working paper 16 31

Earthquakes and House Prices: Evidence from Oklahoma

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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 16-31 December 2016

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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, bring potentially damaging quakes several times each year and perceptible quakes every few days. Using hedonic models, we estimate that prices decline by 3 to 4 percent after a home has experienced a moderate earthquake measuring 4 or 5 on the Modified Mercalli Intensity Scale. Prices can decline up to 9.8 percent after a potentially damaging earthquake with intensity above 6. The correlations between low-intensity (MMI 3) quakes and prices are smaller and vary between specifications. Our findings are consistent with the experience of an earthquake revealing a new disamenity and risk that is then capitalized into house values.

Keywords: Earthquakes, house prices, hedonic price analysis.

JEL classification: Q51, Q53, R31.

Suggested citation: Cheung, Ron, Daniel Wetherell, and Stephan Whitaker, "Earthquakes and House Prices: Evidence from Oklahoma," Federal Reserve Bank of Cleveland, Working Paper no. 16-31.

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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.[1] 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.[2] 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., 2016).[3]

Documentation of earthquakes caused by underground injection of fluid reachs 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 U.S. Army. Induced earthquakes from wastewater disposal have since been recorded in Ashtabula, Ohio; Perry, Ohio; and Cold Lake, Alberta, Canada (Nicholson and Wesson, 1990).[4] 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; Pursley et al. (2013)),

[1]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).

[2]Magnitude 3 earthquakes approach the smallest that can be felt by humans: see Dengler and Dewey, (1998).

[3]The second-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).

[4]Earthquakes can be induced by underground injection wells, fluid reservoirs, and energy resource extraction practices (Ellsworth, 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 (>95 percent) consist of saltwater 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 (Murray (2014)), an Oklahoma rock formation that sits directly above basement rock, then can explain recent increases in seismicity. 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 fracking and 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 9.7 percent decrease in prices following the largest earthquake observed.

This paper proceeds as follows: Section 2 reviews the literature on the impacts of earthquakes, oil and gas development, 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 as 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 $4,650.

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, Seko, and Sumita (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, Saito, and Yamaga (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 to 3-8 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" earthquakes lead to 1.9 percent decreases 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.[5]

Externalities from oil and gas development have been more widely explored with hedonic models, most recently with Gopalakrishnan and Klaiber (2014), and Muelenbachs, Spiller, and Timmins (2012; 2015) who examine the impact of shale gas wells on local property values. They 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 or issue salience may impact whether risks are priced into property values.

This paper contributes an estimation of the impact of more intense and more frequent earthquakes in a US context. Also, we are able to investigate the impact of earthquakes

[5]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.

on properties' time-on-market. Benefield, Cain and Johnson provide an extensive survey of the literature relating home sale prices and time-on-market (2014). 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 that include time-on-market as a control variable in a hedonic price model, and we estimate models 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 date 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 is 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, Spiller, and Timmins (2015), we consider only single-family residences, townhouses, duplexes, and rural homesites in this analysis. We drop properties listed with sales 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.[6] 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). Figure 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. The realtors 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. In the data, the fields are not always populated.[7] 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 begin to appear in the data over time. One key variable that is available in the MLS 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. With the MLS data, we can include the time-on-market as a

[6]Although our data-cleaning procedure is strict, it is not without precedent: to eliminate outlying properties, Boxall, Chan, and McMillan (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.

[7]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.

control.

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 borders that would be felt in Oklahoma.[8] We drop duplicate observations and earthquakes recorded with magnitude less than or equal to M2.9 for earthquakes within Oklahoma and M3 for earthquakes outside of Oklahoma. This results in a dataset consisting of 1,093 earthquakes from Oklahoma and 543 earthquakes from outside of Oklahoma over the period from January 1, 2001, to December 31, 2014.[9] Figure 2 displays the number of these earthquakes occurring in Oklahoma by magnitude by month from January 2001 to February 2016, grouped from M2.9 to M3.9 and from M4.0 and higher. Earthquakes are of low frequency and magnitude from 2001-2008, 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.[10] 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 of higher magnitudes were not observed in Oklahoma during the study period. The maximum MMI experienced during the M5.6 Prague, Oklahoma earthquake was 6.

[8] 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.

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

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

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

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

where

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

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

Figure 3 displays this attenuation function evaluated for earthquakes at a variety of magnitudes at a constant depth of 5km, the median for earthquakes in the Oklahoma dataset. Note that although fractional MMI levels are easily obtained from this function, they are qualitatively meaningless except to say that they are levels of intensity between two qualitatively defined levels of intensity.

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 ArcGIS (a geographic information system) 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.

Figure 5 displays this process for the M 5.6 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 to the earthquake at the MMI5 and MMI6 levels, respectively.[11]

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 towards 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.[12] 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

[11] 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.

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

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 35km 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 water nearby).

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.[13] 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

[13]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 their wells. Class II wells are injection wells strictly associated with oil and natural gas activity.

MMbbl (approximately half the threshold used by Murray (2014) in defining high volume wells, though still a relatively high threshold).

Figure 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 kilometers of a UIC well.[14] To construct a more granular measure of UIC wells, and also be consistent with the distances used to measure fracking-well exposure in Muelenbachs, Spiller, and Timmins (2015), we construct measures of property well exposure equal to the number of wells within 2km of a property.[15] This measure assumes that the noxious effects of wells are not spatially dependent and did not change over time, except through earthquake-related effects.

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

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

[15]We considered the 20km measure also used in Muehlenbachs, Spillter, and Timmins (2015), though the measure adds very little information: properties tended to be either close to many wells or close to none at all.

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.[16] 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 and related activity may have significant, offsetting positive impacts on local housing prices. County-level data on employment in mining industries is available from the County Business Patterns data series.[17] In many counties, the exact employment figure is suppressed to maintain confiden-

[16]The Fujita (F) scale is used from 1950-1/31/2006; 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).

[17]County Business Patterns data is available at http://www.census.gov/programs-surveys/cbp.html. Accessed 12 December, 2016.

tiality. Where this was the case, we replaced the value with the midpoint of the range that corresponds to the suppression code. We calculated the difference between the 2013 and 2008 values as a measure of the increase in mining activity over the study period. For the estimates, we included the growth in employment value.[18]

4 Models

With the above datasets, we specify a log-linear functional form for a model of house sale price dependent on earthquake exposure:

$$\ln(P_h t) = \tau_0 + \tau_1 D^3_{ht} + \tau_2 D^4_{ht} + \tau_3 D^5_{ht} + \tau_4 D^6_{ht} + \alpha X + \gamma Y + \omega Z + \epsilon_{ht}$$

where subscripts h,t denote a unique property h sold at time t, measured in months from January 2001. $ln(P_{ht})$ is the natural logarithm of the sale price of a house in 2014 dollars.

D^Z_{ht} is an indicator equal to 1 if the most intense earthquake experienced by the property through the month before the month of sale was at MMI level Z. No more than one of the D^Z_{ht} indicators can equal one for an observation.

