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Induced earthquakes and housing markets: Evidence from Oklahoma

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ABSTRACT

This paper examines the impact of earthquakes on residential property values using sales data from Oklahoma from 2006 to 2014. Before 2010, Oklahoma had only a couple of earthquakes per year that were strong enough to be felt by residents. Since 2010, seismic activity has increased, bringing potentially damaging quakes several times each year and perceptible quakes every few days. Using repeat-sales and difference-in-differences models, we estimate that prices decline by 3–4 percent after a home has experienced a moderate earthquake measuring 4 or 5 on the Modified Mercalli Intensity Scale. Prices can decline 9 percent or more after a potentially damaging earthquake with intensity above 6. We also find significant increases in the time-on-market after earthquake exposures. Our findings are consistent with the experience of an earthquake revealing a new disamenity and risk that is then capitalized into house values.

1. Introduction

The long-term negative externalities associated with extractive industries have long been part of the public discourse, though the effects of industries ancillary to extraction have often proven difficult to examine. The management and disposal of wastewater from oil and gas operations, for instance, has only recently risen to prominence over concerns about water contamination from hydraulic fracturing, or "fracking," and over concerns of increases in earthquake frequency and severity near areas with booming oil and gas industries.[3] Oklahoma has been the state most affected by induced changes in earthquake frequency. It recorded more magnitude 3.0 (M 3.0) or higher earthquake events than California in 2014, and more than the other 47 contiguous states combined in 2015.[4] The two largest earthquakes in Oklahoma history, an M 5.7 earthquake in Prague on November 5, 2011, and an M 5.8 earthquake in Pawnee on September 3, 2016, are thought to have been induced (Keranen et al., 2013; Yeck et al., 2017).[5]

Documentation of earthquakes caused by underground injection of fluid reaches at least as far back as the study by Healy et al. of the 1962–1979 earthquakes near Rocky Mountain Arsenal, Colorado (Healy et al., 1968; Petersen et al., 2016). Induced earthquakes occurred there following the injection of chemical manufacturing waste by the US Army. Induced earthquakes from wastewater disposal have since been recorded in Ashtabula, Ohio; Perry, Ohio; and Cold Lake, Alberta, Canada (Nicholson and Wesson, 1990).[6] Reductions in wastewater injection volume have been associated with lagged decreases in seismicity in these cases. More recent seismicity, including earthquakes in Milan, Kansas (peak M 4.9; Choy et al. (2016)); Youngstown, Ohio (peak M 3.7; Kim (2013)); Timpson, Texas (peak M 4.8; Frohlich et al. (2014)); and Dagger Draw, New Mexico (peak M 4.1;

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[2] The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Board of Governors of the Federal Reserve System.
[3] Fracking itself has induced some earthquakes in Oklahoma, though the number of induced earthquakes and the peak recorded magnitude of these earthquakes (M 2.9) are far smaller than for earthquakes induced by wastewater injection: See Holland (2013).
[4] Magnitude 3 earthquakes approach the smallest that can be felt by humans: See Dengler and Dewey (1998).
[5] The next largest earthquake, an M 5.5 event in El Reno on April 9, 1952, has been postulated to be induced by injection-well activity, though evidence is sparse: See Hough and Page (2015).
[6] Earthquakes can be induced by underground injection wells, fluid reservoirs, and energy-resource-extraction practices (Ellsworth, 2013).

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Pursley et al. (2013)), has been induced by the disposal of waste fluids from oil and gas development operations.

In this paper, we examine the external welfare impacts of severe changes to earthquake frequency and intensity induced by fluid injection in Oklahoma. Fluids injected for disposal in Oklahoma largely consist of saltwater (>95 percent) extracted along with oil and natural gas. Injections also contain “flowback” water (<5 percent), which is waste fluid that returns to the surface following a hydraulic fracturing operation (Abualfaraj et al., 2014; Walsh and Zoback, 2015). These wastewaters’ high concentrations of total dissolved solids makes it uneconomical to use them for any other purpose, and they must be disposed of properly to protect public safety (Guerra et al., 2011). Injecting the wastewater into underground injection control (UIC) wells is the lowest-cost acceptable disposal method. If the water has to be transported from a production site to a disposal site, then transportation costs make up the vast majority of disposal costs (Welch and Rychel, 2004). Relative cost efficiency can be obtained by injecting large amounts of fluids into a large reservoir using a single well, though these same high-volume wells are thought to be the wells most likely to induce earthquakes in Oklahoma. The injection of large volumes of wastewater increases pore pressure in the rock formation they are injected into; this pressure can propagate below the injection site, eventually spreading to active faults in basement rock (Walsh and Zoback, 2015). The recent increases in injection into the Arbuckle formation, an Oklahoma rock formation that sits directly above basement rock, then can explain recent increases in seismicity (Murray, 2014). Wastewater management costs are a major factor in oil and gas production, and the elimination or severe regulation of the most cost-efficient management strategy would increase costs for producers in a state with substantial economic dependence on oil and gas production.

We measure the welfare effects of these earthquakes by examining their impacts on housing prices. As Koster and van Ommeren (2015) outline, earthquakes may affect housing prices through one of three mechanisms: earthquakes can cause property damage; changes in earthquake frequency may change expectations of future earthquake damages; and even if properties remain undamaged, earthquakes are unpleasant to live with because of injury, discomfort, or fear thereof. Although the analysis presented in this paper is unable to distinguish between these mechanisms, each is more likely to manifest in the Oklahoma property market than in Koster and Ommeren’s area of study in the Netherlands because of the larger frequency and severity of earthquakes in Oklahoma. The peak magnitude is M 5.7 in Oklahoma within the period of study, versus M 3.5 in the Netherlands.

The arrival of induced earthquakes appears to be an exogenous shock to Oklahoma real estate markets. Home sales from a census tract before the induced quakes began can serve as a control group while home sales in the tract post-earthquake serve as the treatment group. We assume buyers and sellers did not anticipate the earthquakes. While it has been known for decades that wastewater disposal can cause seismic activity, some regions with UIC wells experience little or no seismic activity. The experience of a quake reveals to home buyers and sellers that the region has the type of geology that makes it susceptible.

When it becomes known that quakes can occur in their region, current homeowners lose equity proportional to the new risk and disamenity. Until recently, earthquakes were rare in Oklahoma, and they are not usually covered in homeowners insurance policies. In response to the seismic activity, Oklahoma homeowners have begun adding earthquake coverage (Kaelynn, 2015). This expense should be capitalized into home prices (Nyce et al., 2015). To set prices, insurers have to draw on their experiences in naturally earthquake-prone regions and make assumptions about how intense the quakes might become. They also need to adjust for any differences in building practices that are used in earthquake-prone areas but were not thought necessary in Oklahoma. Some home buyers might predict that because the quakes are caused by human activity, the state will ban the activity in the near future, the quakes will subside, and the expense will end (Philips, 2016). Alternately, buyers may consider that the economic benefits to the state are too large for the state government to introduce a ban, and the quakes will continue as long as the demand for oil and gas justify the continued wastewater disposal.

In our analysis, we use information on home sales in Oklahoma from 2006 to 2014, along with a catalog of earthquakes from 2001 to 2014 to measure changes in sale prices due to changes in earthquake exposure. The 2009–2010 onset of earthquakes in Oklahoma, persisting and increasing in frequency to the end of the study period, creates a 3–4 year baseline period of little to no earthquake exposure and a 3–4 year period of geographically varying exposure. Results suggest that there is a minimal, negative if not slightly positive effect of “noticeable” yet nondamaging earthquakes. A negative housing-market impact of earthquakes can be detected for potentially damaging earthquakes, with estimated impacts as large as a 9-percent decrease in prices following the largest earthquake observed.

This paper proceeds as follows: Section 2 reviews the literature on the impacts of earthquakes and other spatially distributed externalities. Section 3 describes the data used in this study. Section 4 presents an econometric model, Section 5 describes the summary statistics, and Section 6 reports results. Section 7 concludes.

2. Literature

Rosen (1974) is the seminal work on hedonic models, noting that the value of goods can be considered a function of their characteristics and that consumers’ marginal willingness to pay for certain attributes of a good can be derived from regression analyses. Brookshire et al. (1985) were the first to apply this model to earthquake risks, modeling them as characteristics of houses and examining the reaction of the California housing market to new information on earthquake risk by region. Although it was known that all Californian households were exposed to earthquake risk, risk maps displaying risk by region created an information shock comparable to that of an actual earthquake event. Brookshire et al. estimated that values differed between high- and low-risk zones by an average of $4650.

