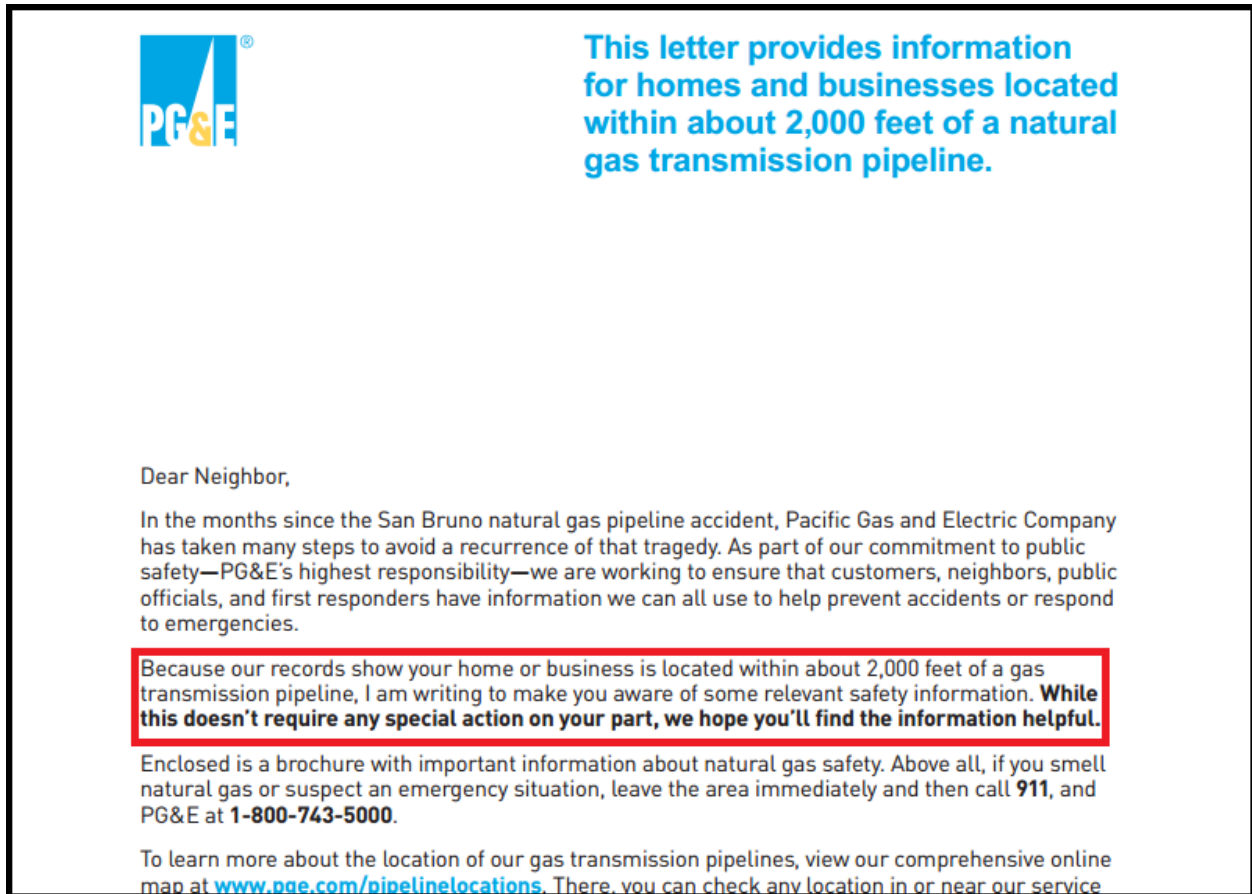
[Figure A.5 about here.]

Figure A.1: Map of San Bruno Damage



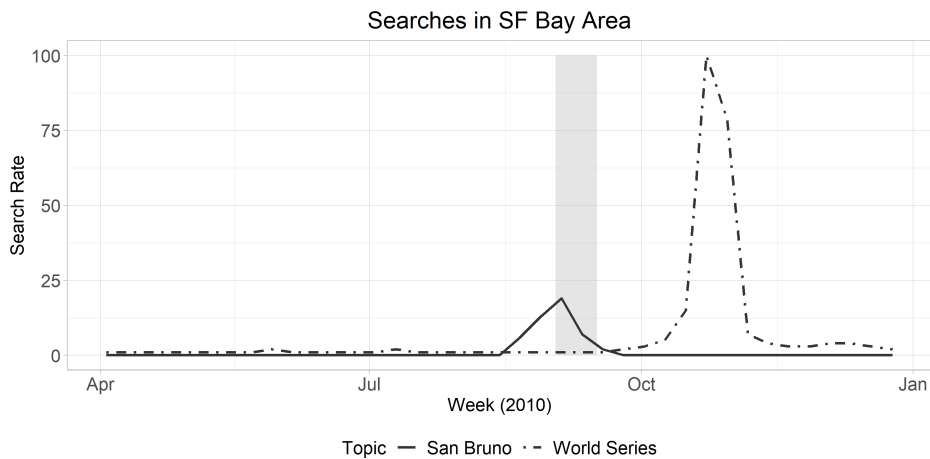
Source: City of San Bruno (<https://sanbruno.ca.gov/civicax/filebank/blobdload.aspx?blobid=22862>)