X is a vector of property characteristics consisting of the building and land plot square footage, the year of the property's construction, and the type of property.[19]

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

Z is a vector of spatial characteristics, including census-tract fixed effects, school-district fixed effects, exposure to UIC wells, distance to the nearest of Oklahoma City or Tulsa, the county-level measure of tornado exposure, and neighborhood demographics.[20]

ϵ_{ht} is an error term, clustered at the census-tract level to account for spatial autocorrelation.[21]

[18] We also tested the levels of employment and the growth in mining establishments and mining payroll totals. The levels from the base year were not significant, while there were significant positive relationships between the 2013 values and house prices. These estimates are available upon request.

[19] Construction years are indicators for 10-year ranges, with a single range for before 1950.

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

[21] We considered both heteroskedastic errors and the implementation of a spatial autoregressive model, though clustering produces more conservative results than the former, and computational constraints prevent

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 M5.6 Prague earthquake at the MMI5 level may have indicated that the local area was at a higher risk for intense earthquakes now relative to any prior point in time. This is commensurate with USGS' seismic hazard maps, which record the level of ground motion that will be exceeded with some probability within some time frame.[22]

When we estimate the cumulative models, C^Z_{ht} is the cumulative earthquake exposure at MMI level Z from January 2001 until the month before the house's sale month. The specification is

$$ln(P_{ht}) = \beta_0 + \beta_1 C^3_{ht} + \beta_2 C^4_{ht} + \beta_3 C^5_{ht} + \beta_4 C^6_{ht} + \alpha X + \gamma Y + \omega Z + \epsilon_{ht}$$

β_1, β_2, β_3 and β_4 are the coefficients of interest, interpretable as the percentage change in a house's sale price attributable to each additional earthquake at the corresponding MMI. Each is estimated conditional on the exposure to the counts at other levels of intensity. All the other variables as defined for model (1).

5 Descriptive Statistics

Table 2 provides summary statistics for the data that will be used for the main models. The mean home sale price is \$130,665, and the standard deviation is \$101,678. Nine percent of homes have experienced an MMI5 earthquake before they are observed to sell. One percent have experienced an MMI6 event. The average cumulative count of exposures to MMI3 earthquakes is 14.83. Exposures to hundreds of MMI3 quakes is common, while maximum exposures to MMI4 and above events remain below 25. Ninety six percent of the observations are single family homes. The vast majority, over 97 percent, are not close enough to UIC

us from using the latter.

[22]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.

wells to experience direct negative externalities.

Table 2 provides the equivalent summary statistics for properties in the most affected counties and those with data in the MLS records. We define the most affected counties as those with 10 or more MMI3 earthquakes and/or at least one high-volume UIC well. Both subsamples are more heavily weighted toward urban areas, which results in higher home prices than are seen in the full county recorder data set. Earthquake exposure is moderately higher in the subsamples. Time on market was truncated at three years, which is above the 99th percentile, to exclude some implausibly large values. The mean value is 3.80 months, with a standard deviation of 3.08 days. We utilize 14 additional MLS house characteristic variables, with architectural style, exterior material, flooring, bathrooms, bedrooms, and garages categorized. We investigated whether there was a difference in the value response of homes with slab foundations versus basements. This could reflect actual or perceived differences in vulnerability to earthquake damage. However, slab homes are 93 percent of the sample, and there are not enough homes with basements to allow the estimation of an interaction.

6 Results

The first set of results presented in table 3 builds up the model relating earthquake exposure to house prices by sequentially adding control variables. The first column presents the coefficients from a regression of indicators of the highest MMI earthquake that the property had experienced by the month before its sale on the log of the sale price. With no controls present, the coefficients are positive and significant. However, this is reflecting that more earthquakes have been experienced in areas of the state with higher property values, specifically more urbanized areas. Similarly, the year-of-sale coefficients in column two are implausibly large and negative. In the case of the year-of-sale indicators, this is reflecting that most of the data in the omitted year of 2006 is from urbanized counties, and more rural counties were added to the data each subsequent year.

When we force the model to use within-census-tract variation by introducing census-tract fixed effects (table 3, column 3), the coefficients on the earthquake indicators become small and negative. In columns 4 and 5, property characteristics and neighborhood measures are introduced. The standard errors on the earthquake coefficients decline as the additional controls are added. Column 5 represents our best estimate of the earthquake impacts. Controlling for tract, school district, year fixed effects, and property and neighborhood characteristics, an MMI4 or MMI5 earthquake reduces a property's sale price by 3 to 4 percent. The impact of ever having experienced an MMI3 earthquake is less than one percent and not statistically significant. The impact of ever having experienced an MMI6 event is a 9.7 percent reduction in a home's sale price.

Among the control variables, the square footage and lot size are also significantly predictive of price, as we would expect. Among neighborhood characteristics, UIC wells appear to exert an independent negative externality of 2.4 percent per well. Growth in mining employment at the county level has a strong positive price impact. It is notable that introducing the local-area controls in column 5, including wells and mining employment, does not greatly reduce the earthquake indicator coefficients relative to their values in column 4.

In the final column of table 3, one set of results is presented in which the observations represent what we will refer to as the "most affected counties." These are limited to Oklahoma County and the thirteen other counties that had ten or more magnitude 3.0 or higher earthquakes over the period of study and at least one high-volume disposal well.[23] In addition to the census-tract fixed effects, this sample limitation further reduces the possibility that the estimated earthquake impacts are reflecting a contrast between low-value areas that were more exposed to earthquakes and higher value areas that were less exposed. In the most-affected counties the estimated impact of any MMI3 exposure is not significantly different from zero. The impacts of MMI4 and MMI5 exposure are between 4 and 5 percent price reductions, but the reduced sample size prevents them from being statistically significant. The impact of an MMI6 exposure is over a percentage point higher in the restricted sample, at 11 percent, and remains highly significant. The coefficients on the various control

[23]The other counties, in descending order of observed sales, are: Garfield, Payne, Pottawatomie, Logan, Lincoln, Woodward, Seminole, Okfuskee, Woods, Noble, Pawnee, Grant, and Alfalfa.

variables remain similar in magnitude and significance in most cases. One exception is the coefficient on mining employment growth. It seems that the strong positive price impact of the employment growth is being estimated with the contrast between the most earthquake-impacted counties and all other counties. In the restricted-sample estimate the coefficient on mining employment growth is very imprecisely measured.

In table 4, the same six models are presented with a count of earthquake exposures in place of the maximum MMI exposure indicators. As in the first set of models, the coefficients change dramatically when the census-tract fixed effects are added. The coefficient on the count of MMI3 exposures remains positive and significant in all specifications. The coefficient on the indicator of any MMI3 exposure was negative, but the indicators take the value of one only if no higher-level earthquake was experienced. They are exclusive and therefore negatively correlated. The count measures have positive correlations between 0.11 and 0.81. The positive coefficient on the MMI3 count estimates the impact conditional on the higher MMI counts. An additional MMI4 exposure is estimated to reduce the sales price by 1.5 percent. The impact of an MMI5 exposure is negative but not significant. Finally, the estimate of the price impact of an MMI6 exposure is a discount of approximately 10 percent. The count and the indicator values are the same for MMI6 properties because there was only one MMI6 event during the study period. Conditioning on the counts of smaller quakes does not change the estimated impact of an MMI6 exposure. Restricting the sample to the fourteen counties with the most earthquake activity changes the coefficient substantially only on the MMI5 counts. It becomes positive but remains insignificant.

