Do School Shootings Erode Property Values?

By Juan Sebastian Munoz   Ruchi Singh *

We find that house prices within a school district decline by 7.8 percent in the three year period after a mass school shooting along with decline in number of transactions. The drop in property prices is stronger among houses with more bedrooms, a measure that serves as a proxy for properties most likely to have school-age children in the household. We also find evidence of decrease in school enrollment and in the number of teachers in the aftermath of the shooting. The analysis suggests that it is the deterioration in school quality that results in lower willingness to pay.

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I. Introduction

On March 24, 1998, two students from Westside Middle School near Jonesboro, Arkansas, opened fire, killing five people and wounding ten others. A year later, two students from Columbine High School in Colorado, killed 13 people and injured 23 others. More recently, a gunman at Sandy Hook Elementary School, in Newtown, Connecticut, killed 20 children, and six staff members. The United States has more mass shootings at schools and elsewhere than any other country. The number rose by more than five times in the period from 2014 to 2017, as shown in Figure 1.[1] About 15 percent of these mass shootings occurred in schools. These incidents have sparked a political debate over gun violence, zero tolerance policies and gun control.

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[1]We define mass shootings as gun-related episodes with three or more victims (excluding perpetrators); these incidents are those that do not involve gangs, drugs, or organized crime.

School shootings are a type of crime that is unpredictable; they are exceptionally traumatic events, but are highly unlikely to be repeated in the same location. Our research examines the effects of such occurrences on residential housing values and sheds light on mechanisms behind the relationship between crime and house prices. This relationship has been broadly documented as negative and strong.[2] Households might avoid areas with high levels of crime because of the associated potential loss if they were to be victimized in the future. This link appears to be the logical explanation for the relationship between crime and housing prices, but it is not the only one. Crime, in fact, may have some externalities that may shift housing demand due to some other understudied or unrecognized channels. In the case of school shootings, potential homebuyers might want to avoid the affected area due to the associated trauma, lower perceived school quality (due to decline in enrollment, scores etc.), or other stigmas associated with the place.

Literature on mass shootings has traditionally focused on the effects on victims. Empirical studies have shown that such horrific shootings can lead to trauma, stress and increased frequency of mental health conditions such as anxiety, fear, depression which might result in poor academic achievement and have implications for long-term outcomes (Nader et al. (1990)).

We extend this literature and analyze whether mass shootings in schools affect house prices in the school districts in which they occur. Our results suggest that house prices within the affected school districts fall by an average of 7.8 percent (or $15,051 on average), and its effects persists for, at least, five years. Additionally, we find that in the wake of such an incident the number of transactions decreases in the affected school district.

We focus on mass shootings that took place in schools during the period 1998 to 2014. Our analysis employs two key sources of data: 1) the Stanford Mass Shootings of America data project; and 2) individual transaction and assessment

[2]See for instance: Thaler (1978); Hellman and Naroff (1979); Linden and Rockoff (2008); Pope (2008); Pope and Pope (2012); Lynch and Rasmussen (2001); Gibbons (2004); Ihlanfeldt and Mayock (2010) ; Abadie and Dermisi (2008); Gautier et al. (2009) ; and Ratcliffe and von Hinke (2015).

records for the school districts where shootings took place and the adjacent school districts for the period from 1991 to 2017. These data were obtained from CoreLogic, Inc., which collects real estate information nationwide. Our analysis uses micro-level transaction data from all U.S. school districts in which a mass shooting took place on a school campus. The coverage of the data makes our results externally valid.

The key challenge in estimating the effect of mass shooting on property values is identifying the counterfactual scenario, i.e., how prices would have evolved in absence of the shooting. Relying on cross-sectional variation alone might lead to biased estimates because house prices might vary across geographic administrative boundaries due to both observed and unobserved characteristics. We address this potential concern by exploiting an exogenous shock in the timing of the shootings and using a difference-in-differences strategy. To estimate the causal effects of school shootings on housing prices, we compare prices in the affected school district with those in neighboring school districts.

Descriptive statistics at the census tract level suggest differences in observable characteristics between affected and neighboring school districts prior to the school shootings. The difference-in-difference strategy will take care of these preexisting differences, but to test the robustness of our results we use two alternative identification strategies. First, we use a boundary discontinuity approach within a difference-in-differences framework to compare houses within half a mile of the school-district boundary to better control for unobserved amenities. The effect is stronger when we restrict the analysis to properties near a school-district boundary; prices in these areas fall by 13.6 percent (or $20,337 on average), and the decline remains persistent again for five years after the shooting.

Second, we use a propensity score matching approach, within the difference-in-difference framework, to reduce preexisting differences. Given that we use repeated cross sections, we match at the census tract level using observable characteristics before the shooting. Then, we compute kernel weights using the propensity score, and use them to weight our observations. This strategy suggest a smaller but still significant decrease in prices of around 3.5 percent.

We also perform additional robustness checks. Our results are not driven by changes in the composition of houses sold. Furthermore, graphical evidence and falsification tests provide no evidence of spurious negative effects due to differential housing price trends. These tests support our findings that the declines we document in housing prices are indeed an outgrowth of the mass shooting incidents.

We then explore mechanisms that explain the decrease in housing demand in affected schools districts. We first rule out the mechanism under which housing demand decrease because homebuyers are afraid of experiencing an associated crime in the aftermath of the shooting episode. We do so by presenting difference-in-differences estimates that suggest that crime does not increase in cities were the shooting occurred.

Next, we evaluate two alternative plausible mechanisms: deterioration in valuation of school quality and place-based stigmas. To discern whether the results are driven by homebuyers valuing school quality, we examine the market for houses that have more bedrooms, which serve as a proxy for family-size households (those that are most likely to include children who attend or will attend local schools). The decline in prices is higher for houses with more bedrooms, suggesting that the response is larger in case the family has children. Furthermore, we find a decrease in enrollment and number of teachers in schools that experienced a school shooting and also in neighboring schools that did not experience the shooting but that are within the same school district. This suggest that the quality of school district has deteriorated and that is being capitalized into house prices. Finally, we find no effect on the price of non-residential properties. These findings suggest that lower perceived quality of schools represent particular concerns for potential homebuyers.

Next we test if place-based stigmas explain the decrease in housing demand. If place-based stigmas explain the decrease in demand, then the properties closer to the area of the shooting should witness a larger decrease in prices. We find, however, that house prices seem to remain unaffected when comparing properties closer to the school where the shooting occurred with those farther away. Therefore, place based stigmas do not seem to explain the observed results.

This paper is the first analysis of the effect of school shootings on house prices. It contributes to two strands of research. First, we contribute to the literature on the capitalization of school quality into house prices. Existing research shows that housing prices respond to local school quality as measured by test scores, value added, level of capital expenditure per pupil, school report cards, popularity of school, etc.[3] These papers suggests a lower willingness to pay for housing in neighborhoods in which schools are reputed to be of poor quality.[4] In fact, in a study of school shootings, Beland and Kim (2016) find that school quality decreases after a school shooting. Thus, our paper adds to this literature by providing further evidence that deterioration in school quality results in decline in house prices.