Figure A.2: PG&E Sample Letter



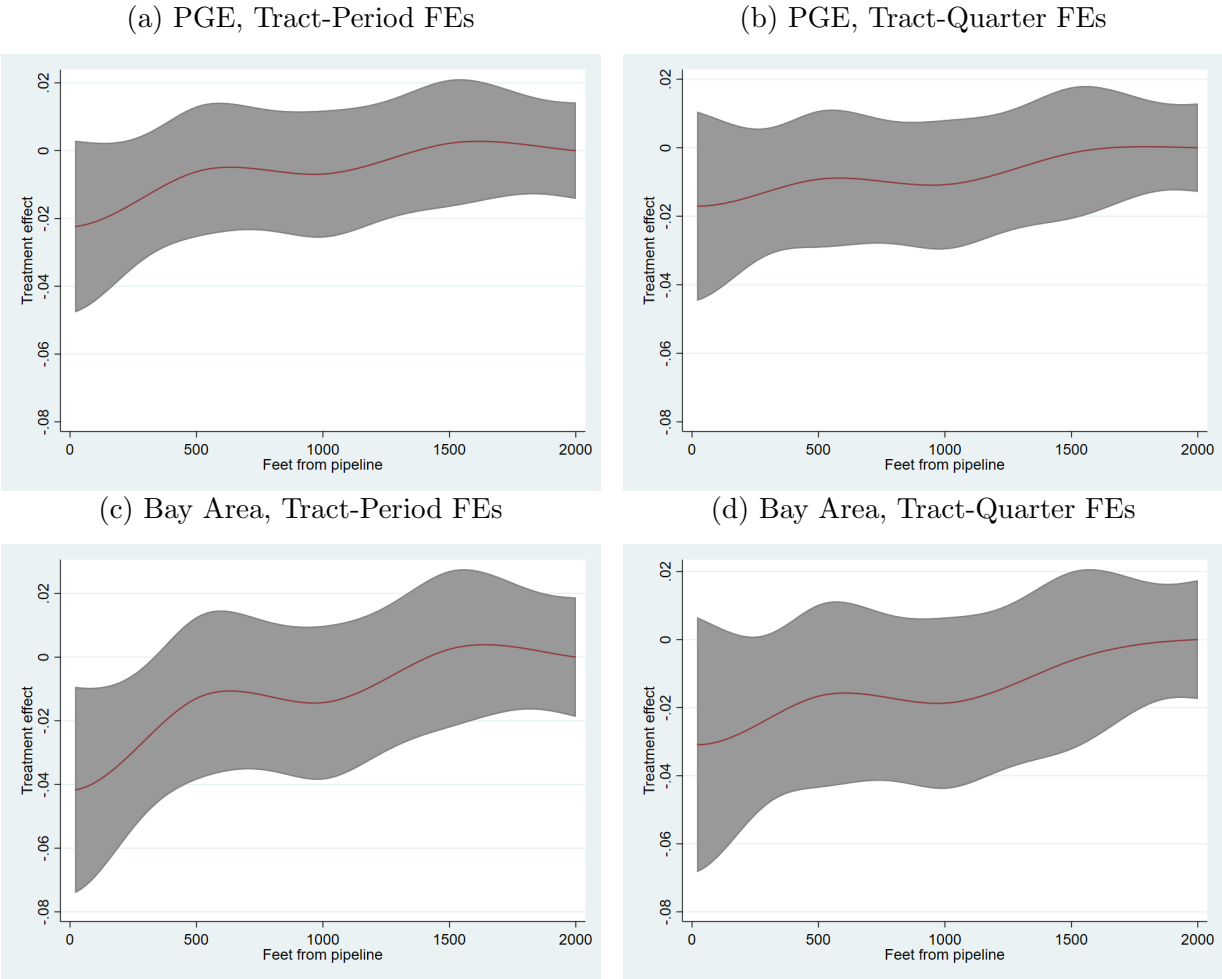
Source: City of San Bruno (<https://sanbruno.ca.gov/civicax/filebank/blobdload.aspx?blobid=22862>)