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 so could be capturing spatially correlated effects otherwise unaccounted for in their model. 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 magnitude of completeness in Oklahoma indicates that earthquakes below M2.0 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 and thereby economic activity in regions experiencing frequent earthquakes, though not necessarily the regions impacted by the largest earthquakes. Our mining-employment-growth measure may not be sufficiently precise to control for the positive impact of fracking on economic activity.

As discussed in the data section, we have the option of incorporating MLS data in the analysis. The advantages of the MLS data are the availability of a time-on-market measure and a richer set of property characteristics. The disadvantage is a more limited set of observations.

The first regression result in table 5 presents the estimate of the main model (table 3, column 5) using the MLS-merged observations, but not the MLS-provided variables. The coefficients on the MMI3, MMI4, and MMI5 maximum exposure indicators are smaller and less precisely measured. In the second model in table 5, the time-on-market measured in months is introduced. The measure is not significant, and it makes only slight changes in the estimates of the earthquake impacts. Previously, when we introduced property and neighborhood characteristics, the coefficients and standard errors both changed substantially, and this occurs again when the MLS property characteristics variables are introduced in the third model. Having a maximum exposure of MMI3 before the sale is estimated to reduce the sale price by 1.8 percent in the third column of table 5. The negative impact of an MMI4 exposure is estimated to be 2.8 percent, which is significant at the 0.05 level. MMI6 exposure is estimated to reduce the sales price by 8.2 percent when the MLS controls are included.

In table 6, three additional models are presented with outcomes other than price. The first model allows time-on-market to be the dependent variable. The estimates suggest there is a statistically significant increase in marketing time associated with a property's exposure to MMI3 and MMI6 earthquakes. However, the economic significance is not as evident. The units of the dependent variable are months, so a property that has a maximum earthquake exposure of MMI3 takes an additional nine days to sell. Exposure to an MMI6 earthquake corresponds to an additional 21 days of marketing time. This is only one-fifth of a standard deviation. If one prorated a month's carrying cost to 21 days, it would very likely be less than the one-half of one percent of the home value. That is comparable to the price models' suggested losses due to MMI3 exposure and far below that of MMI4 and above exposure. So while the time-on-market estimates are consistent in direction with the price-model estimates, it appears that more of the losses are realized through the price than through carrying costs. The second model in table 6 is an alternate specification, the Cox proportional hazard model. The dependent variable is the instanteous odds that the property will sell given that it is on the market. The hazard results are very consistent with the OLS model. Exposure to MMI3 or MMI6 earthquakes moderately reduces the probability that a property will sell at any given point in time.

The final model in table 6 investigates whether earthquake exposure increased or decreased the pace of sales overall.[24] The observations in this model are tract-years, with the count of sales divided by the count of housing units in the tract from the 2010 decennial Census. The property characteristics are aggregated to the tract level. The observation count is much smaller due to the aggregation, so we opted to aggregate the full set of sales rather than only the MLS-merged sales. Of the four coefficients on the earthquake-exposure measures, three are associated with a faster pace of sales. For context, the average pace of sales observed in the data is 2.8 percent of housing units transacting in a year (0.028), with a standard deviation of 2 percentage points. The model implies that exposure to an MMI4 or above earthquake would increase the pace of sales by 0.7 to 1.1 percentage points. To be consistent with the price reductions and extended marketing times, this would imply that the earthquake activity induces a supply shock. After experiencing an earthquake, more home-

[24]We tested some other specifications that had precedent in the literature. 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 impact. There was no discernable pattern in the coefficients, and we believe this is because earthquake activity was increasing throughout the study period, so buyers and sellers did not have the opportunity to "forget" past events. We also tried a specification that interacted a post-Prague-sale indicator with an indicator of the MMI experienced by the property in the Prague event. This specification gave similar results to the main model (table 3, column 5) because the Prague earthquake sequence drives much of the MMI4 and MMI5 exposure and all of the MMI6 exposure.

owners come to market than otherwise would be the case. If demand remains unchanged, prices should decline and quantities rise. If demand dropped because some buyers became wary, then both quantity and price would have dropped.

To frame these price changes in practical terms, reconsider the same five properties A, B, C, D, and E in figure 5, and assume that each of them was sold in December 2014 at the mean price of $130,665. Figure 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 only shows 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 the 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. Note that properties D and E are only 16km away from each other, and both are within a region experiencing large amounts of seismic activity. However, according to the cumulative model, only property E is expected to sell at a lower price, all else equal, due to earthquake exposure.

In the second column of estimates, the results are those implied by the model with an indicator of the maximum earthquake experienced. All of the coefficients on exposure are negative in this model, so all properties are expected to sell for lower prices. The discounts range from under $1,000 to several thousand dollars. A single MMI6 exposure increases the discount to $12,805. The third column of table 7 gives the estimates of impacts based on the models using MLS data. This is an indicator model similar to that underlying column two, and all the coefficients are negative. The price decreases are approximately three times as large for properties A and B, which have minor MMI3 exposure only. The MLS model-implied decreases are smaller for properties C, D, and E, with peak MMIs at 4 and above. As in the indicator model, each estimate is determined by a single coefficient, and the coefficient on the MMI5 indicator is not statistically significant.

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 risk which had not existed in the past came into existence, and all sellers have been forced to re-evaluate the value of their properties given their best estimate of the losses their property could experience or the cost of insuring against them.

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 negative price responses, and even positive price responses, to smaller earthquakes that are unlikely to cause damage. This suggests that the capitalization of earthquake risks into housing may be relative to regional seismic risk. Sale price decreases for the properties affected by the most intense earthquakes are estimated in the 3.4-9.8 percent range.

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.[25] 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.

Although the cause of these earthquakes is well-known, 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

[25]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

those adopted in Kansas, Arkansas, and Ohio under similar circumstances, may increase earthquake risk more than inaction. The OCC began taking substantive action towards 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 1,100 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.[26] Additionally, accumulated pore pressure takes substantial time to diminish even given no further injections occurring in a region: the largest earthquake at Rocky Mountain Arsenal occurred over a year after injection ceased (Horton (2012)), so in Oklahoma seismic response to policy action will likely be lagged.

Wastewater injection does not necessarily lead to harmful seismic activity, and 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.