Second, we contribute to the literature on the effect of crime on house prices by analyzing how crimes with almost zero probability of repetition affect property values. Our work adds to the existing works of Linden and Rockoff (2008) and Pope (2008), who analyze how proximity to the home of a registered sex offender decreases house prices, and to the work of Abadie and Dermisi (2008), Gautier et al. (2009), and Ratcliffe and von Hinke (2015) who analyze the effects of terrorism.

The remainder of the paper is organized as follows: Section 2 describes the data used in our analysis. Section 3 describes our empirical methodology. Section 4 presents the empirical results, and section 5 explores the mechanisms that explain

[3]A summary of this literature is provided by Gibbons and Machin (2008), Black and Machin (2011), Nguyen-Hoang and Yinger (2011) and Machin (2011). There is a consensus estimate of around 34 percent house price premium for one standard deviation increase in school average test scores.

[4]See Black (1999), Agarwal et al. (2016) , Andreyeva and Patrick (2017), Davidoff and Leigh (2008), Fack and Grenet (2010), Gibbons et al. (2013), among others.

our key results. Section 6 concludes.

II. Data

We combine data from two main sources. First, we use arms length real estate transaction data for the period 1996-2017 for the school districts that were affected by mass shooting in schools, and for the neighboring districts that were unaffected.[5] We merge these data with assessment records using a unique property identifier for each property to ascertain the characteristics of the house. Both, the real estate transaction data and assessment records, come from Corelogic Inc., a national real estate company. The data contain information on transaction, price, and date of sale, along with the geographic coordinates of the house and characteristics of the house like size, age, number of bedrooms, baths, presence of garage, fireplace etc.[6]

We match the sales data to the school districts by using the latitude and longitude coordinates of the property. The school-district boundary maps are obtained from the National Center for Education Statistics (NCES). We also identify the corresponding census tract by overlaying the transaction data with Census Tract shapefile (2010 definition) obtained from the U.S. Census Bureau.

Second, we use data for mass shootings in America from the Stanford Mass Shootings of America (MSA) data project (courtesy of the Stanford Geospatial Center and Stanford Libraries). The project started in 2012 in reaction to the Sandy Hook mass shooting incident in Connecticut, and collects data from online

[5]The counties used in our analysis include Craighead, Greene, Lawrence, Jackson, Poinsett in Arkansas; Lane in Oregon; Jefferson, Park, Clear Creek, Gilpin, Boulder, Adams, Denver, Araphoe in Colorado; Rockdale, Dekalb, Gwinnett; Walton; Newton and Henry in Georgia; San Diego, Lake, Modoc, Lassen, Pulmas, Sierra, Nevada, Placer, El Dorado in California; Beltrami, Marshall, Clearwater, Pennigton, Polk in Minnesota; Orange, Almance, Durham, Chatam, Caswell, Person in North Carolina; Lancaster, Chester in Pennsylvania; Multnomah, Clackmass in Oregon; Cuyahoga in Ohio; Saginaw, Bay in Michigan, Geauga, Lake in Ohio, New haven, Fairfield, Litchfield in Connecticut; Washoe, Harney, Carson City, Churchill, Douglas, Humboldt, Lyon, Pershing, Storey in Nevada and Snohomish in Washington.

[6]We drop transactions with sales prices in top and bottom 1 percent of the distribution for each county to eliminate outliers. We also clean the data to remove outliers for any other property characteristics. We normalize the sale prices using quarterly Case-Shiller Home Price Indices for each state to September 2017.

media sources. The project defines mass shootings as those that involve three or more victims (not necessarily fatalities), excluding the shooter. The shootings do not include those that are gang-, drug- or organized crime-related. The dataset includes the time, date, and location of the shooting, along with number of victims and number of fatalities. It also indicates whether the shooting took place at a school or not. We consider all mass shootings at schools that happened after the year 1998.[7]

These data do not include socio-demographic information about homeowners, although it is very rich and descriptive about house prices and amenities. In order to describe the setting, we therefore use census information at the census tract level prior to the shootings (i.e. we use census 1990 data) merged to the affected and non-affected school districts. The first three columns of Table I present average socio-demographic characteristics for census tracts located within an affected school district (treatment), census tracts located within adjacent school districts (controls), and census tracts in the rest of the country. Column (4) presents the p-value of a difference in means between treated and control areas.

Treated and control census tracts differ across majority of characteristics. In general, control areas are wealthier, have a bigger share of white population, less unemployment, more female labor force, and a bigger share of college graduates. Treated areas, on the contrary, are much similar to the average census tract with a population of around 3,200, a median home value of $93,000, a share of white people close to 80%, and a share of college graduates close to 12%. These results suggest a big degree or preexisting differences among treated and control areas. Additionally, we also use crime data at the city level from City-Data.com and the school enrollment and data on number of teachers from National Center for Education Statistics (NCES).

[7]The date and episodes are presented in Appendix Table 1.

III. Empirical Strategy

A. Effect of Mass Shootings on House Prices

Individuals choose where to live based on many factors such as housing characteristics, school quality, local amenities, proximity to labor markets, etc. This individual sorting usually hinders any potential estimation of the effect of crime on housing values. It is expected that there is higher demand for areas with low crime rates but is also the case that crime is endogenously determined in certain locations. Furthermore, unobserved characteristics also play an important role by including potential confounding factors into the estimation.

School shootings, however, are isolated exogenous episodes that homeowners and buyers are not able to predict. They occur in a random fashion, and thus enable a potential estimation framework free of confounding factors such as individual sorting.

The key empirical challenge, nonetheless, is finding a valid counterfactual distribution - i.e., what would have happened if the shooting had not taken place. We, therefore, use a difference-in-differences strategy to compare house prices in the school district where shooting took place ("treated" school district) to the adjacent school districts ("control" school districts).[8] This strategy estimates the ex-post average price difference between treated and control areas by taking into account the preexisting differences across locations. We will call this our main specification.

We append 15 shooting episodes from 1998 to 2014, and analyze a time window of three years before and after the episode. We also explore longer-term effects by varying the temporal window around the incident. Figure 2 describes our

[8]We use school-district boundaries instead of school-attendance zones (as treated and control units) because the attendance boundaries are not available for some of the schools in our datasets. Moreover, it is more difficult to clearly identify the control areas (which are the adjacent areas to the treated unit) for our analysis as the attendance zones overlap. The advantage of using school district-level data is that the schools within the district are subject to the same policies and regulations. For more information on the advantages of school district boundaries see Dhar and Ross (2012). The other key advantage of using school-district boundaries is that they do not change much. To our knowledge, for our sample, the school district boundary has changed only for one school.

strategy using a map for Fairfield County, Connecticut, where the Sandy Hook Elementary School shooting took place in 2012. The blue triangle plots the exact location where the shooting took place. The red area marks the affected school district, whereas the green areas plot the adjacent school districts. Areas in grey are dropped. Our strategy compares the red and green areas.