Beron et al. (1997) were the first to implement this model for an earthquake event, using the 1989 California Loma Prieta earthquake. They find that consumer perceptions of earthquake risk decreased between 26 and 35 percent after the earthquake, indicating initially inflated risk perceptions. Naoi et al. (2009), however, find the opposite result in Japan, indicating that regional expectations of earthquake risk will in part determine market reaction to actual earthquake events. Nakagawa et al. (2007) use a hedonic model based on a recently updated earthquake risk map to examine how consumers’ price sensitivity to earthquake risk can change across time. They find that the difference in discounting of earthquake risk between low- and high-risk areas varied from 3 to 8 percent, increased over time, but did not change in response to major recent earthquake events such as the Great Hanshin-Awaji earthquake. Koster and van Ommeren (2015) were the first to use a hedonic model to examine the impacts of induced seismic events on housing prices, finding that each “noticeable” earthquake leads to a 1.9 percent decrease in property values, with a maximum of 7 earthquakes experienced by a single household. Using a dataset from Groningen, Netherlands, and using an earthquake-attenuation function to estimate household experiences of earthquake events from 2001 to 2013, they examine the impact of small-magnitude-earthquake events on a region and the impact of induced seismic events on a region with little to no previous seismicity. Using a separate measure of exposure to earthquakes that cannot be felt by humans, they argue that their measure of earthquake exposure for “noticeable” earthquakes is conditionally spatially independent of other spatiotemporally correlated factors. They estimated that the total nonmonetary costs of “noticeable” earthquakes in the region amounted to €600 per household, which is comparable in magnitude to the total monetary costs.[7]

A recent paper that focuses on the US experience, and which has some overlap with our data, is Metz et al. (2017). Focusing on properties sold within Oklahoma County, they use a difference-in-differences framework to find a reduction in property values of 3.1–4.7 percent after the onset of seismic activity. Our paper differs from theirs in several respects. A major difference is that we examine the impact of seismic activity on house prices throughout the state of Oklahoma, not just Oklahoma County. The highest levels of seismicity (MMI6, described later) occurred outside Oklahoma County, and we are able to measure the impact of this extreme level. Another difference between our papers is in the definition of the treated group. Metz et al. define a seismically active region as a zip code whose centroid is within 10 km of a 3.0 magnitude earthquake, and the difference-in-differences estimate is based on what happens to prices in a seismically active region after the onset of earthquakes, set for all properties to be 2010. Our measurements of earthquake exposure are much more precise: An attenuation function is used to determine the intensity experienced by each individual property from each quake. Our measures allow the onset of seismic activity to occur in different months for different regions, which is appropriate given our statewide model. Additionally, we investigate time-on-market and the pace of sales as other important housing market indicators. Nevertheless, the results of Metz et al. can be considered complementary to our findings.

Externalities from oil and gas development have been more widely explored with hedonic models. Most recently, a study by Gopalakrishnan and Klaiber (2014) and two articles by Muehlenbachs et al. (2012, 2015) have all examined the impact of shale gas wells on local property values. Muehlenbachs, Spiller, and Timmins find that wells decrease the values of nearby properties, though only consistently for properties dependent on locally sourced well water. This indicates that only the homes most prone to the externality of interest (well-water contamination) have values impacted by the probabilistic externality of contamination. Guignet (2013) and Zabel and Guignet (2012) report null results for similar models of the impacts of leaking underground storage tanks, suggesting that risk salience may impact whether risks are priced into property values.

This paper also contributes an estimation of the impact of earthquakes on properties' time-on-market. Benefield et al. (2014) provide an extensive survey of the literature relating home sale prices and time-on-market. It is widely recognized that time-on-market creates an economically consequential transaction cost. Households usually must pay principal, interest, property taxes, insurance, and utilities each month that a home is on the market. It is possible to underestimate a negative value shock if it is reflected in longer marketing times in addition to lower sale prices. However, price and time are endogenously determined, and there is no widely available and accepted instrument for either measure. We report specifications with time-on-market as the dependent variable.

3. Data

3.1. Real estate data

We accessed data representing property sales in the state of Oklahoma from January 2006 to December 2014 through CoreLogic, a national real estate data provider. The dataset contains information about the sale price and the building and land plot size of a given sold property. The records contain additional information about the circumstances of sale such as whether the sale was a foreclosure or at arm's length. CoreLogic collects the digitized records maintained by county recorders and property tax assessors across the US. Because counties digitized property records in different years, the sales histories are of different lengths. In general, the more populous counties have more complete records, and smaller counties begin to appear throughout the study period. In some instances, the exact dates of the sales are not available, and all sales are reported in a single month of their sale year. When calculating the earthquake exposure for these observations, we treat them as if they had in fact all sold in the month listed. This could be slightly overstating the earthquake exposure if the true sale date was earlier than the date recorded and additional quakes struck between the two dates. Consistent with Muehlenbachs et al. (2015), we consider only single-family residences, townhouses, duplexes, and rural homesites in this analysis. We drop properties listed with sale prices below $10,000 or above $1,000,000 to limit the influence of outliers and data entry errors. The land plot and building sizes are also trimmed of extreme values, and the land plot sizes are logged. Cleaning with respect to sale price occurs after an adjustment of sale prices to December 2014 dollars using the consumer price index for housing.[8] We drop properties that were sold more than three times over the nine-year period, as well as identical entries, leaving 258,058 sales. Using latitude and longitude coordinates, we link this sales dataset to a dataset of earthquakes in the Central and Eastern United States (CEUS). Fig. 1 displays the locations of all houses sold in the dataset.

In a second set of estimates, we make use of another data set collected by CoreLogic from Multiple Listing Services (MLS). Across the US, licensed realtors form regional organizations that host real estate listings. In these systems, a property record is created when a realtor is contracted to market a property. One key variable that is available in the MLS data, and not in the deed recording data, is the number of days on the market. Because houses have high carrying costs for households, the sale price does not perfectly reflect the value the seller captures. The value lost once a house becomes exposed to earthquake risk may be lost through a longer marketing time and higher carrying expenditures. We estimate both repeat-sales and difference-in-differences models to uncover the relationship between earthquake exposure and time-on-market.

The realtors using the MLS can populate a long list of fields with descriptions of features of the house. Descriptions can be provided for architectural style, exterior material, flooring, garages, basements, and several other categories. These features provide a rich set of controls in the difference-in-differences model.[9] MLS regions were formed earlier in more urbanized areas, so the MLS data is similar to the recorded deed data in that less populous counties appear later in the data.

3.2. Earthquake data

We use earthquake data from the Oklahoma Geological Survey (OGS) and the US Geological Survey (USGS). We extract the events in the region defined by the coordinates from 29° N to 45° N and 86° W to 110° W. This allows for earthquakes occurring beyond Oklahoma's

[7] They define "monetary" costs to be costs from damages to property. Homeowners are compensated for these costs by the single natural gas producer in the region. There is no such compensation arrangement in Oklahoma, though several suits for compensatory damages have been filed against injection-well drillers.

[8] Although our data-cleaning procedure is strict, it is not without precedent: To eliminate outlying properties, Boxall et al. (2005) impose sale-price bounds of $150,000 and $450,000 in their analysis of the impact of oil and gas facility proximity on housing prices in Alberta, dropping approximately 10 percent of their observations.

[9] Some MLS data entry systems are coded so that the listing will not post until there are valid entries for mandatory fields. Other agents or the public can contact the MLS to report inaccurate information. The MLS can assess additional fees on agents who repeatedly post or fail to correct inaccuracies. It is possible for inaccuracies to go uncorrected if no individual has an incentive to report them. In extreme cases, buyers can sue an agent if the agent used the MLS to misrepresent a property. The MLS is distinct from states' legal mandates that sellers must disclose home defects in disclosure documents. Disclosure documents cover many problems that only trained home inspectors would be able to detect, and issues that an occupant would observe but a buyer would not, such as leaks during heavy rains. In contrast, the characteristics listed in the MLS are mainly things that can be easily verified by buyers viewing a home.

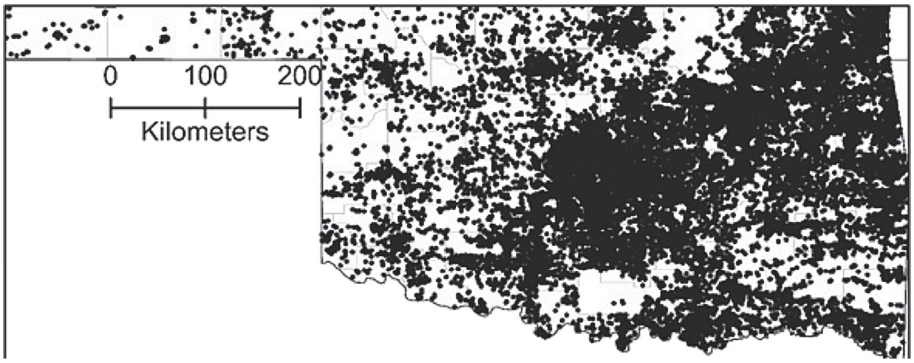

Fig. 1. Housing Sales in Oklahoma, 2006–2014.
Data source: CoreLogic Deeds Data.