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

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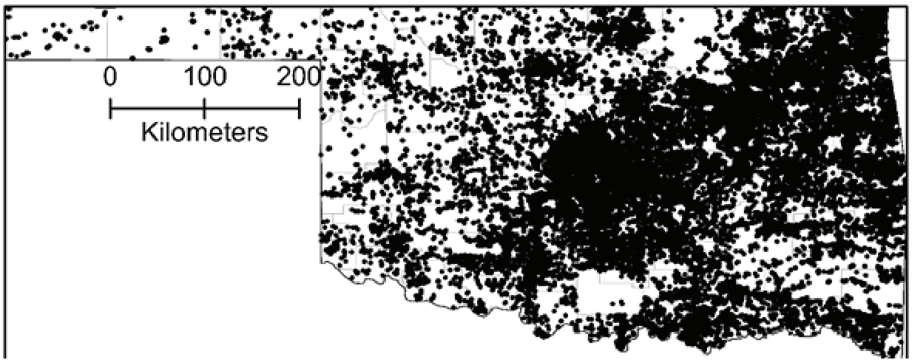

Figure 1: Housing Sales in Oklahoma, 2006-2014. Data source: CoreLogic Deeds Data.

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

Table 1: Modified Mercalli Intensity Scale. Adapted from Wald et al. (2010).

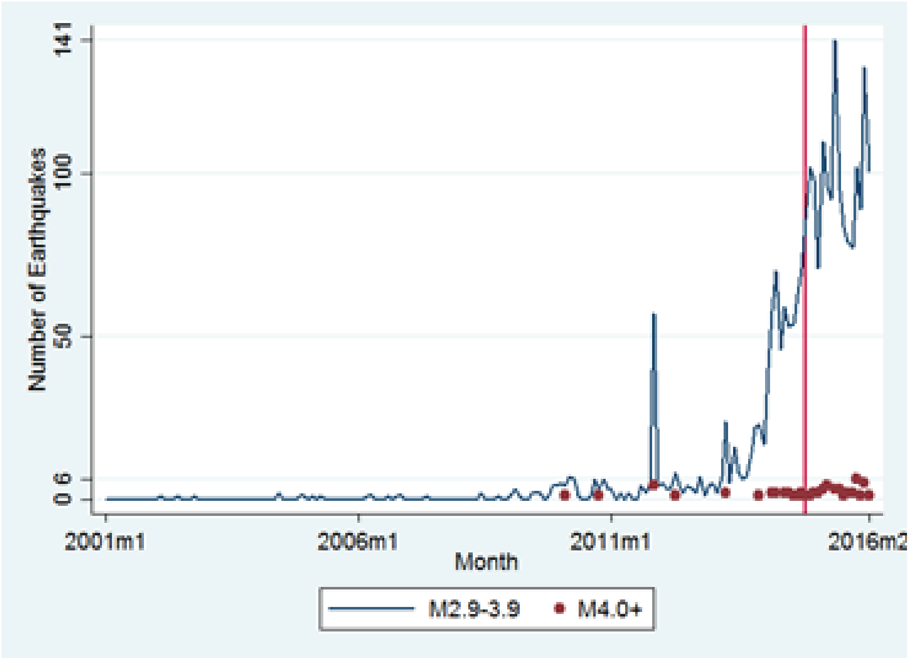

Figure 2: Monthly Earthquake Totals in Oklahoma, 2001-2016. Vertical line denotes the month 11/2014, the last month of exposure used in this study. Data sources: Oklahoma Geological Survey and United States Geological Survey.

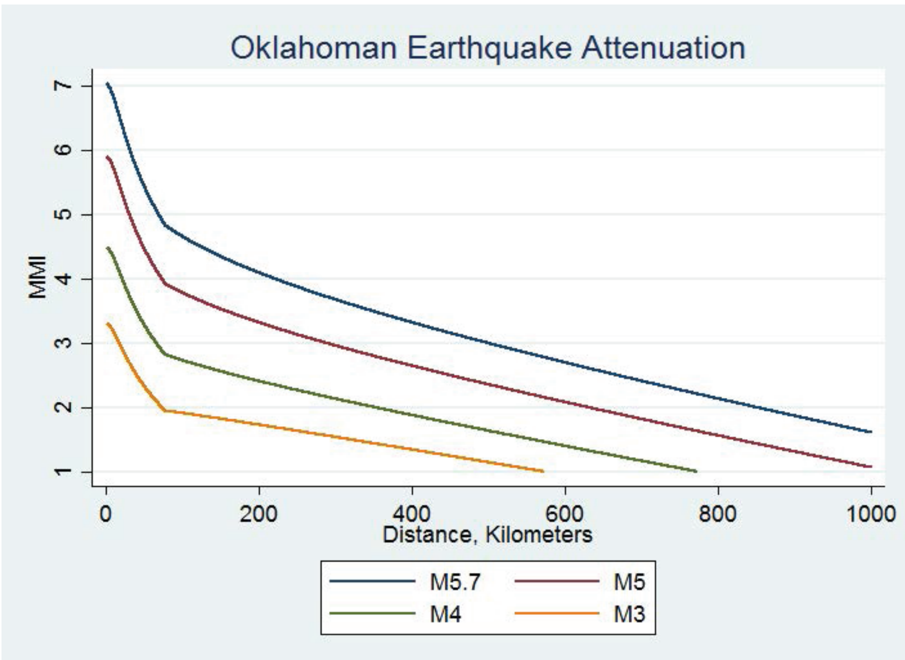

Figure 3: Modified Mercalli Intensity Attenuation function, select magnitudes.

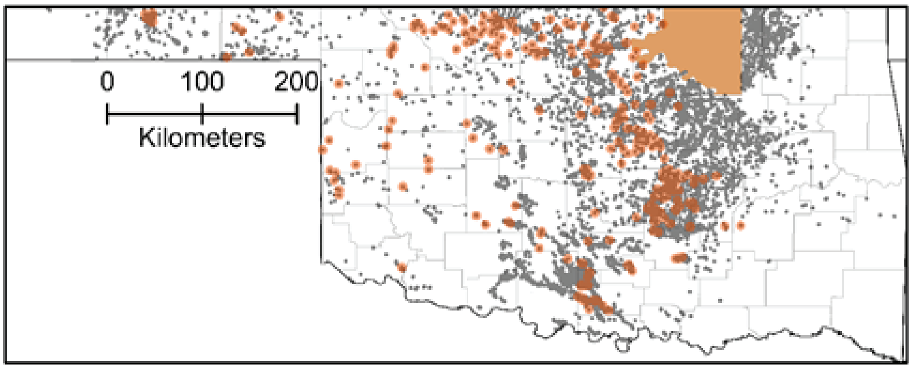

Figure 4: Underground Injection Control (UIC) Wells, 2006-2014. High volume wells are displayed as large orange circles. Osage County is highlighted. Data source: Oklahoma Corporation Commission.

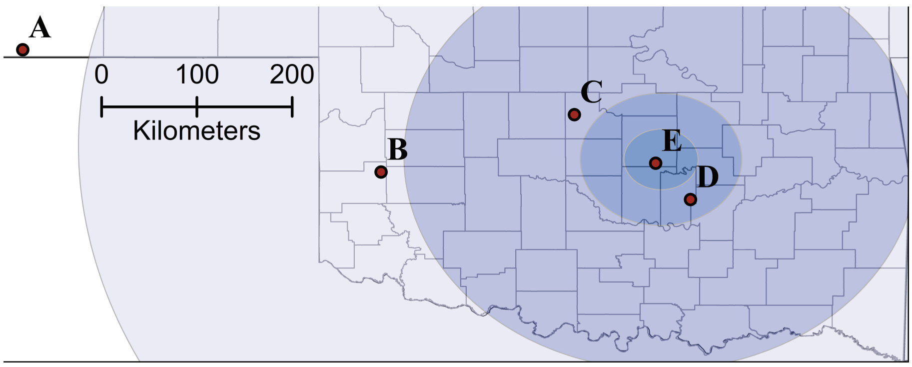

Figure 5: Property Earthquake Exposure from the M 5.7 event centered in Prague, OK. Lettered properties are examples for discussion.