The estimating equation for the effects of mass shootings on house prices is, therefore:

$$\begin{aligned}(1) \qquad \widetilde{ln(p_{ijt})} =& \alpha + \beta_1 T_{ij} + \beta_2 (T_j * 1(\text{After shooting})_t) + \gamma X_{it} + \mu_t \\ &+ \text{Census Tract Fixed Effects} + \sum_{(k=1)}^{14} \mu_t \times 1(\text{episode})_k + \varepsilon_{ijt}\end{aligned}$$

Where $\widetilde{\ln(p_{ijt})}$ is the log of the deflated house price for property i in school district j in year t. T_j is a dummy variable that takes the value of one if the property is inside the treated school district and zero otherwise. X_{it} is a matrix of observable housing characteristics such as log of building area, log of land area, dummy for condos, fireplace, brick construction, etc. We include year-month fixed effects (μ_t) to control for time trends and census tracts fixed effects to control for the unobserved characteristics of the neighborhood. We also include episode specific time trends ($\mu_t * 1(\text{episode})_k$) to account for time-varying trends across episodes.[9] ε_{ijt} is the error term. Standard errors are clustered at the census-tract level.

It is worth noting that the treated area is the school district, and thus our strategy is based on an economic intuition. Homeowners in treated school districts are likely to be affected as their children are likely to attend the affected school, whereas homeowners in control areas are eligible to enroll their children outside the affected school district. Thus, the shooting episode affects homeowners in the

[9] $1(\text{episode})_k$ is a dummy that equals one if the observation corresponds to mass shooting episode k which is interacted with time to control for differing time trends across the regions.

entire school district and not only those living closer to the school.[10]

The difference-in-difference estimator controls for preexisting differences across treated and control areas. However, to further reduce the concern about preexisting differences we employ two alternative strategies as robustness checks. First, we use an alternative identification strategy which compares the affected school districts with the adjacent ones, but restricts the sample to observations within half mile from the school-district boundary. Figure 3 describes this strategy for the shooting in Orange High School, NC, in 2006. The different colors represent the distance from the border. We use the properties marked in blue inside and outside the border as treated and control locations, respectively.[11] The estimation strategy is the same as equation (1), but includes properties which are physically closer and are, thus, likely to be similar in observed and unobserved amenities.

Second, in order to reduce preexisting differences, we additionally employ a propensity score matching approach in which we match census tracts based on observable characteristics. First, we identify the census tracts within treated and control school districts and compute a propensity score based on observable attributes prior to the shooting (we use 1990 census data). Second, we match treated and control census tracts using a kernel that computes weights that minimize the observable differences between both distributions using the propensity score. Lastly, we merge these weights into the individual data and compute a reweighting estimator for equation (1) that is balanced in the pretreatment period and further controls for preexisting unobserved heterogeneity. Columns (5) and (6) of Table I show the average value of the observed characteristics weighted by such kernel weights. Column (7) presents the p-values of a difference in means test. The weights balance quite closely the treatment and control areas.

[10]The previous literature usually defines treated areas to be within an arbitrary radius around the place of the episode. Our strategy does not rely on this, but instead defines treated areas as areas within a given school district where the shooting took place.

[11]We vary the width of the radius around the border in the section detailing robustness checks. The results are consistent across different specifications.

B. Effect of Mass Shootings on Number of Sales

In addition to the effect of school shootings on sales prices, we also estimate the change in number of transactions taking place after the shooting. We aggregate the data at the census tract - year level for one to three years before and after the incident. We then estimate the following difference-in-differences specification.

$$\begin{aligned}(2)\quad \ln(\text{Sales})_{jt} =& \alpha + \beta_1 T_j + \beta_2 (T_j * 1(\text{After shooting})_t) + \text{Year Fixed Effects} \\ &+ \text{Census Tract Fixed Effects} + \varepsilon_{ijt}\end{aligned}$$

Where $\ln(\text{Sales})_{jt}$ is the number of sales in census tract j in year t, T_j is a dummy variable that takes the value of one if the census tract is in the school district where shooting took place, and $1(\text{After shooting})_t$ is a dummy that equals one for observations after the shooting. We also include year and census tract fixed effects, and ε_{ijt} represents the error term.

IV. Results

In this section, we present the graphical evidence and our key findings.

A. Graphical Evidence

The key identifying assumption for our difference-in-differences strategy is the parallel trends assumption (i.e., house prices had similar time trends in treated and control areas before the mass shooting took place).

Figure 4 presents the evolution of house prices in treated and control areas for three years before and after the shooting.[12] Panel (a) compares the school district where shooting took place to the adjacent school districts, while Panel (b) includes only properties within a half mile of the school district boundary. The pre-trends seems to be similar across the treated and control areas in both

[12]Mass shootings took place at different times across the region. Thus, we normalize the time with time period zero reflecting the date of the shooting.

panels.

If mass shootings in schools negatively affect housing prices in the school district, then we should expect a decrease in prices after the incident. This decrease should be, at least, larger in the affected school district as opposed to the adjacent ones. Figure 4 suggests that there is an immediate decrease in the price of properties in treated as well as in neighboring school districts. However, the decrease is larger in the affected school districts, and, in particular, for properties near the school district boundary. This evidence supports the fact that school shootings decrease property prices, in particular, among residents near the school district boundary. The ex-post decline in prices reflects the causal effect of school shooting on house prices.

B. Main Results

In columns (1) to (4) of Table II, we present the estimation result of equation (1), comparing house prices in affected and adjacent school districts three year before the shootings to three year after the incident. For illustrative purposes, we first present estimates including only month-year and census-tract fixed effects, but no other control variables (column 1). The result suggests an average decline of 6.6 percent in affected school districts as compared to house prices in the neighboring school districts over a three year period.

In column (2), we include house characteristics to control for observable heterogeneity in properties. Our most complete specification is shown in column (3) of Table II, where we include episode-specific time trends to account for time varying heterogeneity across shooting episodes. Our estimates suggest that housing prices decline by 7.8 percent in the school district where shooting took place.

Finally, in column (4) we weigh each observation by the inverse of the total number of transactions in each episode before the shooting.[13] We estimate an 11.1 percent decline in house prices when using the weighted regression. This

[13]We sum the number of transactions three years before shooting and weigh each observation by the inverse of this number.

estimator reinforces our results and suggests that our findings are not driven by any specific episode where higher number of transactions have taken place.[14]

Next, we analyze whether the relative decline in house prices in affected districts persist. We estimate equation (1) but compare prices three year prior to the shooting with prices one to five years after the episode. The results are presented in columns (5) to (9) of Table II, and are similar to an event-study analysis. As column (5) shows prices decrease 9.3 percent during the first year after the shooting and then decline by 6.8 percent and 4.5 percent in the second and third year. We observe negative effects even four to five years after the incident. This result implies that the effect of shooting declines but persists up to almost five years in the aftermath of the shooting.