Figure A.3: Google search rates - World Series Comparison



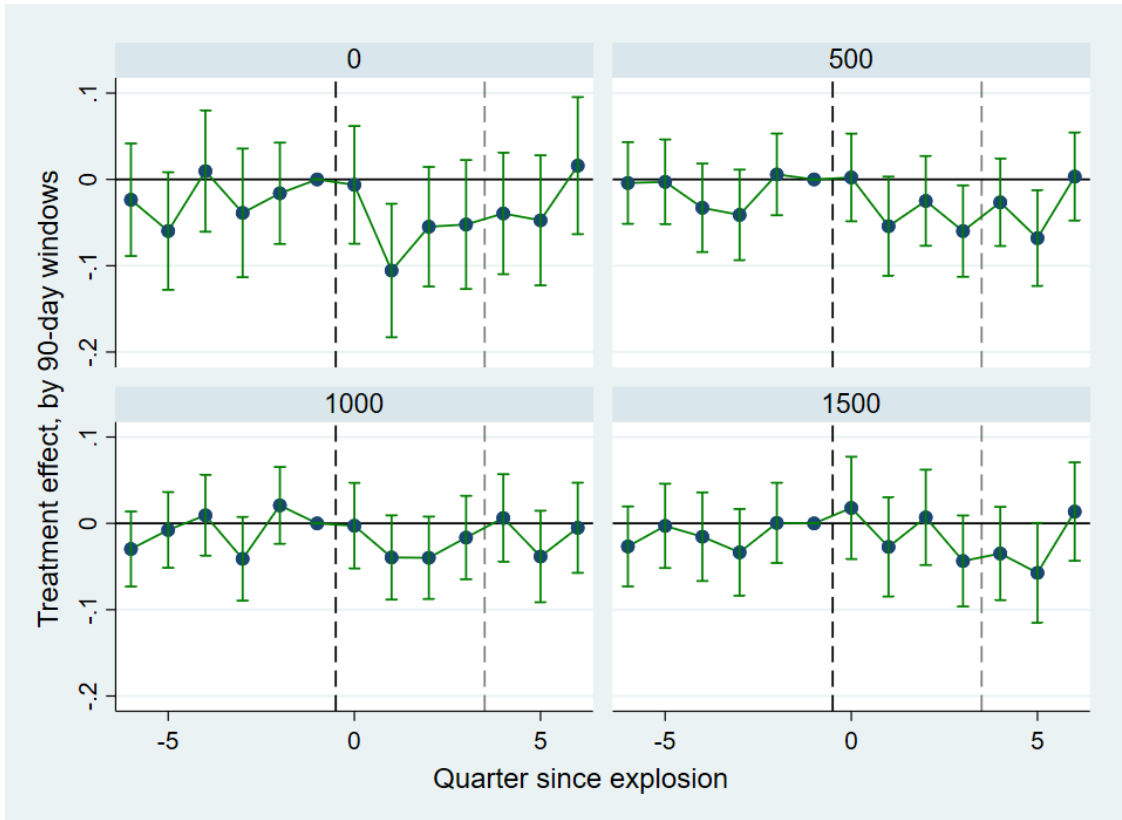
Figures show weekly relative search rates related to the “San Bruno Pipeline Explosion” event and the “World Series” as determined by Google algorithm.

Figure A.4: Spline Estimates



Each figure plots the results from estimating equation 2 with the treatment period interacted with a cubic B-spline in pipeline distance. Knots are placed at 500 foot intervals starting at zero, and the excluded category in each period is properties from 2000-4000 feet from a pipeline. Standard errors are clustered at the tract level, and the shaded area reflects 95% confidence intervals.

Figure A.5: Quarterly Estimates - Bay Area - Spline Knots



This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and a cubic spline in distance from a pipeline interacted with quarter of sample dummies. Panels present the quarterly estimated value of the spline for properties located at the following distances from a pipeline: 0 feet (top left), 500 feet (top right), 1000 feet (bottom left), and 1500 feet (bottom right). The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

A.3 Quarterly estimates for PG&E

[Figure A.6 about here.]

[Figure A.7 about here.]

[Figure A.8 about here.]

A.4 Sample robustness

Our primary sample includes all property types, and all arms length sales types. Here we compare the estimates from this sample to samples where we either restrict the sample to single family dwellings or drop sales flagged as being part of a distress event.

[Table A.1 about here.]

Appendix B Property fixed effect discussion

In our main regression results (Table 3), we presented models with tract fixed effects and with property fixed effects. The two differ both in the composition of the included transactions, and in their ability to control for unobserved confounders. In this section we consider alternative, intermediate specifications to understand the differences between these two models.

Columns 1 and 2 of Table B.2 repeat the tract fixed effect results from Table 3, corresponding to the model in equation 2. In columns 3 and 4, we include census tract - distance bin group fixed effects.

$$\ln P_{it} = \beta_{Post} Close_i \times Post_t + X_{it} \delta + \text{TractBin FE}_{c,i} + \mu_t + \epsilon_{it} \quad (4)$$

Whereas equation 2 assumes that the average difference in the price of near versus close properties across all census tracts in the same in the post period, equation 4 imposes parallel trends at the tract level. In both PGE and the Bay Area samples, this has no discernible effect on the parameters of interest.

[Table B.1 about here.]

In columns 5 and 6, we repeat the tract fixed effect models from columns 1 and 2. However, we restrict the sample to properties which sell at least two times, so it matches the sample from the property fixed effect regressions (repeated in columns 7 and 8). The point estimates on the 600 foot bin group in the Bay Area are now roughly half as large as the estimates in columns 7 and 8. This suggests part the difference between the tract fixed effect and property fixed effect results come from changes in sample composition in the former, although these point estimates are noisy. The remaining difference between the tract fixed effect and property fixed effect models must be driven by differences in unobserved attributes across distance groups within census tract.