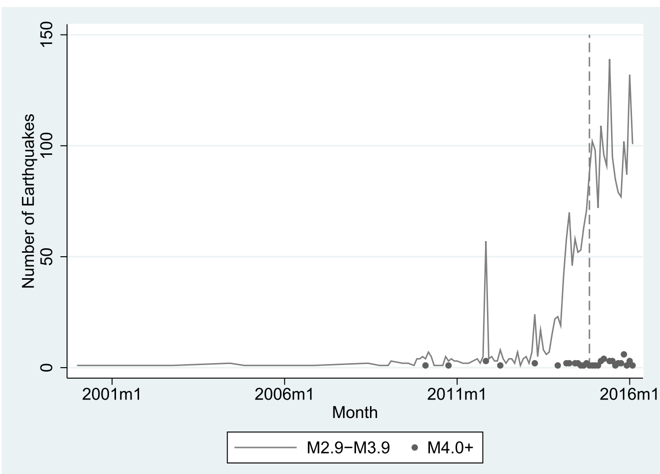

Fig. 2. Monthly Earthquake Totals in Oklahoma, 2001–2016. Vertical line denotes the month 11/2014, the last month of exposure used in this study.
Data sources: Oklahoma Geological Survey and United States Geological Survey.

borders that would be felt in Oklahoma.[10] We drop duplicate observations and earthquakes recorded with magnitude less than or equal to M 2.9 for earthquakes within Oklahoma and M 3 for earthquakes outside of Oklahoma. This results in a dataset consisting of 1093 earthquakes from Oklahoma and 543 earthquakes from outside of Oklahoma over the period from January 1, 2001, to December 31, 2014.[11] Fig. 2 displays the number of these earthquakes occurring in Oklahoma by magnitude by month from January 2001 to February 2016, grouped from M 2.9 to M 3.9 and M 4.0 and higher. Earthquakes are of low frequency and magnitude from 2001 to 2008, increasing in frequency and severity over the 2009–2016 period. As there is no reason to expect a change in the rate of naturally occurring earthquakes over this time frame (Petersen et al., 2016), the substantial spikes in earthquake frequency from 2009 onward may be reasonably considered to be almost entirely induced by human activity.

Using an attenuation function from Atkinson and Wald (2007), we link the earthquake magnitude and the distance of a property to the earthquake epicenter to the Modified Mercalli Intensity (MMI) that an individual property would experience for a given earthquake.[12] Table 1 describes the impacts that experiencing an earthquake at a given MMI would have on a property at different levels of structural resistance and whether that earthquake would be noticeable by people on that property. There are values above 7 on the MMI scale, but quakes capable of causing higher intensities were not observed in Oklahoma during the study period. The maximum MMI experienced during the M 5.7 Prague, Oklahoma earthquake was 7.

The MMI attenuation function allows for earthquake intensity to vary by exact magnitude and depth, making a household earthquake measure that is more accurate to actual experience than a measure of earthquake epicenters within a certain distance of a household. An advantage of the Wald and Atkinson functions is that they specify separate attenuation functions for California and the CEUS. This is advantageous because it incorporates the lower average attenuation of earthquakes in the CEUS region. If unaccounted for, this difference would lead to underestimates of earthquake intensity in our study area. Where M is the magnitude of an earthquake, D is the depth of an earthquake, and S is the surface distance of an earthquake epicenter to a property's centroid, the attenuation function for the CEUS region is estimated to be

$$\begin{aligned} MMI = {} & 11.72 + 2.36(M-6) + 0.1155(M-6)^2 \\ & - .44\log(R) - .002044R + 2.31B + .479M\log(R), \end{aligned}$$

where

$$R = \sqrt{D^2 + S^2 + 289}$$

$$B = \begin{cases} 0 \text{ if } R \leq 80 \\ \log(\frac{R}{80}) \text{ if } R > 80 \end{cases}$$

As an illustration, Fig. 3 displays this attenuation function evaluated for earthquakes at a variety of magnitudes at a constant depth of 5 km, the median for earthquakes in the Oklahoma dataset.

For each earthquake, we use this function to estimate the distance (S) from the epicenter to the points at which MMI equals 3, 4, 5, and 6, setting S equal to zero for a given MMI level when no value of S can result in that MMI level. With these distances, we use the rgeos package in R (Bivand and Rundel, 2017) to estimate the monthly earthquake exposure of every property in the CoreLogic sales dataset for the four corresponding levels of earthquake exposure, corresponding to MMI levels of 3, 4, 5, and 6. For each earthquake, we generate four circular regions with radius S, centered at the earthquake's epicenter: A house is "exposed" to an earthquake if it is within the region defined for a given level of intensity.

Fig. 5 displays this process for the M 5.7 earthquake in Prague for five properties: Property A is unexposed to the earthquake, Property B is exposed to the earthquake only at the MMI3 level, Property C is exposed to the earthquake at the MMI4 level, and Properties D and E are exposed

[10] The vast majority of earthquakes experienced in Oklahoma have epicenters in Oklahoma. Of the extra-Oklahoman earthquakes included, only earthquakes in southern Kansas and several earthquakes in Trinidad, Colorado, affected homes in Oklahoma at relevant intensities.

[11] We choose these earthquake-magnitude thresholds because they are the lowest magnitudes for which all earthquakes in their respective regions have been recorded.

[12] Data adapted from Wald et al. (2010).

Table 1
Modified Mercalli intensity scale.

Modified Mercalli Intensity		1	2–3	4	5	6	7
Perceived Shaking		Not Felt	Weak	Light	Moderate	Strong	Very Strong
Potential Structural Damage	Resistant Structure	None	None	None	Very Light	Light	Moderate
	Vulnerable Structure	None	None	None	Light	Moderate	Moderate/Heavy

Adapted from Wald et al. (2010).

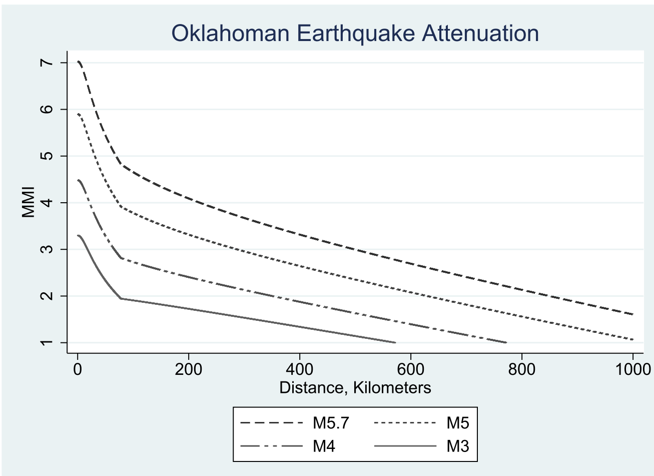

Fig. 3. Modified Mercalli Intensity Attenuation function, Select Magnitudes. Calculations hold the depth constant at the sample average of 5 km.

to the earthquake at the MMI5 and MMI6 levels, respectively.[13]

As housing sales are observed at the monthly level in most models, our independent variables of interest will be indicators of the highest-intensity earthquake that the property has experienced from January 2001 until one month before the sale. We lag exposure one month to prevent cases in which earthquakes occurring after a house's sale would be counted toward its earthquake exposure. Consistent with Koster and van Ommeren (2015), we will also use a measure of cumulative exposure through the month before the sale.[14] The cumulative earthquake exposure variables for MMI3, 4, 5, and 6, are respectively defined as

$$C^3_{ht} = \sum_{t=0}^{t-1} I(4 > MMI_{ht} \geq 3) \tag{1}$$

$$C^4_{ht} = \sum_{t=0}^{t-1} I(5 > MMI_{ht} \geq 4) \tag{2}$$

$$C^5_{ht} = \sum_{t=0}^{t-1} I(6 > MMI_{ht} \geq 5) \tag{3}$$

$$C^6_{ht} = \sum_{t=0}^{t-1} I(MMI_{ht} \geq 6) \tag{4}$$

where $I(B > MMI_{ht} \geq A)$ is an indicator function equal to 1 if the largest MMI experienced by a house for a given earthquake is less than B and greater than or equal to A, and 0 if else. C^Z_{ht} is the cumulative earthquake exposure of household h sold t months after January 2001 at MMI level Z. Because the attenuation function used to define this cumulative measure is not an exact estimate of ground motion in Oklahoma, this cumulative measure will contain some amount of error; this error is likely altogether random, and so is not expected to bias estimates.

3.3. Underground injection control well data

Wastewater injection into underground injection control (UIC) wells is understood to be the cause of earthquakes in Oklahoma, though the spatial relationship between well locations and earthquakes is not exact: Considering a hypothetical case in which only one well in a region is capable of inducing earthquakes, the epicenters of induced earthquakes may be as far as 35 km away from that well (Keranen et al., 2014). Given that well locations and earthquake epicenters are not identical, it is possible to control for any noxious impacts that wells may have on surrounding properties (e.g., noise and traffic from trucks used to transport wastewater).

We use data on the locations of Class II UIC wells in Oklahoma (excluding Osage County) from annual well catalogs available at the Oklahoma Corporation Commission's (OCC) website.[15] Wells are uniquely identified by American Petroleum Institute (API) well numbers, and the well catalog lists wells by their latitude and longitude coordinates, as well as their annual injection volumes for 2006–2010 and monthly injection volumes for 2011–2014. We drop wells listed without coordinates, entries with errors (e.g., coordinates located outside of Oklahoma), and wells with zero annual injection volume to construct a measure of "active" wells for each year (consistent with Murray (2014)). Although classifications for wells are present for some years, the full dataset does not classify whether wells are used for enhanced oil recovery (known as "2R wells," a class which does not include fracking wells) or for salt water disposal wells (known as "2D wells"). We drop wells with duplicate coordinates and different API numbers (duplicates within a year imply that a 2R and a 2D well are active at the same site). As high volume wells may have larger or otherwise distinct noxious effects, we construct a separate measure of wells with annual injection volumes in excess of 1,000,000 MMbbl (approximately half the threshold used by Murray (2014) in defining high volume wells, though still a relatively high threshold).