C. Effect on Number of Transactions

The decline in prices may be explained by shifts in housing supply or demand after the shooting. To understand what drives the decrease we estimate the effect of shootings on the number of sales using equation (2). The results are presented in Table III. Columns (1) to (3) present estimates for the entire school district while Columns (4) to (6) present the result for area half mile around the boundary. Columns (1) and (4) show results for the effect of shooting when we include observations three year before and after the shooting. Columns (2) and (5) include observations two years around the shooting, and columns (3) and (6) repeat the analysis for one year before and after the shooting.

The results are insignificant for the first year. The point estimates increase in magnitude in the following years, revealing a decrease in the number of transactions. After two years, for instance, the number of properties sold in the affected school districts decrease by 8.3 percent and 13.9 percent after three years. We also find suggestive evidence of decline in number of transactions in half mile area

[14] In addition, we estimate in Appendix Table II the same weighted regression but excluding each episode separately. The results hold and are still robust meaning that one episode is not explaining the entire result.

around the school district boundary but the results are not statistically significant, probably due to small sample size. Supply and demand analysis tells us that for prices and quantity (number of transactions) to decrease jointly, the decrease in the demand for housing must be larger than the possible increase in the supply of housing. If demand decreases and supply remains steady, then we may observe a new equilibrium with lower prices and quantities. However, the supply of housing can still increase but not as much as the decrease in demand, and we can also observe a decline in prices and quantities. The above results suggest, therefore, that the underlying cause of the fall in prices in the wake of a school shooting is a significant decrease in demand at least higher than the potential increase in supply.

V. Robustness

A. Alternative Specifications

We now analyze alternative specifications that minimize preexisting differences between treated and control school districts. We first restrict the analysis to properties near the school district boundary, which may be more comparable in observed and unobserved characteristics. Then we use kernel weights obtained from propensity score matching to estimate a weighted estimator that balances the sample of census tracts in the pretreatment period.

Table IV summarizes the results obtained from the regression where we restrict our analysis to houses within half a mile of the school-district boundary. We keep the same structure as Table II. The results suggest that mass shootings decrease property values by 13.6 percent (column 3) over a three year period after the shooting among households who live near the school district border. This result is again robust to alternative specifications and weighing strategy.[15] The effect on properties near the boundary persists as suggested by columns (5) to (8) suggest.

[15]In Appendix Table III we vary the radius around the boundary. We show that the effect is not driven by picking particular radius around the boundary.

In fact, in the first year after the shooting we observe a 17.2 percent decrease in house prices, although such effect decreases monotonically in magnitude.

We then present the results using the propensity score weights in Table V. These estimates resemble a reweighting estimator that balances the observable characteristics between treated and control census tracts. The point estimate suggests a 3.5 percent decline and remains statistically significant.

These results suggest that the estimated effects are robust to alternative methods that further control for preexisting differences among treated and control areas.

B. Falsification Tests

To test the robustness of the previous estimates, we next need to determine whether the shooting was indeed uncorrelated with any other observable or unobservable factor. Moreover, there is a possibility that the estimated decrease in home values is a result of differential trends between affected and non-affected areas before the shooting. This would be a serious concern for our estimates because if the affected areas were experiencing a relatively slower decline in prices, our findings could be due to a spurious negative effect. To test for these concerns, we perform placebo experiments by leveraging the length of our transaction dataset. Instead of using the actual year of the mass shooting, we use false shooting dates two, three, and four years before the actual shooting. We estimate the placebo test for the entire school district and for properties within a half mile boundary of the school district, and re-estimate equation (1) using a one-year windows before and after the fake episode.[16]

The results of the placebo experiments are presented in Table VI. Neither of the six specifications reveal a negative and significant decline after the fake episode, suggesting no systematic differences between treated and control areas previous to the shooting. These results suggest that the decline in housing prices after the

[16] We use one-year windows because we do not have enough observations for all the episodes to estimate three-year windows in the pre-shooting period that do not include observations after the shooting.

shooting is indeed a result of the mass shooting itself.

C. Composition of Houses

A final potential concern is the possibility that the types of houses being sold before and after the incident are different. This could happen if the potential sellers of expensive houses in affected school districts had decided to postpone placing their houses on the market in the hope that housing prices would eventually recover after some time passed. Thus, our results might not be capturing the dis-amenity due to mass shootings but instead might be reflecting the changes in composition of houses being sold by virtue of a market characterized by having more houses available at the lower end of the price range and fewer houses available at the higher end of the market. To test this we compare the observable characteristics of the houses sold before and after the incident. We use the same model as in equation (1), but instead of using house prices as the dependent variable, we include one-by-one the housing characteristics. Results are presented in Table VII. We do not find any evidence of changes in composition of houses on the market.

VI. Mechanisms

The relationship between crime and property values may be explained by many potential channels. Perhaps the most prominent channel is that housing demand in high-crime areas is low because individuals do not want to personally experience crime. However, the probability that a school district experiences a shooting again is very low, and is no different from the probability that any other school district experiences its first school shooting.

In fact, we test for this by estimating a difference-in-differences model at the city level using yearly crime rates from 2002 to 2016 as the dependent variable. We use cities where the school shooting took place as treated units and neighboring cities as controls.[17] The results are presented in Table VIII. Each column uses the number of crimes per 100,000 as dependent variable, except for column (9) that uses a principal component index computed using the previous eight columns. The results provide suggestive evidence of decline in crime. Therefore, increase in crime (i.e. a higher probability of repetition) is not the reason for the decline in house prices.

Two other potential channels might be driving the observed decrease in demand for affected areas. First, parents might want to avoid the area because of a possible decline in perceived school quality. Beland and Kim (2016), in fact, find strong evidence of a decrease in school quality after a school shooting. School shootings may give strong negative signals to homebuyers about the quality of the schools within the school district and also about the future quality of those schools. Second, place based stigmas may motivate people to avoid the area in general. Both explanations may shift the demand for housing in a particular location, and may coexist in the case of school shootings. We find strong evidence for the mechanism concerning perceived school quality, but not for the mechanism concerning broader social stigma.

A. Deterioration of School Quality

If deterioration in school quality is driving the results, we would expect the effects to be stronger for families with school-age children. In our dataset, we cannot directly observe which families have children. Thus, we use the number of bedrooms in a house as a proxy for family size because families are likely to have houses with more bedrooms. Our prior assumption posits that houses with more bedrooms will witness a larger decrease in prices as compared to houses with fewer bedrooms.

In Table IX, we estimate equation (1) for properties with one, two, three, and four bedrooms. In the last two columns we pooled properties with fewer and more

[17] This analysis does not cover all of the cities but only cities where data was available.

than two bedrooms. We find that the effect becomes stronger as the number of bedrooms increases, whereas one-bedroom houses have a positive point estimate. These estimates support the fact that families with children are driving the price decrease, presumably because of a deterioration in the perceived school quality, or a desire to avoid low quality schools.