B.1 Coarsened Exact Matching

An alternative empirical strategy would be to explicitly match properties near and far from a pipeline within the same census tract. As was discussed in section 3, observable property characteristics are not balanced across groups within census tract. This imbalance on observables could result in biased treatment effect estimates, to the extent that the functional form imposed on observed characteristics is not correct. Furthermore, this imbalance suggests that *unobserved* attributes might also be imbalanced. Ensuring that properties near and far from pipelines are balanced on *observable* dimensions may allay these concerns, and recover an unbiased estimate of the post period price response under the assumptions parallel trends.

Given that we have many housing characteristic controls, including some that are continuous (like square footage and age) we construct matches using coarsened exact matching (CEM) (Iacus et al., 2012). To implement this, we must first define two distinct groups to match across. We begin by combining the two distance bins in our main specification into a single treatment group containing all properties less than 2000 feet from a pipeline. These are then matched to properties between 2000 and 4000 feet from a pipeline within the same census tract sold within the same sample period (ie pre or post explosion). In addition to matching exactly on census tract and period, we match exactly on the properties “use code” (ie single family, condo, etc) and distressed sale indicator, and coarsely on bedrooms, baths, age, and square footage.

After matching, we re-estimate the model in equation 2, weighting observations using the CEM match weights as described in Iacus et al. (2012). Table B.3 presents the results. Column 1 repeats the tract-period model from Table B.2 on this matched sample. Although noisy, these models yield a treatment effect for the 600 foot group of approximately -.01 in PGE and -.02 in the Bay Area, which accords with the property fixed effects tract-period estimates. Column repeats the tract - distance bin fixed effect specification from column 3 of Table B.2. The PGE results are essentially unchanged, while the Bay Area results are now larger than the property fixed effect model, at -0.034.

[Table B.2 about here.]

In columns 3 and 4 of Table B.3, we repeat the entire exercise including only properties less than 600 feet from a pipeline in the treatment group. As above, these are matched to properties 2000-4000 feet away from a pipeline within the same census tract in the same sample period. As CEM requires two distinct groups, the motivation for these models is to ensure the balance achieved during the matching step corresponds with the treatment groups in the regressions. Both the specifications in columns 3 and 4 look more similar to column 1 than column 2. Although the estimates are noisy, given the small sample after matching, these estimates substantiate the main findings from the property fixed effects models.

Table B.1: Sample robustness

(a) PGE

	(1)	(2)	(3)	(4)	(5)	(6)
Bin600_Post	-0.0093 (0.0076)	-0.0090 (0.0082)	-0.013 (0.0085)	-0.0095 (0.0095)	-0.019 (0.015)	-0.014 (0.021)
Bin2000_Post	-0.00090 (0.0058)	-0.0014 (0.0066)	-0.0045 (0.0063)	-0.00062 (0.0073)	-0.010 (0.011)	-0.013 (0.016)
Single Family Only			X	X		
Drop Distress					X	X
Group FE	Property	Property	Property	Property	Property	Property
Tract-Time FE	Period	Quarter	Period	Quarter	Period	Quarter
Observations	509383	476664	381348	343699	252406	204754
R-Squared	0.95	0.97	0.95	0.97	0.95	0.97

(b) Bay Area

	(1)	(2)	(3)	(4)	(5)	(6)
Bin600_Post	-0.021** (0.010)	-0.019* (0.011)	-0.029** (0.012)	-0.017 (0.013)	-0.019 (0.017)	-0.022 (0.024)
Bin2000_Post	-0.0075 (0.0081)	-0.0076 (0.0095)	-0.013 (0.0091)	-0.0061 (0.011)	-0.010 (0.012)	-0.020 (0.018)
Single Family Only			X	X		
Drop Distress					X	X
Group FE	Property	Property	Property	Property	Property	Property
Tract-Time FE	Period	Quarter	Period	Quarter	Period	Quarter
Observations	303511	285415	202299	180824	175643	149263
R-Squared	0.93	0.96	0.93	0.96	0.93	0.97

Table B.2: Treatment effects by sample

(a) PGE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bin600_Post	0.0011 (0.0053)	0.0016 (0.0055)	0.0027 (0.0050)	0.0021 (0.0053)	-0.0058 (0.0070)	-0.0026 (0.0077)	-0.0093 (0.0076)	-0.0090 (0.0082)
Bin2000_Post	-0.00027 (0.0037)	0.000012 (0.0039)	-0.00021 (0.0035)	-0.00021 (0.0037)	-0.0041 (0.0052)	-0.0036 (0.0059)	-0.00090 (0.0058)	-0.0014 (0.0066)
Sample	All	All	All	All	Multi-sale	Multi-sale	Multi-sale	Multi-sale
Group FE	Tract	Tract	Tract-Bin	Tract-Bin	Tract	Tract	Property	Property
Tract-Time FE	Period	Quarter	Period	Quarter	Period	Quarter	Period	Quarter
Observations	924318	914165	924260	914099	509570	492125	509383	476664
R-Squared	0.87	0.90	0.88	0.91	0.88	0.92	0.95	0.97