Fig. 4 displays the locations of all active UIC wells in Oklahoma over the 2006–2014 period. As a 2014 position statement from the Oklahoma Geological Survey notes, 80 percent of Oklahoma is within 15 km of a UIC well.[16] To construct a more granular measure of UIC wells, and also be consistent with the distances used to measure fracking-well exposure in Muehlenbachs et al. (2015), we construct measures of property well exposure equal to the number of wells within 2 km of a property.[17]

[13] Although one could consider measures where, for instance, Property C would be exposed at the MMI3 and MMI4 levels, these measures do not lend themselves to straightforward interpretations when used in regression models. Nevertheless, the results presented in this paper are robust to using those measures.

[14] A start year before 2001 would yield little to no variation in cumulative exposure: Seismicity rates were essentially constant at two small earthquakes per year over the late 20th century in Oklahoma.

[15] Regulation of Class II UIC wells in Osage County has not been delegated by the US Environmental Protection Agency to the OCC, so the OCC does not maintain data on these wells. Class II wells are injection wells strictly associated with oil and natural gas activity.

[16] The position statement is available at http://www.ogs.ou.edu/pdf/OGS_POSITION_STATEMENT_2_18_14.pdf.

[17] We considered the 20 km measure also used in Muehlenbachs et al. (2015), though the measure adds very little information: Properties tended to be either close to many wells or close to none at all.

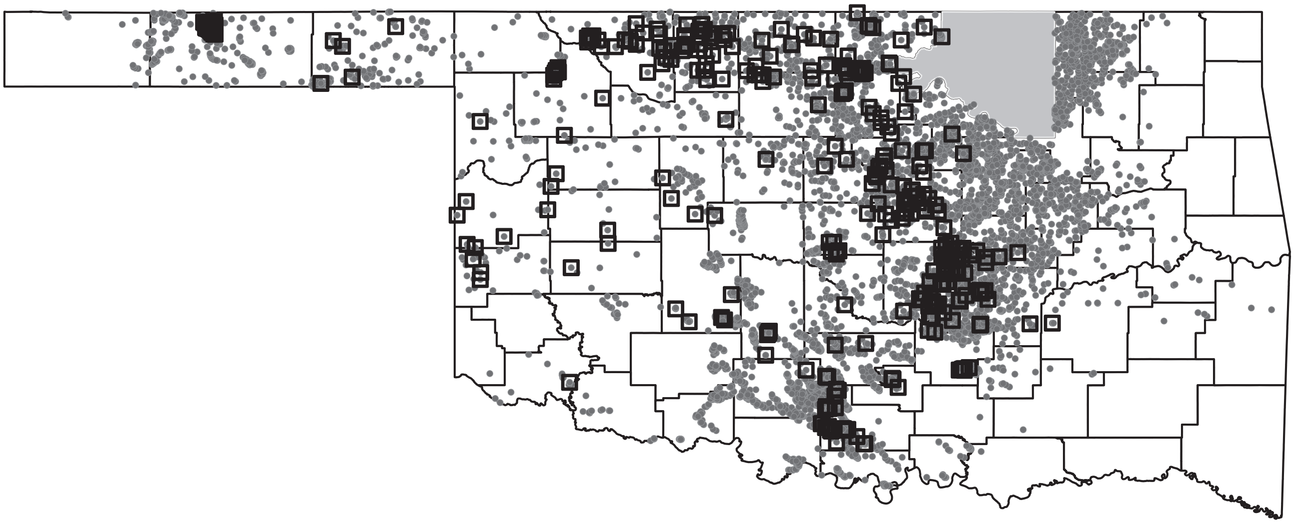

Fig. 4. Underground Injection Control (UIC) Wells, 2006–2014. High volume wells are displayed as squares. Osage County (shaded light grey) is not included in the data. Data source: Oklahoma Corporation Commission.

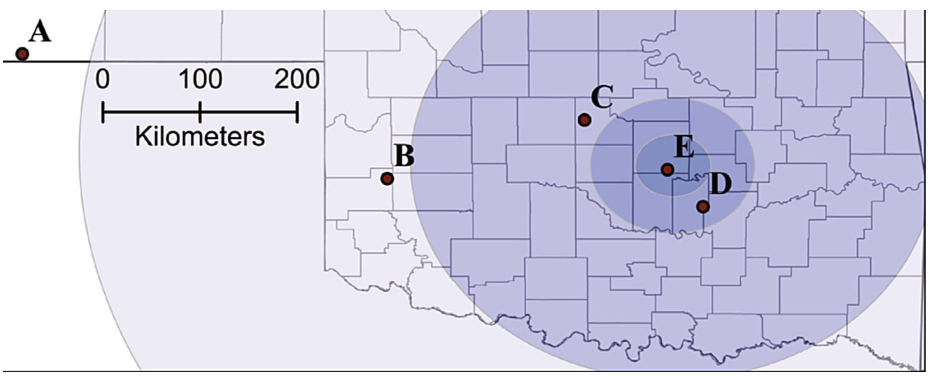

Fig. 5. Property Earthquake Exposure from the M 5.7 Event Centered in Prague, OK. From lightest to darkest, shading indicates exposure at MMI 3, 4, 5 and 6. Lettered properties are examples for discussion.

3.4. Demographic data

We obtain census-tract-level data from the American Community Survey (ACS) to control for possible demographic impacts on regional housing prices. Tract-level data for all tracts in Oklahoma are only available from the ACS 5-year estimates. These are useful as estimates of demographic levels over a longer time period but poor for understanding short-term trends. The 2010–2014 estimates, combined with the 2005–2009 estimates, create the first possible set of 5-year estimates without overlapping time periods. As the household data in this study span 2006–2014, and as no major earthquakes had occurred as of the end of 2009 (and so there is little reason to expect that earthquakes would have affected demographics in the 2009 portion of the sample), we assign tract-level demographic data from the ACS 2005–2009 5-year estimates to properties sold from 2006 to 2009, and demographic data from the ACS 2010–2014 5-year estimates to properties sold from 2010 to 2014. We utilize data on the median income (adjusted to 2014 dollars using the consumer price index), the percentage of adults who graduated from high school, and the percentages of African American and Native American residents for each census tract. We further include data on school district boundaries from the 2010 Census Topologically Integrated Geographic Encoding and Referencing website. We create a measure of relative urbanity and rurality by calculating a house's distance to the nearest of the central business districts of Oklahoma City or Tulsa.

3.5. Tornado data

Risk preferences for earthquakes and tornadoes may be similar for a given individual in the housing market, and tornado risk may also be capitalized into house prices. Ewing et al. (2007) find temporary, 0.5 to 2.0 percent decreases in local housing prices following large tornado events. Simmons and Sutter (2007) find house sale-price premiums in excess of tornado shelter costs for houses with shelters in Oklahoma City. Given these findings, we construct a county-level measure of tornado risk using data from the National Oceanic and Atmospheric Administration on all tornadoes occurring in Oklahoma from 1950 to 2014. We sum the number of F3 and higher tornadoes whose central paths at some point enter a given county, then scale by county land area to yield a measure of severe tornadoes per 10 square miles.[18] Tornadoes occur most frequently in Oklahoma, Cleveland, and Tulsa Counties after accounting for land area. Although the recentness of tornadoes may influence any price impacts, the purpose of our control variable is to establish a long-run measure of tornado risk.

3.6. Mining employment data

Although earthquakes may be expected to have negative local welfare impacts, related increases in local economic activity from increasing oil and gas development may have significant, offsetting positive

[18] The Fujita (F) scale is used from 1950 to 1/31/2007; The Enhanced Fujita (EF) is used from 2/1/2007 forward. F3 and EF3 are used as cutoffs for likely severe property damage. Differences between the two scales are outlined in Doswell et al. (2009).

Table 2
Summary Statistics.