To explain the mechanism better, we test whether school quality has deteriorated after shooting. We observe a remarkable decrease in school enrollment and the number of teachers, which is in line with Beland and Kim (2016). In Table X, we present difference-in-difference estimates at the school level using the number of students and teachers as dependent variable. Columns (1) and (2) present the results on enrollment, whereas columns (3) and (4) present the results for the number of teachers. We present only the interaction term of the difference-in-differences model, and in columns (1) and (3) we define treated schools as those within the school district of the school where the shooting occur. In the remaining columns we estimate separately the effect for the schools where the shooting occurred and for neighboring schools that are within the affected school district but did not experience the shooting directly.

The results show an overall decrease of 16 percent in enrollment and 8 percent in the number of teachers among all the schools within the school district where the shooting occurred. When we look separately at the schools where the shooting took place we see a bigger reduction of 17.6 percent in enrollment and 12.6 percent in the number of teachers. Furthermore, in neighboring schools within the affected school district (excluding the directly affected one) we also observe a decrease of 7.5 percent in enrollment and 5.2 percent in the number of teachers, although the latter is not precisely estimated.

These results suggest that school shootings reduce enrollment and the number of teachers across the entire school district. In fact, not only schools where the shooting took place where affected, but we also find some spillover effects to neighboring schools within the same school district. This argument reinforces the mechanism that school quality deteriorates after shooting and results in decline in house prices.

Finally, if deterioration in school quality is the key reason for decline in house prices, then we should not expect prices of commercial and industrial properties to decline. Thus, we estimate equation (1) for non-residential properties and present the results in Appendix Table IV. The coefficients of these regressions turn out to be positive and insignificant, suggesting no effect on prices of non-residential properties.

B. Place-Based Stigmas

To determine if place-based stigmas, and not valuation of school quality, explain the decrease in demand for housing we analyze what happens with housing values within the school district. In particular, the entire school district has to experience a decrease in prices if perceived school quality is what really declined. That is, if stigmas about the area led to decline in prices, then properties closer to the shooting will have a larger decrease in prices compared to the ones farther away, but if school quality concerns drive the decreases, then everyone within the district will experience a price decrease. To test for this, we limit our estimation to properties close to the shooting, and compare the effect on properties within this limited range of houses.

Following Linden and Rockoff (2008) and Pope (2008), we construct radius of 0.3, 0.5, and one mile around the school, and compare property value inside these radii to properties outside of it. For consistency, we again restrict the time frame to three years before and after the shooting. The results of these estimations are presented in Table XI. Columns (1) to (3) include properties within three miles of the shooting, whereas columns (4) to (6) include properties within five miles.

We do not find any differential effects among properties closer to and farther from the affected schools. The point estimates are not statistically different from zero. These results suggest that stigmas may not be driving the result; if they were, properties closer to the school would have been "more stigmatized" than properties farther away. Instead, the results imply a general erosion of property values within the entire school district. This supports our contention that valuation of school quality drives the shift in demand, and not potential place based stigmas.

VII. Conclusion

In this paper, we estimate the effect of mass shooting in schools using a difference-in-differences framework. We find that, on average, the home values in affected school districts decrease by 7.8 percent (or $15,051) one year after the shooting. The effect is stronger when we look at homes closer to the school district boundary (about 13.6 percent or $20,337).[18] We also observe some persistence in this effect for, at least, five years throughout the district. Additionally, we find a decrease in the number of transactions taking place after the shooting.

Furthermore, we find strong evidence that our results are driven by the trauma witnessed by school children and perceived deterioration in school quality. Literature has suggested that schools are a highly valued amenity among households. Our results validate these findings and suggest that potential homebuyers avoid school districts in which a shooting has taken place, and that school quality decreases (lower enrollment rates, scores etc.) after the shooting. We do not find much evidence of place based stigmas as being the mechanism for decline in house prices.

The magnitude we estimate for the entire school district (around 7.8 percent over a three-year period) is slightly larger compared to previous estimates of the effects of schooling outcomes on property values. For instance, Black (1999) estimates a 2.5 percent increase in housing values for a 5 percent increase in test school scores, whereas Gibbons et al. (2013) estimate a 3 percent increase in prices

[18]The average price of houses in affected school districts prior to the shooting was around $192,961. A 7.8 percent decrease then implies a decrease of approximately $15,051. The average value of a house near the school-district boundary was $149,539, so a 13.6 percent decrease is equivalent to approximately $20,337.

for an increase of one standard deviation in average value added.

The decrease in prices we find near the school-district boundary (around 13.6 percent) is comparable to the dis-amenity found by Linden and Rockoff (2008) in work conducted in North Carolina that examines the effect on prices of houses in close proximity to the residence of a registered sex offender (a decline of 11.6 percent). Our results are also similar to the effects on house prices that stem from the discovery of a cancer cluster of child leukemia (a decline in values of 14 percent) (Davis (2004)), and the temporary, one-year effect of getting a school quality rating of "A" rather than "B" (20 percent) found by Figlio and Lucas (2004).

Overall, our results suggest that households have a strong preference to reside in a good school district. Incidents such as school shootings that deteriorate the school quality, might therefore lead to decline in house prices in that school district. Future research is needed to understand how to deal with locations affected by crime shocks, particularly with school- related crime.

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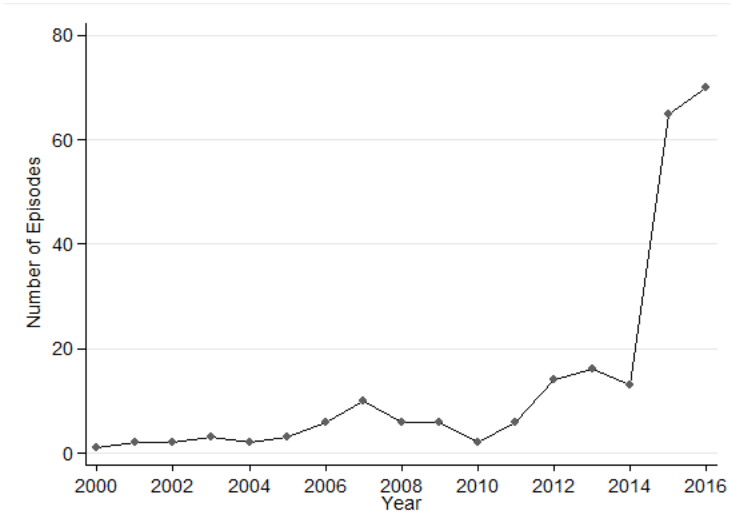
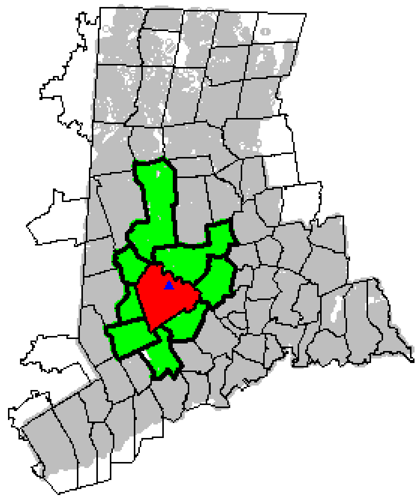
Figures

Figure I : Number of Mass Shootings 2000-2016



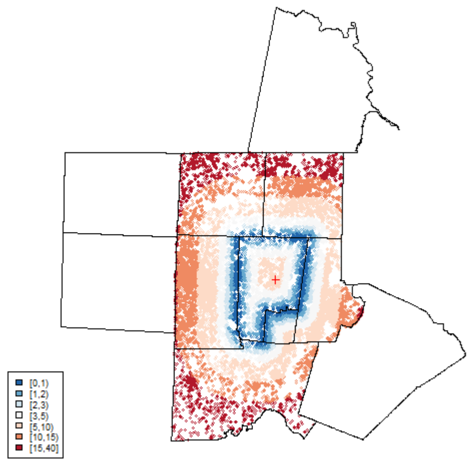
Note: Note: Data source is the Stanford Mass Shooting in America data Project. Episodes included had more than three victims and were not drugs, gangs, or organized crime related.