(b) Bay Area

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bin600_Post	-0.0061 (0.0069)	-0.0042 (0.0072)	-0.0043 (0.0065)	-0.0027 (0.0068)	-0.012 (0.0087)	-0.0087 (0.0097)	-0.021** (0.010)	-0.019* (0.011)
Bin2000_Post	-0.0089* (0.0051)	-0.0078 (0.0054)	-0.0090* (0.0048)	-0.0076 (0.0051)	-0.0093 (0.0071)	-0.011 (0.0082)	-0.0075 (0.0081)	-0.0076 (0.0095)
Sample	All	All	All	All	Multi-sale	Multi-sale	Multi-sale	Multi-sale
Group FE	Tract	Tract	Tract-Bin	Tract-Bin	Tract	Tract	Property	Property
Tract-Time FE	Period	Quarter	Period	Quarter	Period	Quarter	Period	Quarter
Observations	549315	544260	549286	544232	303598	294017	303511	285415
R-Squared	0.83	0.87	0.84	0.87	0.85	0.89	0.93	0.96

Table B.3: CEM Estimates by Sample

(a) PGE

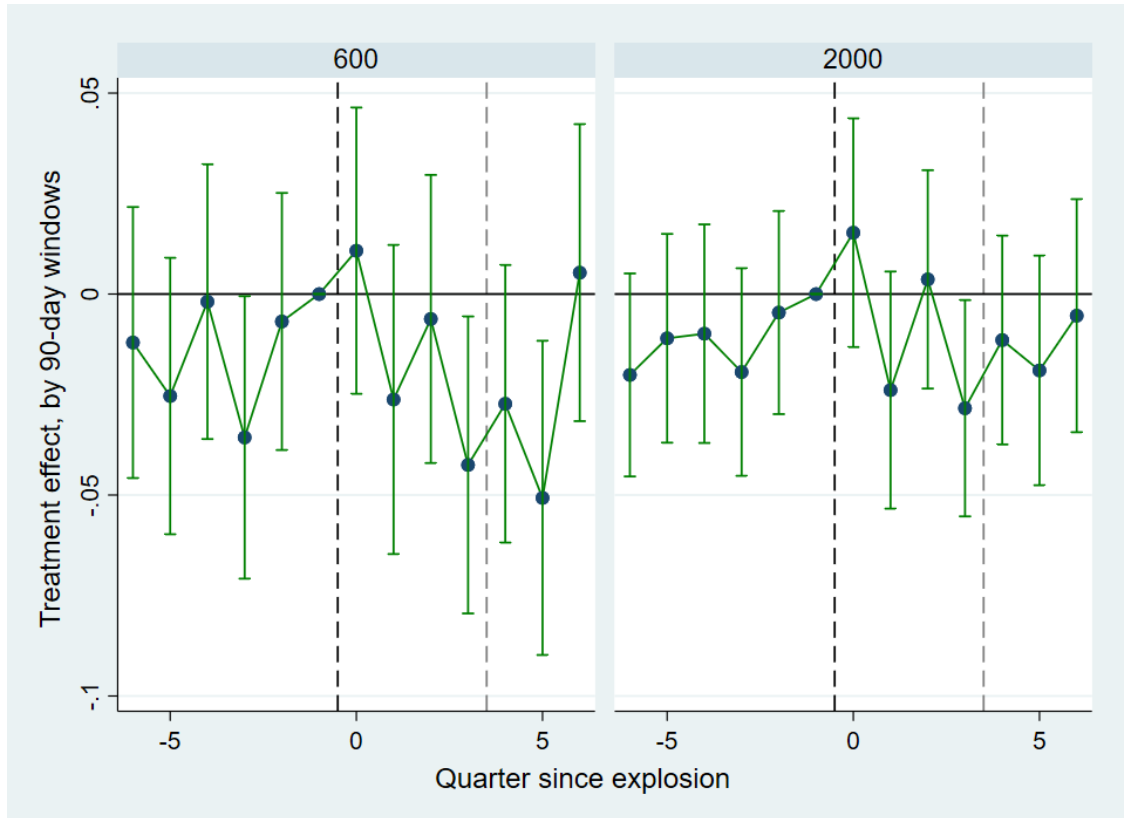
	(1)	(2)	(3)	(4)
Bin600_Post	-0.0099 (0.0098)	-0.012 (0.010)	-0.012 (0.012)	-0.0098 (0.012)
Bin2000_Post	-0.0025 (0.0058)	-0.0031 (0.0058)	0 (.)	0 (.)
Group FE	Tract	Tract-Bin	Tract	Tract-Bin
Tract-Time FE	Period	Period	Period	Period
Observations	31794	31375	7199	6957
R-Squared	0.94	0.95	0.95	0.96