	Mean	SD	Min	Max
Sale price (all sales)	137, 099	108, 074	10, 000	999, 909
Log sale price (all sales)	11.52	0.84	9.21	13.82
Sale price (repeat sales, bef./aft. 2011)	148, 331	107, 361	10, 000	999, 909
Log sale price (repeat sales, bef./aft. 2011)	11.64	0.79	9.21	13.82
Months on market (MLS sample)	4.51	2.88	0.03	23.95
Sales per 1000 housing units (tract, year)	31.72	24.00	0.29	197.04
MMI3 peak exposure indicator	0.15	0.36	0.00	1.00
MMI4 peak exposure indicator	0.31	0.46	0.00	1.00
MMI5 peak exposure indicator	0.07	0.25	0.00	1.00
MMI6 peak exposure indicator	0.01	0.08	0.00	1.00
MMI3 exposure count	10.46	24.28	0.00	273.00
MMI4 exposure count	0.72	1.49	0.00	18.00
MMI5 exposure count	0.08	0.30	0.00	3.00
MMI6 exposure count	0.01	0.08	0.00	1.00
MMI4 treatment group indicator	0.80	0.40	0.00	1.00
MMI5 treatment group indicator	0.18	0.38	0.00	1.00
MMI6 treatment group indicator	0.02	0.13	0.00	1.00
UIC wells within 2 km	0.52	2.06	0.00	111.00
High volume UIC wells within 2 km	0.02	0.15	0.00	19.00
Oil/Gas production wells within 2 km	1.44	3.04	0.00	55.00
Mining employment (county)	0.04	0.04	0.00	0.41
Building square footage (1000s)	1.97	0.76	0.67	4.91
Land square footage (1000s)	9.60	1.23	0.00	14.05
Townhouse/Rowhouse	0.00	0.03	0.00	1.00
Duplex	0.00	0.07	0.00	1.00
Rural homesite	0.08	0.27	0.00	1.00
Single family residence	0.92	0.28	0.00	1.00
Year built	1975.85	25.97	1800	2014
Log distance (km) to OKC or Tulsa	47.59	54.47	0.55	468.89
Tornadoes within 10 km, 1950–2006	16.48	8.90	1.49	44.80
Percent African American (tract)	6.36	10.82	0.00	90.80
Percent Native American	0.10	0.50	0.00	46.80
Percent high school graduates (tract)	0.86	0.09	0.28	1.00
Median age (tract)	36.89	5.55	15.50	57.70
Median income ($10,000s) (tract)	5.66	2.33	0.62	16.80

Data Sources: CoreLogic Deeds Data and Tax Data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns. Unless otherwise indicated, descriptive statistics represent all sales. N = 426,526.

impacts on house prices. To control for this, we use county-level data on employment in mining industries from the County Business Patterns data series.[19] The employment estimates for 2006 through 2014 are scaled by the total employment in the county and merged with the sales by the year of the sale. In many counties, the exact employment figure is suppressed to maintain confidentiality. Where this is the case, we used the midpoint of the range that corresponds to the suppression code.

3.7. Oil and gas well data

Similar to mining industry employment, local oil and gas well operations may be expected to increase local economic activity, and in turn increase housing prices. However, local oil and gas development may also result in several harmful local impacts, including increased traffic, noise, and environmental degradation. Data on oil and gas production-wells are available from the OCC's website. Similar to the UIC well data, we remove duplicate wells, wells with zero production in a given year, and wells without valid coordinates to construct a measure of active wells within a year. There are 280,990 well-years in the final dataset. To match the UIC well measures, we construct production well exposures using all active wells within 2 km of a property in its year of sale.

[19] County Business Patterns data are available at http://www.census.gov/programs-surveys/cbp.html. Accessed 12 December 2017.

4. Models

With the above datasets, we estimate the impact of earthquake exposure on home sale prices. We begin with a repeat-sales model and a log-linear functional form:

$$\ln(P_{ht}) = \tau_0 + \tau_1 D^3_{ht} + \tau_2 D^4_{ht} + \tau_3 D^5_{ht} + \tau_4 D^6_{ht} + \delta\mathbf{H} + \omega\mathbf{Z} + \gamma\mathbf{Y} + \epsilon_{ht}. \tag{5}$$

Subscripts h and t denote a unique property h sold in month t. ln (P_{ht}) is the natural logarithm of the sale price of a house in 2014 dollars. In what we refer to as "indicator" models, D^m_{ht} is an indicator equal to 1 if the most intense earthquake experienced by the property, between January 2001 and the month before the month of sale, was at MMI level m. No more than one of the D^m_{ht} indicators can equal 1 for an observation. We will also present what we call "count" models, in which D^m_{ht} is replaced with C^m_{ht} as in equations (1) through (4) above. These are the counts of earthquakes of intensity m that the property has experienced through the month before the sale. In the count models, the coefficients τ_1 through τ_4 are interpretable as the percentage change in a house's sale price attributable to each additional earthquake at the corresponding MMI. Each coefficient is estimated conditional on the exposure to the counts at the other levels of intensity.

H is a vector of individual property fixed effects, to absorb unobserved time-invariant property and location characteristics.

Z is a vector of time-varying spatial characteristics, including proximity to UIC and oil and gas production wells.

Y is a vector of indicators of the year of sale.

ϵ_{ht} is an error term, clustered at the census-tract level to account for

Table 3
Repeat Sale Models. Dependent variable is the log sale price. Robust standard errors appear below in parentheses. Significance Key: ***p < 0.001, **p < 0.01, *p < 0.05.

Repeat Sales: Earthquake Measure:	Before/After 2011 Indicators	Before/After 2011 Counts	All Indicators	All Counts
MMI3	0.005	0.000*	0.055***	0.000
	(0.008)	(0.000)	(0.007)	(0.000)
MMI4	−0.035*	−0.004	0.002	0.001
	(0.014)	(0.003)	(0.013)	(0.003)
MMI5	−0.036*	−0.002	0.013	−0.003
	(0.017)	(0.009)	(0.016)	(0.009)
MMI6	−0.087**	−0.049	−0.033	−0.042
	(0.030)	(0.029)	(0.030)	(0.029)
UIC Wells	0.004	0.004	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
High Volume UIC Wells	−0.010	−0.013	−0.019	−0.015
	(0.020)	(0.020)	(0.020)	(0.020)
Oil/Gas production wells	−0.011***	−0.010***	−0.013***	−0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
Mining Employment	1.151***	1.145***	1.024***	1.046***
	(0.133)	(0.134)	(0.130)	(0.131)
Sale year 2007	−0.010	−0.010	0.023**	0.023**
	(0.010)	(0.010)	(0.008)	(0.008)
Sale year 2008	−0.038***	−0.040***	0.011	0.012
	(0.009)	(0.009)	(0.007)	(0.007)
Sale year 2009	−0.053***	−0.052***	0.035***	0.056***
	(0.009)	(0.009)	(0.008)	(0.007)
Sale year 2010	−0.096***	−0.096***	0.044***	0.071***
	(0.011)	(0.010)	(0.008)	(0.008)
Sale year 2011	−0.026**	−0.034***	0.010	0.033***
	(0.010)	(0.009)	(0.009)	(0.008)
Sale year 2012	0.060***	0.026**	0.042**	0.044***
	(0.017)	(0.009)	(0.016)	(0.008)
Sale year 2013	0.031	−0.005	0.043**	0.045***
	(0.017)	(0.009)	(0.015)	(0.008)
Sale year 2014	0.016	−0.022*	0.103***	0.103***
	(0.016)	(0.009)	(0.015)	(0.008)
Constant	11.636***	11.636***	11.556***	11.555***
	(0.008)	(0.008)	(0.007)	(0.007)
N	108, 305	108, 305	150, 613	150, 613
R^2	0.82	0.82	0.80	0.80

Data Sources: CoreLogic Deeds Data and Tax Data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns.

spatial autocorrelation.

We focus more on the peak-exposure-indicator models because the experience of an earthquake at a higher level of intensity than previously experienced may cause a shift in the expectation of a region's relative earthquake risk. For instance, the experience of the M 5.7 Prague earthquake at the MMI5 level may have indicated that the local area was at a higher risk for intense earthquakes relative to any prior point in time. This is commensurate with USGS's seismic hazard maps, which record the level of ground motion that will be exceeded with some probability within some time frame.[20]

We also present results from a difference-in-differences model specified as:

$$\ln(P_{ht}) = \beta_0 + \beta_1 D^4_{ht} + \beta_2 D^5_{ht} + \beta_3 D^6_{ht} + \lambda_0 T^4 + \lambda_1 T^5 + \lambda_2 T^6 + \alpha\mathbf{X} + \omega\mathbf{Z} + \gamma\mathbf{Y} + \tau_a + \tau_c + \tau_s + \epsilon_{ht}. \quad (6)$$

β_1, β_2, and β_3 are the coefficients of interest, interpretable as the percentage change in a house's sale price attributable to exposure to a peak earthquake at the corresponding MMI. Again, the frame of reference for this exposure variable is from January 2001 through the month before the month of sale. T^4, T^5, and T^6 indicate whether the house is in one of three "treatment groups." The Ts take a value of 1 if the property ever experiences an earthquake of the magnitude corresponding to the superscript, either before or after the observed sale. The λs represent the pre-existing price difference in these areas relative to the reference region, which includes only houses that are never treated by earthquakes of MMI4 or greater. In this specification, we have to include the properties that will eventually be treated by MMI3 earthquakes in the control group because all areas of Oklahoma have experienced at least one MMI3 earthquake by the end of the study period.[21] The trend that is common to the treated and control groups is absorbed by the year fixed effects, and the βs express the additional price changes due to the MMI4, MMI5, and MMI6 treatments. When the indicators are replaced with counts, the model is no longer a difference-in-differences specification. The count model is a hedonic model with an additional treatment-group control.