Figure II : Sandy Hook and Adjacent School Districts



Note: Note: This map plots Sandy Hook school district in Newton, CT. The blue triangle indicates the location of the 2012 shooting. The red area indicates the affected school district whereas the green area the adjacent school districts.

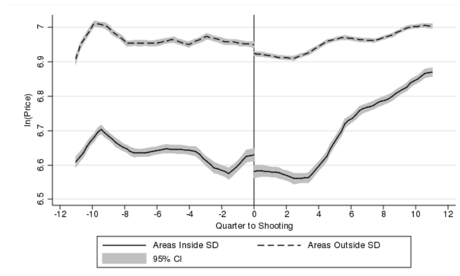
Figure III : Distance of Properties to Border in Orange School District, NC



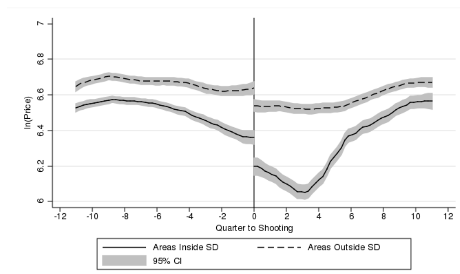
Note: Note: This map plots Orange County, NC County. The red cross indicates the location of Orange high school, where a shooting took place in 2006. The different colors show the distance to the school district boundary.

Figure IV : Price Evolution before and After the Shooting of Affected and Adjacent School Districts

(a) All School District



(b) Half Mile from Boundary



Note: Note: Both panels present the results of a kernel-weighted local polynomial regression for treated and control areas. Bottom panel includes only properties within half mile to the school district boundary, whereas the top panel includes the full school district. The plots include observations three years before and after the shooting.

Tables

Table I: Summary Statistics at the Census Tract Level for Affected and Non-affected School Districts

Covariate	Raw				Weighted		
	Treated	Controls	Rest	P-values (1) vs (2)	Treated	Controls	P-values (5) vs (6)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Population	3217.9	3337.2	3423.7	0.094	3269.7	3267.0	0.967
Median Home Value	93003.3	112291.2	101291.1	0.000	97926.3	98490.8	0.810
Median Rent	415.8	462.0	391.9	0.000	424.5	434.4	0.112
Income Per Capita	14054.6	16066.7	14447.5	0.000	14425.5	14738.0	0.167
Median Household Income	31940.4	35519.4	32079.0	0.000	33138.3	33702.3	0.306
Percentage White	80.1%	82.6%	83.2%	0.026	83.7%	85.0%	0.219
Percentage Black	15.1%	10.6%	10.9%	0.000	11.2%	10.1%	0.276
Percentage Hispanic	4.9%	6.6%	6.9%	0.000	5.3%	5.0%	0.306
Labor force	50.4%	53.2%	49.5%	0.000	51.8%	52.0%	0.435
Employment Rate	91.6%	94.5%	93.3%	0.000	93.1%	93.3%	0.404
Unemployment Rate	8.4%	5.5%	6.7%	0.000	6.9%	6.7%	0.404
Manufacturing Share	16.7%	16.7%	17.3%	0.830	16.2%	16.5%	0.497
Female Labor Force	58.9%	61.3%	56.6%	0.000	60.3%	60.6%	0.490
Self-Employment Share	6.6%	7.4%	7.7%	0.000	6.9%	6.9%	0.925
Share College Graduates	12.0%	17.1%	13.0%	0.000	12.6%	12.8%	0.477
Percentage Married	40.4%	43.2%	43.4%	0.000	41.9%	42.2%	0.408
Poverty Rate	14.2%	9.9%	12.8%	0.000	12.2%	11.3%	0.059
White Poverty Rate	7.1%	6.1%	7.8%	0.000	7.3%	7.1%	0.597
Percentage of Old Houses	39.0%	32.4%	40.1%	0.000	35.0%	35.6%	0.627

Note: This table presents summary statistics from the census 1990 at the census tract level. Columns (1)-(3) presents mean values using raw data. Columns (5) and (6) present weighted mean values that use weights from a kernel propensity score matching algorithm. Census tracts are matched using 1990 characteristics, and the sample is restricted to the common support. Columns (4) and (7) present the p-values of a difference in means test between affected and non-affected school districts for the raw and the weighted averages, respectively.

Table II: Average Effect of School Shootings in the School District

	Dependent Variable : ln(Price)								
	3 year window around the shooting				Persistence (Comparing to three years before episode)				
					<1 year	1-2 years	2-3 years	3-4 years	4-5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(Within Affected SD) *1(After Shooting)	-0.066***	-0.075***	-0.078***	-0.111***	-0.093***	-0.068***	-0.045***	-0.038***	-0.046***
	(0.013)	(0.013)	(0.011)	(0.016)	(0.012)	(0.011)	(0.010)	(0.010)	(0.011)
Observations	797,611	797,611	797,611	797,611	484,259	495,798	492,208	478,298	470,415
R-squared	0.643	0.752	0.758	0.706	0.764	0.769	0.773	0.769	0.761
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted Regression				Yes					

Note: The dependent variable is the log of the deflated price per property. Estimations include all properties within the school district. Columns (1) to (4) include observations three years before and after the shooting. Columns (5) to (9) compares observations three years before with observations 1,1-2, 2-3, 3-4, and 4-5 years after the shooting, respectively. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. The regression in column 4 weighs the observations by the inverse of the total number of properties sold within each episode. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table III: Effect of School Shooting on the Number of Sales at the Census Tract Level

	Dependent Variable: ln(Sales)					
	Full School District			Half Mile Around Boundary		
	+3\-3 yr	+2\-2 yr	+1\-1 yr	+3\-3 yr	+2\-2 yr	+1\-1 yr
	(1)	(2)	(3)	(4)	(5)	(6)
1(Within Affected SD)	-0.139***	-0.083*	0.016	-0.101	-0.039	-0.023
*1(After Shooting)	(0.044)	(0.045)	(0.051)	(0.078)	(0.083)	(0.110)
Observations	14,331	4,804	4,744	3,049	1,055	2,924
R-squared	0.725	0.826	0.777	0.727	0.825	0.850
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: These regressions are done at the census tract-year level. The dependent variable is the log of the number of sales at the census tract and year. Columns (1) to (3) include the full school district. Columns (4) to (6) include properties one mile from boundary. Columns (1) and (4) include observations on the number of transactions three years before and after the shooting. Columns (2) and (5) include observations of the number of transactions two years before and after the episode. Columns (3) and (6) include observations of the number of transactions one year before and after the shooting. Property characteristics include the average log of area of land, the log of area of building, percentage of apartments, percentage of condos, percentage of properties with fireplace, percentage of properties constructed with brick, and the average number of bedrooms. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table IV: Effect of School Shootings in Properties Half Mile around School District Boundary