(b) Bay Area

	(1)	(2)	(3)	(4)
Bin600_Post	-0.019 (0.013)	-0.034*** (0.013)	-0.019 (0.015)	-0.021 (0.016)
Bin2000_Post	-0.0060 (0.0081)	-0.0092 (0.0079)	0 (.)	0 (.)
Group FE	Tract	Tract-Bin	Tract	Tract-Bin
Tract-Time FE	Period	Period	Period	Period
Observations	13773	13535	3281	3131
R-Squared	0.93	0.93	0.94	0.94

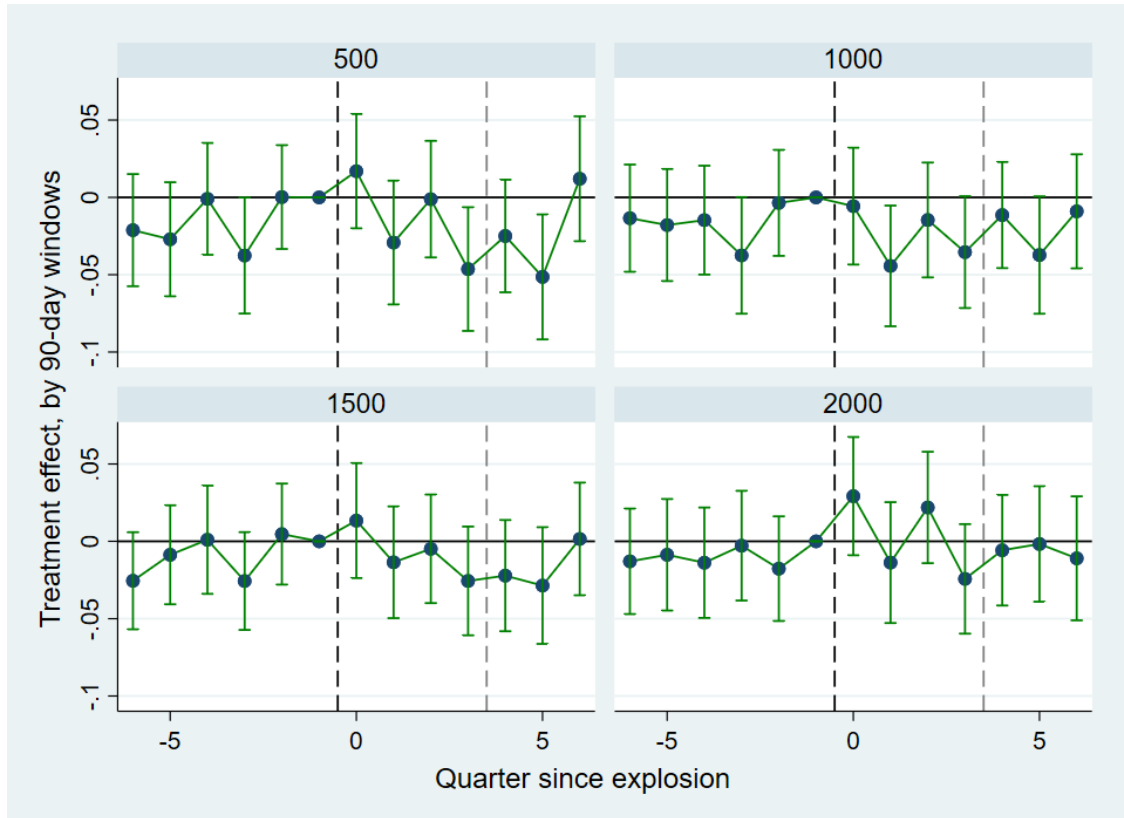
The dependent variable in each regression is log house price. Properties are divided into two groups, less than 2000 feet from a pipeline, and 2000-4000 feet. Within this sample, properties are matched across groups within tract - period, based on hedonic characteristics. The log house price is then projected onto tract-bin dummies, month of sample dummies, and indicator for the close properties during the treatment periods, with observations weighted by the CEM weights. All models contain month of sample dummies and housing characteristic controls. Standard errors clustered by census tract are reported in parentheses.