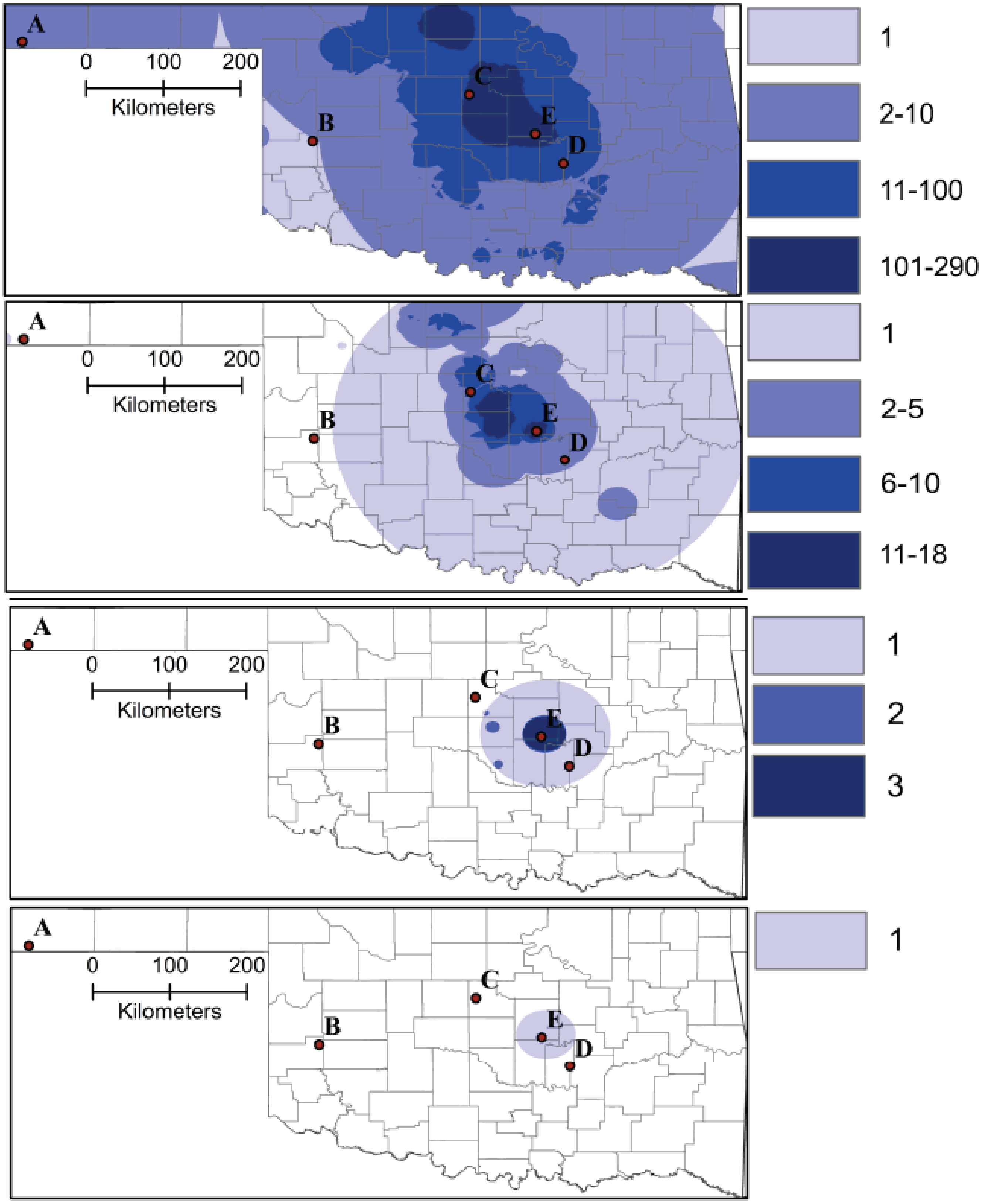

Figure 6: Earthquake Exposure Counts, 1/2001-11/2014. Top: MMI3; Second: MMI4; Third: MMI5; Bottom: MMI6. Data sources: Oklahoma Geological Survey and Unite States Geological Service. Lettered properties are examples for discussion.

Table 2: Summary Statistics. Data Sources: CoreLogic Deeds Data and Tax Data, CoreLogic Multiple Listing Service data, Oklahoma Geological Survey, United States Geological Service, Oklahoma Corporation Commission, National Oceanic and Atmospheric Administration, American Community Survey, County Business Patterns. Most affected counties: Oklahoma, Garfield, Payne, Pottawatomie, Logan, Lincoln, Woodward, Seminole, Okfuskee, Woods, Noble, Pawnee, Grant, and Alfalfa counties. These counties had 10 or more M 3.0 or above earthquakes during the study period and at least one high-volume disposal well.