In the difference-in-differences and hedonic models, X is a vector of property and neighborhood characteristics including square footage, year of construction, distance to the nearest of Oklahoma City or Tulsa, the county-level measure of tornado exposure, and neighborhood demographics.[22] Z and ϵ are the time-varying local controls and error term. τ_a, τ_c and τ_s are sets of house age, census tract and school district fixed effects, respectively.

[20] For instance, maps from 2008 list the region with the highest earthquake risk in Oklahoma as having a 2 percent probability of the peak ground acceleration caused by an earthquake exceeding 26 percent g in 50 years. 26 percent g approximately corresponds to an MMI7 earthquake.

[21] Nearby properties in surrounding states are also all affected, so they cannot serve as controls for MMI3-treated properties.

[22] Census tracts from the 2014 ACS are used. There are only small, insignificant differences between 2014 tracts and those used in the 2009 ACS.

Table 4
Difference-in-differences and Hedonic Models. Dependent variable is the log sale price. Standard errors are clustered by census tract and appear below in parentheses. Significance Key: ***p < 0.001, **p < 0.01, *p < 0.05.

Earthquake Measure:	Indicator	Counts
MMI3 treated		0.001*** (0.000)
MMI4 treated	−0.048*** (0.010)	−0.016** (0.005)
MMI5 treated	−0.004 (0.020)	0.026 (0.015)
MMI6 treated	−0.103*** (0.029)	−0.131*** (0.036)
MMI4 treatment group	0.277** (0.103)	0.264* (0.103)
MMI5 treatment group	0.271* (0.108)	0.264* (0.107)
MMI6 treatment group	0.414*** (0.124)	0.412*** (0.124)
UIC Wells	−0.001 (0.002)	−0.001 (0.002)
High Volume UIC Wells	−0.001 (0.022)	−0.005 (0.022)
Oil/Gas wells within 2 km	−0.007*** (0.001)	−0.006*** (0.001)
Mining Employment	1.177*** (0.229)	1.092*** (0.231)
Square Feet (thousands)	0.410*** (0.006)	0.411*** (0.006)
Land Plot (ln(sqft))	0.076*** (0.004)	0.075*** (0.004)
Townhouse/Rowhouse	−0.012 (0.064)	−0.020 (0.062)
Duplex	−0.083* (0.039)	−0.093* (0.039)
Rural Homesite	−0.148*** (0.020)	−0.151*** (0.020)
Built 1800–1949	−0.601*** (0.023)	−0.599*** (0.023)
Built 1950–1959	−0.442*** (0.021)	−0.439*** (0.021)
Built 1960–1969	−0.294*** (0.021)	−0.291*** (0.020)
Built 1970–1979	−0.180*** (0.021)	−0.178*** (0.021)
Built 1980–1989	−0.110*** (0.020)	−0.107*** (0.020)
Built 1990–1999	0.006 (0.020)	0.009 (0.020)
Built 2000–2009	0.038* (0.017)	0.041* (0.017)
Distance to OKC or Tulsa	−33.117*** (3.658)	−33.885*** (3.548)
Tornados	−0.080*** (0.012)	−0.082*** (0.011)
Percent African American (tract)	−0.271*** (0.024)	−0.276*** (0.023)
Percent Native American (tract)	0.014* (0.007)	0.013* (0.006)
Percent high school graduates (tract)	0.243*** (0.067)	0.222** (0.068)
Median age (tract)	−0.001 (0.002)	−0.002 (0.002)
Median income ($10,000s) (tract)	0.017* (0.008)	0.017* (0.007)
Sale year 2007	0.021* (0.009)	0.021* (0.009)
Sale year 2008	−0.004 (0.011)	−0.006 (0.011)
Sale year 2009	−0.005 (0.011)	−0.008 (0.011)
Sale year 2010	0.012 (0.012)	0.003 (0.012)
Sale year 2011	−0.052*** (0.013)	−0.072*** (0.012)
Sale year 2012	−0.019 (0.017)	−0.060*** (0.013)
Sale year 2013	−0.019 (0.018)	−0.066*** (0.014)
Sale year 2014	−0.015 (0.017)	−0.079*** (0.015)
Year built missing	−0.473*** (0.024)	−0.470*** (0.024)
Building sqft missing	−0.077*** (0.013)	−0.078*** (0.013)
Census tract FE	Y	Y
School district FE	Y	Y
Constant	174.413***(18.263)	178.283***(17.712)
N	426, 526	426, 526
R^2	0.57	0.57

Data Sources: CoreLogic Deeds Data and Tax Data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns.

5. Descriptive statistics

Table 2 provides summary statistics for the full data set and the outcome variables in the repeat-sales and MLS subsamples. The mean home sale price is $137,100, and the standard deviation is $108,075. The proportion of homes that have experienced an MMI5 earthquake before they are observed to sell is 7 percent, and the proportion of those that have experienced an MMI6 event is 1 percent. The average cumulative count of exposures to MMI3 earthquakes is 10.46. Properties are observed selling that have experienced dozens or even hundreds of MMI3 quakes within the study period. Thirty-eight percent of sales involve homes that have been through at least one MMI4 earthquake, but only 12 percent have experienced multiple quakes of that magnitude. MMI5 and MMI6 exposure is limited to approximately 31,000 of the 426,000 sold properties.

Seventy-nine percent of the sales occur without a UIC well within 2 km while 15 percent of the sales are observed with one or two wells within that range. Proximity to high-volume UIC wells is much more limited, with less than 2 percent of properties being located near one. When the data are limited to only properties with repeat sales observed or properties that can be merged with the MLS data, the descriptive statistics change moderately. This suggests the subsamples are not strongly selected toward higher- or lower-valued properties, or areas with more or less exposure.

6. Results

The first set of results presented in Table 3 is from models estimated with repeat sales. In the first model, properties are included only if they have a sale observed before 2011 and a sale observed in 2011 or later. This enables us to observe almost all the properties in both treated and untreated statuses. Properties that have experienced an MMI4 or MMI5 earthquake before their sale sell for 3.5 and 3.6 percent less than comparable untreated properties. Exposure to an earthquake with an intensity of above MMI6 causes an 8.7 percent decrease in the sale price. The second model in Table 3 replaces the indicator of the maximum exposure with the counts of exposure at each intensity. The coefficients on the MMI4 through MMI6 counts remain negative but

Table 5
Time-on-Market and Pace-of-Sales Models. Dependent variables are the months on market and the number of sales per 1000 housing units in the census tract in the year. Standard errors appear below in parentheses. Significance Key: ***p < 0.001, **p < 0.01, *p < 0.05.

	Months on market Repeat Sales	Months on market Dif in Dif	Sales per 1000 Housing Units
MMI3 peak exposure indicator	0.193***		
	(0.033)		
MMI4 peak exposure indicator	0.323***	−0.048	0.905*
	(0.044)	(0.043)	(0.453)
MMI5 peak exposure indicator	0.101	−0.243***	3.471***
	(0.065)	(0.073)	(0.946)
MMI6 peak exposure indicator	0.786***	0.383**	−0.926
	(0.160)	(0.137)	(2.717)
MMI4 treatment group		0.032	1.194
		(1.155)	(1.258)
MMI5 treatment group		0.028	1.801
		(1.158)	(1.172)
MMI6 treatment group		−0.103	4.420
		(1.179)	(2.440)
UIC wells within 2 km	−0.001	0.005	−0.155
	(0.004)	(0.003)	(0.161)
High volume UIC wells within 2 km	−0.139	0.157	−3.004*
	(0.126)	(0.101)	(1.491)
Oil/Gas wells within 2 km	0.006	0.008	0.157
	(0.006)	(0.006)	(0.097)
Mining employment	−5.359***	−5.853***	−28.227***
	(1.346)	(1.256)	(7.617)
Building square footage (1000s)		0.237***	Decile FE
		(0.021)	
Land square footage (1000s)		0.033*	Decile FE
		(0.014)	
Townhouse/Rowhouse		−0.682***	−5.126
		(0.151)	(11.490)
Duplex		0.177	−3.903
		(0.111)	(5.502)
Rural homesite		0.178***	2.793*
		(0.053)	(1.347)
MLS property characteristics		Y	
Log distance (km) to OKC or Tulsa		0.707*	−1.083**
		(0.324)	(0.364)
Tornadoes within 10 km, 1950–2006		0.083***	−0.060
		(0.020)	(0.042)
Year of listing FE	Y	Y	Y
Decade of construction FE		Y	Y
Tract demographics		Y	Y
Census tract FE		Y	
School district FE		Y	
Missing value indicators		Y	
Constant	4.330***	−0.401	67.472***
	(0.038)	(2.57)	(5.558)
N	197, 243	228, 634	7139
R^2	0.42	0.07	0.30

Data Sources: CoreLogic Deeds Data and Tax Data, Corelogic MLS data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns.

are smaller in magnitude because the counts are positively correlated, and the price impact is in per-earthquake terms. The other two sets of results in Table 3 are also estimated with repeat sales, but the sample is not limited to properties with sales both before and after the sharp increase in seismic activity. Without the year restrictions on the sample, the negative price impacts cannot be identified. Property fixed effects are included in each of the repeat-sales models, so only time-varying controls can be included.[23]

Table 4 presents the results of the difference-in-differences and hedonic models. The sample now includes all the repeat sales as well as 318,221 properties that were observed to sell only once. If an MMI4 earthquake was the most intense earthquake to impact a property before it sold, this is estimated to lower the sale price by 4.8 percent. The properties that experienced an MMI6 quake see price reductions of 10.3 percent. Both of these coefficients are similar in magnitude to those estimated by the first repeat-sales model. The first repeat-sales model suggests that the sale prices of MMI3-affected houses are similar to the control group, so shifting the MMI3-affected properties into the control group should not cause a large change in the estimated impact of the MMI4 and above exposures. Curiously, the difference-in-differences model does not identify a significant difference between the sale prices of houses that experienced an MMI5 quake and the reference group. When the hedonic count model estimates the MMI treatment effects conditional on one another, the MMI6 coefficient is more negative than it was in the indicator model, at −13.1 percent. The coefficient on MMI4 remains negative and significant. The coefficient on the count of MMI3 exposures is small, positive and significant, which is

[23] Although ACS tract demographics do evolve from year to year, they are estimated with multiyear aggregations. There is not enough time variation in the estimates to provide a useful control, so they are omitted from the repeat-sales models.