Figure B.1: Quarterly Estimates - PGE: 0 - 600 ft and 600 - 2000 ft bins



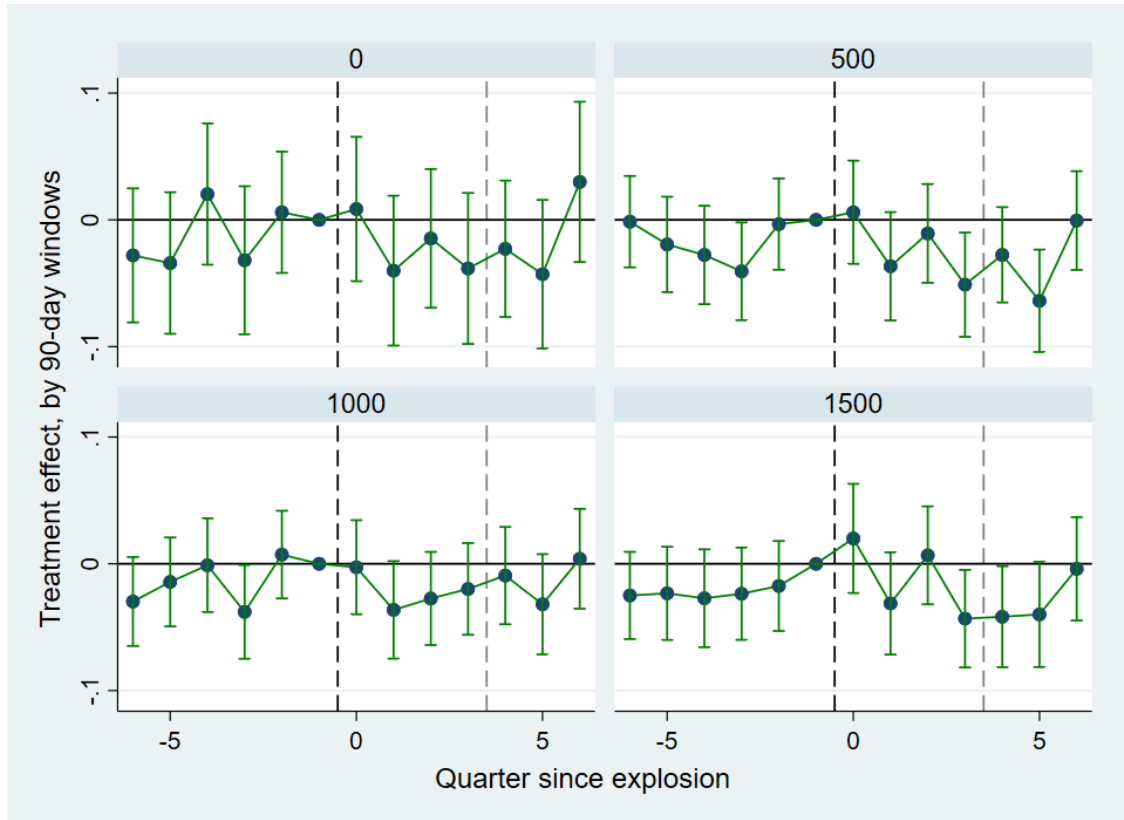
This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and our treatment distance group by quarter of sample fixed effects. The left panel presents the quarterly coefficient on properties between 0 and 600 feet from the pipeline, and the right panel presents the coefficient on properties between 600 and 2000 feet from the pipeline. The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

Figure B.2: Quarterly Estimates - PGE - 500 ft bins



This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and our treatment distance group by quarter of sample fixed effects. Panels present the quarterly coefficient on properties 0-500 feet (top left), 500-1000 feet (top right), 1000-1500 feet (bottom left), and 1500-2000 feet (bottom right). The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

Figure B.3: Quarterly Estimates - PGE - Spline Knots



This figure presents the results from a single regression of log house prices on to property fixed effects, census tract - quarter fixed effects, month of sample fixed effects, and a cubic spline in distance from a pipeline interacted with quarter of sample dummies. Panels present the quarterly estimated value of the spline for properties located at the following distances from a pipeline: 0 feet (top left), 500 feet (top right), 1000 feet (bottom left), and 1500 feet (bottom right). The black line corresponds to the date of the San Bruno disaster. The gray line corresponds to the approximate date that PG&E began sending out letters.

Notes

1. Source: <https://www.eia.gov/naturalgas/crudeoilreserves/>.
2. FERC Commissioner Cheryl LaFleur (1/27/2015), <https://www.ferc.gov/media/videos/lafleur/2015/012715-lafleur.pdf>.
3. There is abundant evidence which suggests these benefits could be large, at least in the short run. Due to plant closures, New England's electric power grid is increasingly reliant on natural gas. This past winter, due to transmission constraints, New England states had the four highest electricity prices in the continental United States (and six of the top eight) (EIA State Energy Data System, accessed April 1, 2019). In Westchester County, New York, gas utility Con Ed recently implemented a moratorium on new residential natural gas hookups in response to supply constraints ("Con Ed Cuts Off New Gas Hookups in New York Suburb," *The New York Times* March 21, 2019)
4. Over the 20-year period of 1995–2014, local distribution system accidents accounted for 279 fatalities and more than 1,000 injuries, while transmission systems accounted for 42 fatalities and 174 injuries, or about one-seventh of the total. Over the 4-year period of 2011–2014, there has only been one single transmission-related fatality (United States Department of Energy, 2015, pp NG-54).
5. In addition to the incident studied in this paper, other prominent recent explosions include Allentown, PA in 2011, where four adults and a toddler were killed, and Massachusetts in 2018, where a Columbia Gas leak caused the emergency evacuation of several Boston suburbs.
6. There is also some survey evidence consistent with this. Brogan (2017) conducted a survey of 738 individuals, and found that respondents randomly provided with additional information about pipeline risks and a salient account of a recent pipeline incident were significantly more likely to oppose pipeline expansion.
7. Our empirical strategy relies on panel-data variation, relating changes in an amenity to changes in home prices. Ignoring any other confounders, this capitalization effect will still only reflect willingness to pay under stringent conditions (Klaiber and Smith, 2013; Kuminoff and Pope, 2014). Banzhaf (2021) argues that this capitalization effect will be a lower bound on true surplus gains.
8. In contrast, Ando et al. (2017) find no response from a similar exercise in Sweden.
9. While the paper finds that houses closer to the pipeline sold at a discount after the explosion but not before, there is no formal test of the difference between these coefficients. In addition, areas near the pipeline may have been adversely affected due to the loss of nearby parkland to the ensuing fire. In our context, we consider the impact on houses in the "shadow" of pipelines much further away that could not have been affected by the direct disamenity of the San Bruno explosion.
10. While an increasing amount of natural gas being shipped as liquefied natural gas (LNG) on enormous tankers, the costs of liquefaction are prohibitively high except on very large scales in the presence of substantial price differentials.
11. This trend is expected to continue, with annual domestic natural gas production increasing from a current level of 27 tcf to 45 tcf in 2050 in the Energy Information Administration's 2018 Annual Energy Outlook.
12. Appendix Figure A.1 provides a sense of the scale of the damage.
13. See, respectively, "PG&E slapped with record \$1.6 billion penalty for fatal San Bruno explosion" (April 9, 2015); "San Bruno blast: PG&E settles nearly all remaining lawsuits for a \$565 million total" (Sept. 9, 2013); and "PG&E loses ruling in San Bruno explosion trial" (Nov. 17, 2016); all in the *San Jose Mercury News*.
14. For example: "PG&E Says the Valley has 4 High Risk Gas Pipelines", *KMPH News* (Sept. 21, 2010); "Natural gas transmission lines run near Highway 101 in Marin", *Marin Independent Journal* (Sept. 13, 2010); "Pipeline in San Bruno blast runs through Palo Alto", *Palo Alto Online* (Sept. 20, 2010).