	All Sales		Most Affected Counties		MLS merged Sales	
	Mean	SD	Mean	SD	Mean	SD
Sale Price	130,665	101,678	137,271	107,410	154,291	104,878
Log Sale Price	11.49	0.81	11.54	0.80	11.73	0.69
MMI3 peak exposure indicator	0.19	0.39	0.24	0.43	0.18	0.39
MMI4 peak exposure indicator	0.37	0.48	0.22	0.41	0.42	0.49
MMI5 peak exposure indicator	0.09	0.29	0.14	0.35	0.12	0.33
MMI6 peak exposure indicator	0.01	0.10	0.02	0.14	0.01	0.11
MMI3 exposure count	14.83	27.58	23.15	35.12	19.60	31.05
MMI4 exposure count	0.88	1.65	1.04	2.17	1.11	1.87
MMI5 exposure count	0.11	0.33	0.16	0.40	0.14	0.36
MMI6 exposure count	0.01	0.10	0.02	0.14	0.01	0.11
Thousand Square Feet, Building	2.00	0.84	2.04	0.89	2.19	0.87
Thousand Square Feet, Land Plot	9.61	1.18	9.41	0.98	9.42	0.97
Townhouse/Rowhouse	0.00	0.03	0.00	0.05	0.00	0.03
Duplex	0.01	0.08	0.01	0.11	0.01	0.08
Rural Homesite	0.03	0.17	0.02	0.12	0.02	0.15
Single Family Residence	0.96	0.19	0.97	0.17	0.97	0.18
Year built	1970.82	25.07	1968.59	24.93	1975.52	23.80
Mining Employment Growth	0.17	0.47	0.24	0.33	0.16	0.36
UIC Wells within 2km	0.02	0.18	0.04	0.23	0.03	0.19
High Volume UIC Wells within 2km	0.00	0.03	0.00	0.04	0.00	0.03
Percent African American (tract)	0.07	0.12	0.11	0.15	0.08	0.12
Percent Native American (tract)	0.05	0.05	0.04	0.04	0.04	0.04
Percent high school graduates (tract)	0.87	0.10	0.87	0.11	0.89	0.09
Median Age (tract)	36.76	5.80	35.81	6.02	36.50	5.62
Median Income ($10,000s) (tract)	5.34	2.28	5.51	2.59	5.90	2.50
Log distance (km) to OKC or Tulsa	3.32	1.20	2.81	1.07	2.85	0.93
Tornados within 10km, 1950-2006	18.13	10.60	22.11	11.72	20.06	10.39
Months on market					3.89	3.08
Association Fee					0.05	0.17
Traditional					0.64	0.48
Ranch					0.07	0.25
Bungalow					0.06	0.24
Contemporary					0.04	0.20
Dallas					0.07	0.25
Air Conditioning					0.94	0.23
Brick					0.24	0.43
Siding					0.07	0.25
Fireplace					0.69	0.46
Hardwood					0.22	0.42
Tile					0.38	0.49
Vinyl (floor)					0.12	0.33
Basement					0.07	0.26
1 Car Garage					0.17	0.38
2 Car Garage					0.57	0.49
3+ Car Garage					0.15	0.36
Electric Heat					0.15	0.35
Split Level					0.05	0.21
Second Story					0.32	0.46
2 Bath					0.61	0.49
3+ Bath					0.13	0.33
2 Bedroom					0.12	0.33
4+ Bedrooms					0.26	0.44
Septic System					0.11	0.31
Well Water					0.10	0.30
Obersvations	258,058		128,435		127,879	

Table 3: House price impacts of the highest level of earthquake experienced before sale. Dependent variable is the log sale price. Standard errors are clustered by census tract and appear below in parentheses. Significance Key: *** p<0.01, ** p<0.05, * p<0.1. 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.

	Exposure Indicator	Year Indicators	Census Tracts	Property Controls	Local Controls	Affected Counties
MMI3 peak exposure	0.174***	0.305***	−0.001	−0.006	−0.006	0.011
	(0.020)	(0.043)	(0.009)	(0.007)	(0.007)	(0.011)
MMI4 peak exposure	0.207***	0.445***	−0.034*	−0.039**	−0.034**	−0.043*
	(0.025)	(0.060)	(0.014)	(0.013)	(0.012)	(0.019)
MMI5 peak exposure	0.232***	0.487***	−0.042	−0.041*	−0.037*	−0.048
	(0.046)	(0.089)	(0.022)	(0.020)	(0.019)	(0.027)
MMI6 peak exposure	−0.137	0.122	−0.041	−0.099***	−0.097***	−0.110***
	(0.086)	(0.102)	(0.029)	(0.023)	(0.022)	(0.027)
Year of Sale 2007		−0.032	−0.026***	0.070***	0.069***	0.079***
		(0.019)	(0.008)	(0.008)	(0.008)	(0.008)
Year of Sale 2008		−0.279***	−0.066***	0.033**	0.032**	0.037**
		(0.036)	(0.011)	(0.013)	(0.012)	(0.014)
Year of Sale 2009		−0.328***	−0.056***	0.039***	0.039***	0.023
		(0.044)	(0.011)	(0.011)	(0.011)	(0.013)
Year of Sale 2010		−0.262***	−0.046***	0.038**	0.039**	0.026
		(0.046)	(0.012)	(0.012)	(0.013)	(0.016)
Year of Sale 2011		−0.352***	−0.038**	0.030*	0.031*	0.016
		(0.049)	(0.013)	(0.013)	(0.014)	(0.018)
Year of Sale 2012		−0.520***	−0.016	0.050**	0.048**	0.048
		(0.074)	(0.018)	(0.017)	(0.017)	(0.025)
Year of Sale 2013		−0.423***	−0.035	0.034	0.033	0.058*
		(0.075)	(0.018)	(0.018)	(0.018)	(0.024)
Year of Sale 2014		−0.429***	−0.017	0.042*	0.040*	0.072**
		(0.075)	(0.019)	(0.018)	(0.018)	(0.025)
Square Feet (thousands)				0.419***	0.413***	0.393***
				(0.006)	(0.006)	(0.011)
Land Plot (ln(sqft))				0.104***	0.108***	0.100***
				(0.004)	(0.004)	(0.006)
Townhouse/Rowhouse				0.021	0.022	0.002
				(0.058)	(0.059)	(0.060)
Duplex				−0.101*	−0.102*	−0.098*
				(0.046)	(0.046)	(0.046)
Rural Homesite				−0.101***	−0.100***	−0.099***
				(0.017)	(0.016)	(0.028)
Mining Employment Growth					0.178***	−0.211
					(0.050)	(0.222)
UIC Wells					−0.024**	−0.028**
					(0.008)	(0.009)
High Volume UIC Wells					−0.033	−0.044
					(0.032)	(0.030)
Percent African American					−0.137	−0.063
					(0.130)	(0.149)
Percent Native American					−0.287	−0.329
					(0.151)	(0.227)
High school graduates					−0.028	0.002
					(0.109)	(0.142)
Median Age					0.000	0.000
					(0.001)	(0.002)
Income (thousands)					0.007	0.008
					(0.006)	(0.007)
Distance to OKC or Tulsa					−0.008	0.082
					(0.061)	(0.091)
Tornados					0.003	−0.000
					(0.002)	(0.003)
Decade of Construction FE				Y	Y	Y
Census Tract FE			Y	Y	Y	Y
School District FE					Y	Y
Constant	11.360***	11.556***	11.022***	9.887***	9.866***	9.496***
	(0.029)	(0.036)	(0.009)	(0.042)	(0.413)	(0.522)
N	258,058	258,058	258,058	258,058	258,058	132,954
R^2	0.02	0.03	0.48	0.68	0.69	0.72

Table 4: House price impacts of an additional earthquake experienced at indicated level before sale. Dependent variable is the log sale price. Standard errors are clustered by census tract and appear below in parentheses. Significance Key: *** p<0.01, ** p<0.05, * p<0.1. 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.