Table 6
Alternate Specifications. Dependent variable is the log sale price. All models include the same controls as the main specifications in Tables 3 and 4. Standard errors are clustered by census tract. Significance Key: ***p < 0.001, **p < 0.01, *p < 0.05. Unless otherwise indicated, N = 108,305 for repeats sales and N = 426,526 for difference-in-differences.

	Repeat Sales	Dif in dif
MMI3 1–6 months before sale	0.011 (0.006)	
MMI3 6–12 months before sale	0.009 (0.006)	
MMI3 12–18 months before sale	−0.005 (0.007)	
MMI3 18–24 months before sale	0.014 (0.007)	
MMI4 1–6 months before sale	0.007 (0.009)	0.016* (0.007)
MMI4 6–12 months before sale	0.015 (0.009)	0.023** (0.007)
MMI4 12–18 months before sale	0.027** (0.010)	0.013 (0.012)
MMI4 18–24 months before sale	0.028* (0.011)	0.018* (0.009)
MMI5 1–6 months before sale	−0.032 (0.027)	0.019* (0.009)
MMI5 6–12 months before sale	0.025 (0.020)	0.030 (0.017)
MMI5 12–18 months before sale	0.015 (0.022)	0.088*** (0.022)
MMI5 18–24 months before sale	0.006 (0.018)	0.056** (0.020)
MMI6 1–6 months before sale	−0.144* (0.061)	−0.105** (0.036)
MMI6 6–12 months before sale	0.104 (0.062)	−0.021 (0.032)
MMI6 12–18 months before sale	−0.025 (0.067)	−0.014 (0.055)
MMI6 18–24 months before sale	0.023 (0.056)	0.016 (0.031)
R^2	0.82	0.57
Post-Prague Sale Date	0.064 (0.035)	0.082** (0.031)
Post*MMI4 treatment group	−0.073**(0.027)	−0.131***(0.029)
Post*MMI5 treatment group	−0.073**(0.028)	−0.081* (0.032)
Post*MMI6 treatment group	−0.104**(0.036)	−0.175***(0.037)
MMI4 treatment group		0.311** (0.106)
MMI5 treatment group		0.302** (0.110)
MMI6 treatment group		0.444*** (0.126)
R^2	0.82	0.57
Continuous MMI	−0.004 (0.006)	0.004 (0.008)
R^2	0.82	0.57
MMI3 without public water	0.012 (0.025)	
MMI4 without public water	−0.064 (0.038)	−0.067* (0.031)
MMI5 without public water	−0.039 (0.049)	−0.034 (0.054)
MMI6 without public water	−0.112 (0.075)	−0.152 (0.078)
N	12, 017	50, 738
R^2	0.83	0.53

Data Sources: CoreLogic Deeds Data and Tax Data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns.

consistent with the coefficients in the repeat sales model.

To account for property and neighborhood characteristics, the difference-in-differences and hedonic models rely on control variables rather than property fixed effects. The coefficients on the measures of square footage and lot size are significantly predictive of price, as we would expect. Among neighborhood characteristics, oil and gas production wells appear to exert an independent negative externality of 0.7 percent per well. Mining employment at the county level has a strong positive price impact.

In all of the model estimates that include an MMI3 measure, the coefficient on that measure is positive. Koster and van Ommeren (2015) offer a precedent for positive coefficients on earthquake measures, arguing that the weaker earthquakes in their sample were not spatially independent in the presence of other factors in their model and thus could be capturing spatially correlated effects otherwise unaccounted for. The analysis in this paper is particularly susceptible to such arguments, as we are unable to construct Koster and van Ommeren's measure of weak earthquakes from a separate sample of earthquakes. The relatively high level of completeness in Oklahoma indicates that earthquakes below M 2.0 are likely to be endogenously recorded. That is, regions experiencing larger earthquakes are more likely to receive additional instrumentation with which to better record all earthquakes, leading to the systematic under-recording of small earthquakes in regions experiencing relatively few earthquakes. An alternate explanation for the positive coefficient may be housing-price increases due to regional growth in oil and gas industrial activity in regions experiencing frequent earthquakes, though not necessarily the regions impacted by the largest earthquakes. Our mining-employment measure may not be sufficiently precise to control for the positive impact of fracking on economic activity.

The three model results presented in Table 5 consider the possibility that there are other dimensions of adjustment in housing markets in response to the earthquakes. To measure time-on-market and the percent of homes in a tract that sell each year, we merge in the MLS time-on-market data and the tract's count of housing units from the ACS. We utilize 14 additional MLS house characteristic controls including architectural style, exterior material, flooring, bathrooms, bedrooms, garages, and foundations. Time-on-market was truncated at two years, which is above the 99th percentile, to exclude some implausibly large values. As presented in Table 2, the mean value is 4.51 months, with a standard deviation of 2.88 months.

In the repeat-sales estimates, exposure to any intensity of earthquake extends the time-on-market by 6–24 days. The estimates of the extended time-on-market are of similar magnitude in the difference-in-differences specification. While the coefficients are highly significant, it seems that time-on-market is a smaller adjustment than the estimated price adjustments. Delays of a few weeks could require at most one additional payment for the mortgage, taxes, insurance, and utilities. This would be less than 1 percent of the house value except in unusual circumstances.

The pace-of-sales model in Table 5 considers the possibility of the market responding to the onset of earthquakes through changes in quantities as well as prices. If we observe an increased pace of sales along with price reductions and extended marketing times, this would imply that earthquake activity induces a supply shock. After experiencing an earthquake, more homeowners come to market than otherwise would be the case. If demand remains unchanged, prices should decline and quantities rise. If demand dropped because buyers also became wary of the earthquakes, then we would expect both quantity and price to decline.

The pace-of-sales observations are census-tract-years. They are serially correlated, so the model is estimated with a Cochran-Orcutt correction. The property characteristic control variables are measured as the percentage of the sold homes in the tract with each characteristic. The results are mixed, with the MMI6 coefficient being negative and the MMI4 and MMI5 coefficients being positive. As with the time-on-market measures, the difference appears to be statistically significant without being economically significant. The mean of the pace measure is 31.72 sales per 1000 housing units per year, and the standard deviation is 24. The coefficients are all less than one-seventh of a standard deviation, suggesting there has been no major change in the pace of sales in response to the earthquakes. Observing a price decline coincident with approximately unchanged quantities sold suggests there were offsetting increases in supply and decreases in demand. The coincident increase in prices and decline in quantities in the MMI3 treatment group would require a decrease in the supply of houses.

Four alternate specifications are presented in Table 6. We specified models that allowed the price impact of earthquakes to vary by how many months had passed between the quake and the sale. The hypothesis is that more recent quakes are more salient and have a larger negative impact. The only set of coefficients that decline monotonically are those on the MMI6 indicators in the difference-in-differences model. The other sets offer little evidence of declining salience. We believe these mixed results are due to the increase of earthquake activity throughout the study period. In this situation, buyers and sellers did not have the opportunity to "forget" past events. We also tried a specification that interacted a post-Prague-earthquake indicator with an indi-