15. “Quick closure of N. Sacramento school debated”, *Sacramento Bee* (Nov. 20, 2010).
16. That is, these numbers can be interpreted as the “search rate”, and are comparable across search terms and/or geographies within a given graph.
17. This issue was raised in a press release by a real estate disclosure firm (<http://www.firstamsms.com/content/natural-gas-pipelines-now-disclosed-1>), and confirmed by Kate Konschnik of the Harvard Environmental Law Clinic (*Personal Communication*, 2016).
18. As of July 1, 2013, all contracts for the sale of residential real property in California must contain a specified notice pertaining to gas and hazardous liquid transmission pipelines (California AB 1511, year 2012). However, this notice simply informs the buyer that pipelines exist (not necessarily near the property), and that they should go to the NPMS to find out if there is one nearby. It does not discriminate on the basis of actual pipeline proximity in any way. Unfortunately, our housing data ends prior to this law going into effect.
19. Specifically, we drop any pipe from a system with a name that indicates distribution activity or if the diameter is known to be less than 6 inches. We also drop a pipe if the diameter is missing, unless it has information about the system it belongs to or is an interstate pipeline. Our results are very similar using the full network of pipelines.
20. These counties are Alameda, Amador, Butte, Calaveras, Colusa, Contra Costa, Glenn, Humboldt, Lake, Marin, Mariposa, Mendocino, Merced, Monterey, Napa, Sacramento, San Benito, San Francisco, San Joaquin, San Mateo, Santa Clara (excluding Palo Alto, which is serviced by a municipal utility), Santa Cruz, Solano, Sonoma, Stanislaus, Sutter, Tehama, Tuolumne, Yolo, and Yuba.
21. In the extreme case where $\gamma_{Pre} = 0$ and $\gamma_{Post} = 1$, $\beta_{Post} = \alpha$. We discuss this assumption further in section 6
22. The Bay Area is defined as properties in the following counties: San Mateo, Santa Clara, San Francisco, Alameda, Contra Costa and Marin.
23. In appendix A.2 we replace the binary $Close_i$ groups definition in equation 2 with basis functions from a cubic spline in distance to the pipeline.
24. Analogous figures for PGE are provided in Appendix A.3.
25. The letter campaign was announced in a press release on April 20, 2011. However, we do not know the exact rollout dates of these letters, and attempts to obtain them from PG&E or the California Public Utilities Commission have been unsuccessful. The limited news coverage we found indicates that Berkeley residents received letters during the last week of June 2011, while Napa residents received them in mid-July.
26. The importance of the baseline level of information is also demonstrated in Walsh and Mui (2017). They study the impact of hazard disclosure, and find that the extent to which home prices response is inversely related to the baseline level of information.
27. The present value of a perpetuity is equal to the flow benefit divided by the discount rate. Data on mortgage rates was obtained from the St. Louis Federal Reserve (<https://fred.stlouisfed.org/series/MORTGAGE30US>).
28. It should be noted that pipeline explosions entail other real costs beyond the risk of death. The estimated WTP would reflect the value of avoiding those costs as well.
29. Pending pipelines based on the list of proposed pipeline projects maintained by the Energy Information Administration, <https://www.eia.gov/naturalgas/pipelines/EIA-NaturalGasPipelineProject.xlsx>, accessed in August 2022. Projected additions taken from a 2016 study prepared for the INGAA Foundation (International, 2016).