	Dependent Variable : ln(Price)								
	3 year window around the shooting				Persistence (Comparing to three years before episode)				
					¡1 year	1-2 years	2-3 years	3-4 years	4-5 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(Within Affected SD) *1(After Shooting)	-0.144***	-0.142***	-0.136***	-0.176***	-0.172***	-0.133***	-0.107***	-0.100***	-0.118***
	(0.039)	(0.038)	(0.036)	(0.042)	(0.044)	(0.042)	(0.031)	(0.028)	(0.030)
Observations	59,948	59,948	59,948	59,948	38,896	38,754	38,367	37,093	36,992
R-squared	0.670	0.711	0.718	0.679	0.697	0.698	0.698	0.700	0.691
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted Regression				Yes					

Note: The dependent variable is the log of the deflated price per property. Estimations include properties within 1 mile of the school district boundary. Columns (1) to (4) include observations three years before and after the shooting. Columns (5) to (9) compares observations three years before with observations 1,1-2, 2-3, 3-4, and 4-5 years after the shooting, respectively. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. The regression in column 4 weighs the observations by the inverse of the total number of properties sold within each episode. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table V: Effect of School Shootings using Propensity Score Matching Weights

	Dependent Variable: ln(Price/HPI)		
	(1)	(2)	(3)
1(Within Affected SD)*1(After Shooting)	-0.026*	-0.035**	-0.046***
	(0.015)	(0.015)	(0.014)
Constant	6.867***	2.009***	113.709***
	(0.041)	(0.081)	(42.381)
Observations	771,530	771,530	771,530
R-squared	0.640	0.731	0.738
Year*Month FE	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes
Property Characteristics		Yes	Yes
Episode Specific Trend			Yes

Note: The dependent variable is the log of the deflated price per property. Estimations include all properties within census tracts matched with a kernel propensity score algorithm using census 1990 characteristics at the census tract level. All observations are weighted by the kernel weights generated in the propensity score algorithms. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table VI: Falsification Test using Placebo Episodes Prior to the Shooting

	Dependent Variable: ln(Price)					
	Full School District			Half Mile Around Boundary		
	2 years before	3 years before	4 years before	2 years before	3 years before	4 years before
	(1)	(2)	(3)	(4)	(5)	(6)
1(Within Affected SD)	0.006	-0.024	-0.007	0.025	-0.016	-0.016
	(0.027)	(0.033)	(0.036)	(0.035)	(0.038)	(0.043)
1(After X years before shooting)*1(Within SD)	-0.004	0.008	-0.010	-0.019	0.017	0.003
	(0.005)	(0.006)	(0.007)	(0.012)	(0.012)	(0.012)
Observations	223,916	198,927	158,096	19,263	17,988	15,825
R-squared	0.751	0.759	0.755	0.706	0.727	0.724
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the log of the deflated price per property. Columns (1) to (3) include the full school district. Columns (4) and (6) include properties half a mile from boundary. Columns (1) and (4) use a dummy that takes the value of one for a placebo test two prior to the shooting. Columns (2) and (5) use a dummy that takes the value of one for a placebo test three years prior to the shooting. Columns (3) and (6) use a dummy that takes the value of one for a placebo test four years prior to the shooting. All regressions include a one year window before and after the placebo shooting date. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table VII: Balance Test of Housing Characteristics

	Full School District			Half Mile Around Boundary		
House Characteristic	Coefficient (1)	Std. Error (2)	P-value (3)	Coefficient (4)	Std. Error (5)	P-value (6)
1(Fireplace)	0.040	0.033	0.228	0.010	0.024	0.668
1(Brick)	-0.044	0.034	0.194	-0.020	0.023	0.391
1(Condo)	0.057	0.037	0.120	0.036	0.023	0.114
Number of Bedrooms	-0.002	0.061	0.971	-0.051	0.078	0.512
ln(land)	0.135	0.159	0.395	0.250	0.160	0.119
ln(Building)	-0.040	0.024	0.097	-0.015	0.032	0.650
Years Since Built	4.017	2.200	0.068	1.001	1.446	0.489

Note: Each row of the table presents a different housing characteristic. We estimate a linear regression using equation (1) and varying the outcome. Columns (1) to (3) include observations in the complete school district. Columns (4) to (6) include properties half mile around the boundary. Coefficients, standard errors, and p-values associated with the treatment parameter are presented.

Table VIII: Average Effect on Crime

	Dependent Variable: Crime Rate								PCA index
	Murders	Rapes	Robberies	Assaults	Burglaries	Thefts	Auto Thefts	Arson	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1(Within Affected City)	-0.532	-5.155	-9.161	-104.704***	-85.046	261.614**	-133.462***	-18.292*	-24.523
*1(After Shooting)	(1.300)	(4.099)	(15.465)	(37.139)	(85.028)	(117.979)	(27.772)	(10.247)	(17.907)
Observations	1,514	1,490	1,491	1,476	1,474	1,474	1,475	1,450	1,474
R-squared	0.447	0.589	0.837	0.799	0.784	0.823	0.752	0.496	0.854
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions are estimated at the city level using the affected city as treated and surrounding cities as controls. All dependent variables are rates per 100,000, except for the PCA index in column (9) which corresponds to a principal component index of the variables in columns (1) to (8). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table IX: Average Effect of School Shootings by House Size

	1 BR (1)	2 BR (2)	3 BR (3)	4 BR (4)	Less than 2 BR (5)	More than 2 BR (6)
1(Within Affected SD)*1(After Shooting)	0.084***	-0.036***	-0.054***	-0.118***	-0.033**	-0.087***
	(0.032)	(0.013)	(0.011)	(0.015)	(0.013)	(0.012)
Observations	24,556	155,870	386,242	183,028	180,426	617,185
R-squared	0.805	0.792	0.732	0.765	0.787	0.753
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the log of the deflated price per property. All specifications include properties with different number of bedrooms. Column (5) and (6) pool together properties with less and more than two bedrooms, respectively. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table X: Average Effect on School Enrollment and Number of Teachers