	Cumulative Exposure	Year Indicators	Census Tracts	Property Controls	Local Controls	Affected Counties
MMI3 exposures count	0.006***	0.006***	0.000*	0.001***	0.001***	0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
MMI4 exposures count	−0.044**	−0.051**	−0.010*	−0.015***	−0.015***	−0.013**
	(0.016)	(0.016)	(0.004)	(0.004)	(0.004)	(0.004)
MMI5 exposures count	−0.076	−0.087	−0.001	−0.007	−0.008	0.009
	(0.048)	(0.050)	(0.013)	(0.009)	(0.009)	(0.011)
MMI6 exposures count	−0.559***	−0.563***	−0.022	−0.097***	−0.098***	−0.088***
	(0.104)	(0.106)	(0.029)	(0.020)	(0.019)	(0.019)
Year of Sale 2007		−0.032	−0.026***	0.068***	0.067***	0.079***
		(0.018)	(0.008)	(0.008)	(0.008)	(0.008)
Year of Sale 2008		−0.265***	−0.069***	0.026*	0.025*	0.036**
		(0.035)	(0.011)	(0.012)	(0.012)	(0.014)
Year of Sale 2009		−0.180***	−0.060***	0.025*	0.026**	0.028**
		(0.032)	(0.009)	(0.010)	(0.010)	(0.010)
Year of Sale 2010		−0.040	−0.053***	0.018	0.020	0.027*
		(0.026)	(0.009)	(0.010)	(0.011)	(0.012)
Year of Sale 2011		−0.115***	−0.053***	0.001	0.003	0.005
		(0.031)	(0.010)	(0.011)	(0.012)	(0.014)
Year of Sale 2012		−0.089**	−0.046***	0.009	0.010	0.007
		(0.034)	(0.011)	(0.012)	(0.012)	(0.015)
Year of Sale 2013		−0.011	−0.068***	−0.016	−0.013	0.011
		(0.039)	(0.011)	(0.012)	(0.012)	(0.015)
Year of Sale 2014		−0.087	−0.049***	−0.013	−0.012	0.031
		(0.049)	(0.013)	(0.013)	(0.014)	(0.023)
Square Feet (thousands)				0.419***	0.414***	0.393***
				(0.006)	(0.006)	(0.011)
Land Plot (ln(sqft))				0.104***	0.109***	0.100***
				(0.004)	(0.004)	(0.006)
Townhouse/Rowhouse				0.017	0.019	0.004
				(0.057)	(0.058)	(0.060)
Duplex				−0.108*	−0.109*	−0.102*
				(0.046)	(0.046)	(0.046)
Rural Homesite				−0.106***	−0.105***	−0.101***
				(0.016)	(0.016)	(0.028)
Mining Employment Growth					0.181***	−0.211
					(0.050)	(0.221)
UIC Wells					−0.025**	−0.027**
					(0.008)	(0.008)
High Volume UIC Wells					−0.038	−0.050
					(0.031)	(0.030)
% African American					−0.166	−0.061
					(0.130)	(0.151)
% Native American					−0.290	−0.326
					(0.148)	(0.229)
% high school graduates					0.017	0.017
					(0.111)	(0.143)
Median Age					−0.000	0.000
					(0.001)	(0.002)
Income (thousands)					0.007	0.008
					(0.005)	(0.007)
Distance to OKC or Tulsa					−0.007	0.082
					(0.061)	(0.091)
Tornados					0.003	−0.000
					(0.002)	(0.003)
Decade of Construction FE				Y	Y	Y
Census Tract FE			Y	Y	Y	Y
School District FE					Y	Y
Constant	11.447***	11.556***	11.026***	9.891***	9.830***	9.488***
	(0.024)	(0.036)	(0.009)	(0.042)	(0.414)	(0.523)
N	258,058	258,058	258,058	258,058	258,055	132,954
R^2	0.02	0.03	0.48	0.68	0.69	0.72

Table 5: Multiple List Service Data models. Dependent variable is the log sale price. Standard errors are clustered by census tract and appear to the right in parentheses. Significance Key: *** p<0.01, ** p<0.05, * p<0.1. 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.

	MLS merged observations only		Time on Market Control		MLS Characteristic Controls	
MMI3 peak exposure	−0.004	(0.009)	−0.005	(0.009)	−0.018*	(0.008)
MMI4 peak exposure	−0.020	(0.011)	−0.020	(0.011)	−0.028 **	(0.010)
MMI5 peak exposure	−0.002	(0.016)	−0.002	(0.016)	−0.014	(0.015)
MMI6 peak exposure	−0.078***	(0.023)	−0.079***	(0.023)	−0.082***	(0.021)
Months on Market			0.001	(0.001)	0.000	(0.000)
Association Fee ($k)					0.204***	(0.020)
Traditional					−0.033***	(0.005)
Ranch					−0.025***	(0.007)
Bungalow					−0.010	(0.007)
Contemporary					−0.012	(0.006)
Dallas					−0.012 **	(0.004)
Air Conditioning					0.332***	(0.009)
Brick					0.045***	(0.007)
Vinyl Siding					0.026***	(0.006)
Fireplace					0.092***	(0.005)
Hardwood					0.093***	(0.003)
Tile					0.068***	(0.004)
Vinyl (floor)					−0.029***	(0.005)
Basement					−0.058***	(0.010)
1 Car Garage					0.066***	(0.007)
2 Car Garage					0.158***	(0.009)
3+ Car Garage					0.204***	(0.010)
Electric Heat					0.009*	(0.004)
Split Level					0.009	(0.006)
Second Story					0.038***	(0.008)
2 Bath					0.081***	(0.006)
3+ Bath					0.151***	(0.008)
2 Bedroom					−0.072***	(0.005)
4+ Bedrooms					0.006	(0.004)
Septic System					0.060***	(0.009)
Well Water					−0.003	(0.008)
Year of Sale 2007	0.077***	(0.008)	0.076***	(0.008)	0.041***	(0.007)
Year of Sale 2008	0.055***	(0.009)	0.054***	(0.009)	0.014	(0.008)
Year of Sale 2009	0.040***	(0.012)	0.040***	(0.012)	0.001	(0.011)
Year of Sale 2010	0.032*	(0.012)	0.031*	(0.012)	−0.008	(0.012)
Year of Sale 2011	0.024	(0.013)	0.023	(0.014)	−0.019	(0.013)
Year of Sale 2012	0.022	(0.015)	0.021	(0.015)	−0.022	(0.015)
Year of Sale 2013	0.025	(0.015)	0.025	(0.015)	−0.023	(0.014)
Year of Sale 2014	0.014	(0.015)	0.014	(0.015)	−0.034*	(0.014)
Square Feet, (thousands)	0.375***	(0.007)	0.374***	(0.007)	0.257***	(0.007)
Land Plot (ln(sq ft))	0.108***	(0.005)	0.108***	(0.005)	0.101***	(0.004)
Townhouse/Rowhouse	−0.055	(0.042)	−0.055	(0.042)	−0.088*	(0.037)
Duplex	−0.173***	(0.030)	−0.173***	(0.030)	−0.057*	(0.025)
Rural Homesite	−0.065***	(0.017)	−0.066***	(0.017)	−0.082***	(0.014)
Mining employment growth	−0.102	(0.152)	−0.102	(0.152)	−0.083	(0.139)
UIC Wells	−0.022*	(0.009)	−0.021*	(0.009)	−0.023 **	(0.008)
High Volume UIC Wells	−0.062	(0.034)	−0.062	(0.034)	−0.026	(0.031)
% African American	−0.101	(0.111)	−0.104	(0.111)	−0.058	(0.098)
% Native American	−0.066	(0.187)	−0.062	(0.187)	−0.034	(0.169)
% high school graduates	0.028	(0.113)	0.022	(0.113)	−0.003	(0.104)
Median Age	0.002	(0.001)	0.002	(0.001)	0.001	(0.001)
Median Income	0.004	(0.005)	0.004	(0.005)	0.004	(0.005)
Distance to OKC or Tulsa	−0.007	(0.061)	−0.006	(0.061)	−0.007	(0.047)
Tornados	0.001	(0.002)	0.001	(0.002)	−0.000	(0.002)
Decade of Construction FE	Y		Y		Y	
Census Tract FE	Y		Y		Y	
School District FE	Y		Y		Y	
Constant	9.485***	(0.338)	9.480***	(0.337)	9.266***	(0.268)
N	128,435		127,879		127,879	
R^2	0.76		0.76		0.80	

Table 6: Time on Market and Sales Pace models. The column headings indicate the dependent variable. Standard errors are clustered by census tract and appear to the right in parentheses. Significance Key: *** p<0.01, ** p<0.05, * p<0.1. 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. (a) To represent the distribution of building and plot square footage, we create decile indicators and collapse these to the percentage of properties within the tract that fall in each decile.