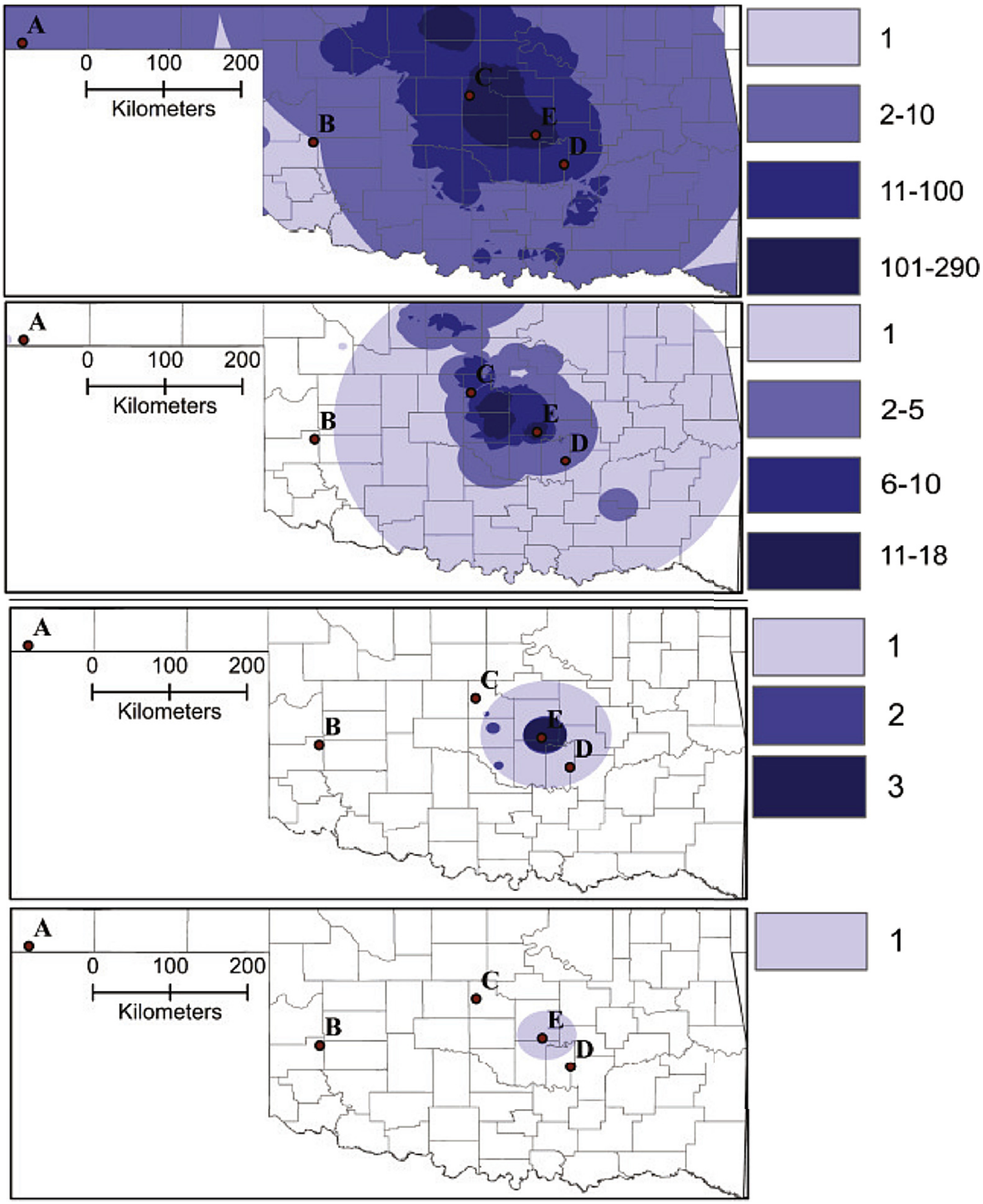

Fig. 6. Earthquake Exposure Counts, 1/2001–11/2014. Top: MMI3; Second: MMI4; Third: MMI5; Bottom: MMI6.
Data sources: Oklahoma Geological Survey and United States Geological Services. Lettered properties are examples for discussion.

cator of the property's maximum MMI during the study period. This specification gives results similar to the indicator models in Tables 3 and 4 because the Prague earthquake sequence drives much of the MMI4 and MMI5 exposure and all of the MMI6 exposure.

We attempted to use a continuous measure of the maximum intensity a property had experienced before its sale. The coefficients on this value (see Table 6) are close to zero and not significant. We believe this is because the relationship is not linear, and imposing a linear relationship does not fit the data well. The categorized indicators in our main results allow the earthquakes' impacts to vary with their intensity. A log of the continuous MMI would require omitting all the sales with a true maximum MMI of zero.

Several previous papers have highlighted the importance of well-water contamination by UIC wells. While we already include two con-

Table 7
Predicted Sale Price Impacts of Earthquake Exposure for Properties Depicted in Figs. 6 and 5. Estimates are calculated using the results presented in Table 3, column 1, and Table 4, column 1.

Property	MMI3	MMI4	MMI5	MMI6	Price Change	
					Repeat Sale, Indicator	Dif in dif, Indicator
A	5	0	0	0	$686	$0
B	5	0	0	0	$686	$0
C	110	6	0	0	-$4799	-$6581
D	162	7	3	0	-$4936	$548
E	134	11	3	1	-$11,928	-$14,121

trols for UIC wells, it is possible that earthquakes have a greater impact in areas that are well-water dependent because the earthquakes raise awareness of the danger that UIC wells pose to water quality. When the models are estimated separately on properties with well water, we find similar patterns in the coefficients on the earthquake variables (see Table 6). The magnitudes are higher in the well-water subsample, but the coefficients are less precisely measured because the sample is much smaller.

To frame these price changes in practical terms, consider the five properties A, B, C, D, and E in Fig. 5, and assume that each of them was sold in December 2014 at the mean price of $137,100. Fig. 6 shows each of these houses on maps depicting the three earthquake-exposure gradients generated by summing regional exposure over the full period from 2001 to 2014. Exposure is defined such that the MMI3 map shows only earthquakes experienced above MMI3 but below MMI4, and so on. Note that although Property A was unexposed to the M 5.6 Prague earthquake, as well as most seismicity within Oklahoma over this period, it was still exposed to several of the large earthquakes occurring near Trinidad, Colorado.

Table 7 lists the cumulative earthquake exposure of each of the five properties over the 14-year period, as well as the expected price change for each house attributable to earthquake exposure. Properties A and B have only MMI3 exposure, so no decreases are predicted. The repeat-sales model predicts losses of $4799 and $4936 for properties C and D, and a loss of $11,928 for property E. The difference-in-differences model predicts price decreases of $6581 for property C and $14,121 for property E.

7. Conclusion

This study intends to demonstrate the potential welfare impacts of induced earthquakes as part of a larger literature examining the costs and benefits of oil and natural gas extraction. A new risk came into existence, and all buyers and sellers have been forced to re-evaluate the value of the properties given their best estimates of the losses the properties could experience or the cost of insuring against those losses.

Oklahoma provides an exceptional case study as the state most affected by sudden changes in seismic frequency and intensity. With the expectation that the welfare costs of earthquakes may be capitalized into housing prices, we examine housing-sale-price changes in response to earthquake exposure across four levels of intensity. In contrast to literature finding substantial price impacts of small earthquakes, we find substantial price effects for properties affected by the strongest earthquakes in the region. We also find small positive price responses to the low-intensity earthquakes that are unlikely to cause damage. Sale-price decreases for the properties affected by the most intense earthquakes are estimated to be in the range of 3.5–10.3 percent.

The price changes reported in this paper, however, are attributed to all seismicity in the region, as no catalog exists categorizing all earthquakes in the region as either induced or natural. Although the Oklahoma Geological Survey has recognized that the majority of earthquakes are likely to be induced, the extent of this majority is unknown.[24] Given this, estimates should be treated as an upper bound on the potential impacts of strictly induced seismicity. Nevertheless, the recent change in seismicity rates, induced or not, has inflicted substantial costs on homeowners in Oklahoma.

Even as consensus forms around the cause of these earthquakes, the safest way to reduce earthquakes is still being investigated. The Oklahoma Corporation Commission (OCC), the regulatory body responsible for the underground injection control wells known to induce earthquakes, has publicly noted that sudden moratoriums on wastewater injection, such as those adopted in Kansas, Arkansas, and Ohio under similar circumstances, may increase earthquake risk more than inaction. The OCC began taking substantive action toward understanding and mitigating earthquake risk in 2013, with the adoption of a “traffic light” system for well permitting that increased scrutiny for new well permitting in areas with established seismic risk. Increased reporting requirements for disposal wells injecting into the Arbuckle formation were implemented in September 2014. Directives implemented from March 2015 to present have focused on reducing injection volume and plugging back injection wells active below the Arbuckle formation. Whether these measures will be effective in reducing earthquakes is yet to be seen: Although reducing injection volumes reduced seismicity in Paradox Valley, Colorado (where changes in injection regimes led to a decrease in seismic activity from over 1100 events per year to 60; see Ake et al. (2005)), and moratorium measures have worked to eliminate most seismicity in central Arkansas, factors specific to Oklahoma’s geology may lead to different responses altogether.[25] Additionally, accumulated pore pressure takes substantial time to diminish even given after injections cease. The largest earthquake at Rocky Mountain Arsenal occurred over a year after injection ceased, so in Oklahoma the seismic response to policy action will likely be lagged (Horton, 2012).

Wastewater injection does not necessarily lead to harmful seismic activity, so careful and responsive regulatory practices may prove as effective in seismic risk mitigation as banning wastewater injection outright. Although regulatory procedures will likely entail additional direct costs for injection-well operators, they should diminish the externalities imposed on homeowners that we have identified here.

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[24] See their Statement on Oklahoma Seismicity from April 21, 2015, accessible at http://wichita.ogs.ou.edu/documents/OGS_Statement-Earthquakes-4-21-15.pdf.

[25] Reducing injection depth reduces the risk of injected fluids contacting basement rock.

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