	Dependent Variable: Ln(Enrollment)		Dependent Variable: Ln(Teachers)	
	(1)	(2)	(3)	(4)
1(Affected SD)*1(After Shooting)	-0.161***		-0.083*	
	(0.042)		(0.044)	
1(Affected School)*1(After Shooting)		-0.176**		-0.126*
		(0.085)		(0.069)
1(Surrounding School within SD)*1(After Shooting)		-0.075*		-0.052
		(0.042)		(0.035)
Constant	6.103***	5.537***	3.341***	2.561***
	(0.065)	(0.097)	(0.061)	(0.073)
Observations	26,115	26,115	25,255	25,255
R-squared	0.254	0.818	0.315	0.820
Year FE	Yes	Yes	Yes	Yes
Episode FE	Yes	Yes	Yes	Yes
School District FE	Yes		Yes	
School FE		Yes		Yes

Note: Regressions are done at the school level using the total number of students and teachers as dependent variable. Columns (1) and (3) present the pooled effect for all the schools within the affected school district. Columns (2) and (4) present results separately for the schools where the shooting occurred, and non-affected schools within the affected school district. Columns (1) and (3) include school district fixed effects. Columns (2) and (4) include school fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table XI: Average Effect of School Shootings Using as Treatment a Radius around Affected School

	Properties within 3 Miles			Properties within 5 Miles		
	0.3 Mile	0.5 Mile	1 Mile	0.3 Mile	0.5 Mile	1 Mile
	(1)	(2)	(3)	(4)	(5)	(6)
1(Within X Mi.)*1(After Shooting)	0.050	-0.002	-0.003	0.055	0.001	0.010
	(0.065)	(0.043)	(0.022)	(0.065)	(0.044)	(0.023)
Observations	49,229	49,229	49,229	109,924	109,924	109,924
R-squared	0.735	0.735	0.735	0.734	0.734	0.734
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend	Yes	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the log of the deflated price per property. Columns (1) to (3) include only observations within a three mile radius from school shooting. Columns (4) to (6) include only observations within a five mile radius from school shooting. Columns (1) and (4) use properties within 0.3 miles around the school as treated units. Columns (2) and (6) use as treatment properties within 0.5 miles around the school. Columns (3) and (6) use as treatment properties within one mile around the school. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix: Tables(For Online Publication)

Appendix Table I: School Shooting Episodes

	Year	School	City	State	Victims	Fatalities
1	1998	Westside School	Jonesboro	Arkansas	15	5
2	1998	Thurston High School	Springfield	Oregon	29	4
3	1999	Columbine High School	Littleton	Colorado	37	13
4	1999	Heritage High School	Conyers	Georgia	6	0
5	1999	Fort Gibson Middle School	Fort Gibson	Oklahoma	4	0
6	2001	Santana High School	San Diego	California	15	2
7	2006	Orange High School	Hillsborough	North Carolina	3	1
8	2006	West Nickel Mines Amish School	Lancaster	Pennsylvania	10	5
9	2007	Springwater Trail High School	Gresham	Oregon	10	0
10	2007	Success Tech Academy	Cleveland	Ohio	4	1
11	2007	South Middle School Football Game	Saginaw	Michigan	4	0
12	2012	Chardon High School	Chardon	Ohio	6	3
13	2012	Sandy Hook Elementary School	Newtown	Connecticut	29	27
14	2013	Sparks Middle School	Sparks	Nevada	3	1
15	2014	Marysville-Pilchuck High School	Marysville	Washington	5	4

Appendix Table II: Taking out one episode at a time

	(1) Chardon	(2) Cleveland	(3) Columbine	(4) Conyers	(5) Fort Gibson	(6) Gresham	(7) Hillsborough	(8) Jonesboro
1(Within Affected SD)	-0.120***	-0.040**	-0.124***	-0.118***	-0.113***	-0.114***	-0.113***	-0.111***
*1(After Shooting)	(0.017)	(0.016)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)
Observations	787,851	728,053	612,455	676,761	791,852	784,542	750,846	797,611
R-squared	0.710	0.712	0.711	0.720	0.703	0.707	0.710	0.706
	(9) Lancaster	(10) Marysville	(11) Newton	(12) Saginaw	(13) San Diego	(14) Sparks	(15) Springfield	
1(Within Affected SD)	-0.112***	-0.121***	-0.111***	-0.071***	-0.124***	-0.142***	-0.128***	
*1(After Shooting)	(0.016)	(0.018)	(0.016)	(0.011)	(0.018)	(0.019)	(0.018)	
Observations	788,216	762,995	788,427	788,506	604,951	724,930	778,558	
R-squared	0.707	0.706	0.703	0.699	0.673	0.703	0.721	
			Yes	Yes	Yes	Yes	Yes	
Year*Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Episode Specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Weighted Regression	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

Note: All columns use a three-year window around the episode. For each column we dropped observations for one of the episodes and estimate the model in the remaining ones. All the regressions are weighted by one over the total number of transactions per episode. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table III: Effect of School Shootings around Boundary with Different Radius

	(1) 0.3 Mi.	(2) 0.5 Mi.	(3) 1 Mi.	(4) 2 Mi.	(5) 3 Mi.
1(Within Affected SD)	0.054	0.050	0.044	0.025	0.021
	(0.046)	(0.040)	(0.041)	(0.036)	(0.034)
1(Within Affected SD)*1(After Shooting)	-0.104***	-0.114***	-0.125***	-0.126***	-0.112***
	(0.037)	(0.032)	(0.023)	(0.016)	(0.013)
Constant	352.736***	334.771***	298.816***	191.569***	-26.281
	(62.475)	(51.393)	(40.065)	(33.737)	(49.847)
Observations	11,855	19,661	39,481	70,548	98,493
R-squared	0.733	0.739	0.726	0.735	0.744
Census Tract FE	Yes	Yes	Yes	Yes	Yes
Year*Month FE	Yes	Yes	Yes	Yes	Yes
Episode Specific Trend	Yes	Yes	Yes	Yes	Yes
Property Characteristics	Yes	Yes	Yes	Yes	Yes

Note: The dependent variable is the log of the deflated price per property. All the columns vary the radius around the school district boundary. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not is an apartment, a dummy for whether or not is a condo, a dummy if the property has a fireplace, a dummy if the house is constructed with brick, and the number of bedrooms. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table IV: Average Effect of School Shootings on Non-Residential Properties

	Dependent Variable : ln(Price)			
	(1)	(2)	(3)	(4)
1(Within Affected SD)*1(After Shooting)	0.011	0.005	0.033	0.091*
	(0.048)	(0.043)	(0.042)	(0.047)
Constant	7.054***	2.052***	201.955	-99.178
	(0.438)	(0.344)	(366.194)	(435.684)
Observations	13,151	13,151	13,151	13,151
R-squared	0.509	0.621	0.623	0.633
Year*Month FE	Yes	Yes	Yes	Yes
Census Tract FE	Yes	Yes	Yes	Yes
Property Characteristics		Yes	Yes	Yes
Episode Specific Trend			Yes	Yes
Weighted Regression				Yes

Note: The dependent variable is the log of the deflated price per property. Estimations include all non-residential properties (i.e. industrial and commercial properties) within the school district. Property characteristics include the log of area of land, the log of area of building, a dummy for whether or not the property is an apartment. The regression in column 4 weighs the observations by the inverse of the total number of properties sold within each episode. Standard errors clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.