	Time on Market (Months)		Time on Market Hazard Model		Sales/Housing units (Tract-Year)	
MMI3 peak exposure	0.308***	(0.064)	−0.095***	(0.019)	−0.002*	(0.001)
MMI4 peak exposure	0.205*	(0.083)	−0.057*	(0.024)	0.008***	(0.002)
MMI5 peak exposure	0.110	(0.114)	−0.006	(0.037)	0.011***	(0.003)
MMI6 peak exposure	0.698***	(0.194)	−0.226***	(0.056)	0.007*	(0.003)
Association Fee ($k)	0.527***	(0.089)	−0.157***	(0.029)		
Traditional	0.079	(0.044)	−0.031*	(0.013)		
Ranch	0.050	(0.042)	−0.019	(0.013)		
Bungalow	0.178***	(0.044)	−0.065***	(0.015)		
Contemporary	0.304***	(0.047)	−0.117***	(0.015)		
Dallas	0.164 **	(0.053)	−0.057***	(0.016)		
Air Conditioning	0.090	(0.052)	−0.010	(0.017)		
Brick	0.108*	(0.043)	−0.041 **	(0.014)		
Vinyl Siding	0.068	(0.038)	−0.034 **	(0.012)		
Fireplace	0.023	(0.032)	−0.011	(0.011)		
Hardwood	−0.028	(0.025)	0.015	(0.009)		
Tile	0.079***	(0.022)	−0.022 **	(0.007)		
Vinyl (floor)	0.116***	(0.030)	−0.041***	(0.010)		
Basement	0.057	(0.057)	−0.019	(0.018)		
1 Car Garage	−0.229***	(0.041)	0.081***	(0.014)		
2 Car Garage	−0.284***	(0.044)	0.104***	(0.014)		
3+ Car Garage	−0.420***	(0.062)	0.142***	(0.019)		
Electric Heat	0.134***	(0.031)	−0.050***	(0.010)		
Split Level	0.429***	(0.053)	−0.140***	(0.015)		
Second Story	0.494***	(0.040)	−0.160***	(0.012)		
2 Bath	−0.008	(0.032)	0.002	(0.011)		
3+ Bath	0.128*	(0.053)	−0.034*	(0.017)		
2 Bedroom	0.056	(0.034)	−0.021	(0.012)		
4+ Bedrooms	0.195***	(0.030)	−0.076***	(0.009)		
Septic System	0.222***	(0.066)	−0.055 **	(0.019)		
Well Water	0.091	(0.057)	−0.034*	(0.017)		
Year of Sale 2007	0.467***	(0.049)	−0.189***	(0.018)	−0.007***	(0.001)
Year of Sale 2008	0.603***	(0.055)	−0.237***	(0.021)	0.002	(0.001)
Year of Sale 2009	0.433***	(0.066)	−0.192***	(0.022)	−0.004 **	(0.001)
Year of Sale 2010	0.438***	(0.072)	−0.184***	(0.024)	−0.010***	(0.001)
Year of Sale 2011	0.801***	(0.079)	−0.315***	(0.026)	−0.014***	(0.001)
Year of Sale 2012	0.485***	(0.102)	−0.222***	(0.034)	−0.020***	(0.002)
Year of Sale 2013	0.100	(0.109)	−0.081*	(0.036)	−0.014***	(0.002)
Year of Sale 2014	−0.137	(0.107)	0.017	(0.035)	−0.014***	(0.002)
Square Feet (thousands)	0.400***	(0.030)	−0.131***	(0.009)	(a)	
Land Plot (ln(sq ft))	0.021	(0.020)	−0.009	(0.006)	(a)	
Townhouse/Rowhouse	−0.640***	(0.147)	0.328***	(0.074)	−0.034***	(0.007)
Duplex	0.116	(0.150)	−0.024	(0.044)	−0.012*	(0.006)
Rural Homesite	0.140	(0.099)	−0.040	(0.028)	−0.003*	(0.001)
Mining employment growth	−0.571	(0.377)	0.135	(0.102)	−0.000	(0.002)
UIC Wells	0.037	(0.062)	−0.020	(0.022)	−0.002	(0.001)
High Volume UIC Wells	−0.185	(0.197)	0.049	(0.067)	0.001	(0.005)
% African American	0.888	(0.645)	−0.302	(0.203)	−0.011***	(0.002)
% Native American	−1.087	(1.142)	0.287	(0.373)	0.009	(0.010)
% high school graduates	0.468	(0.683)	−0.086	(0.242)	0.006	(0.006)
Median Age	−0.001	(0.008)	0.000	(0.003)	0.000	(0.000)
Median Income	−0.014	(0.060)	0.004	(0.020)	0.004***	(0.000)
Distance to OKC or Tulsa	0.135	(0.151)	−0.030	(0.051)	0.002	(0.002)
Tornados	0.006	(0.007)	−0.002	(0.002)	−0.000	(0.000)
Decade of Construction FE	Y		Y		Y	
Census Tract FE	Y		Y		Y	
School District FE	Y		Y		Y	
Constant	6.635***	(1.056)			0.018	(0.016)
N	127,879		127,879		5,807	
R^2	0.09				0.52	

Property	MMI3	MMI4	MMI5	MMI6	Price Decrease (Increase) Cumulative	Price Decrease (Increase) Indicator	Price Decrease (Increase) MLS, Indicator
A	5	0	0	0	($653)	$784	$2,352
					(0.5%)	0.6%	1.8%
B	5	0	0	0	($653)	$784	$2,352
					(0.5%)	0.6%	1.8%
C	110	6	0	0	($2,613)	$4,443	$3,659
					(2.0%)	3.4%	2.8%
D	162	7	3	0	($4,312)	$4,835	$1,829
					(3.3%)	3.7%	1.4%
E	134	11	3	1	$19,992	$12,805	$10,751
					15.3%	9.8%	8.2%

Table 7: Expected sale price changes from earthquake exposure for properties depicted in figures 6 and 5. Estimates are calculated using the results presented in table 3, column 5, table 4, column 5, and table 5, model 3.