Mass shootings, employment, and housing prices: Evidence from different geographic entities[*§]

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Abstract

This paper investigates the economic effects of mass shootings taking advantage of a unique dataset with detailed information about their location. Using recent advances in difference-in-differences methods, we assess the influence of the attacks on employment and housing prices at three levels of geographical disaggregation. Obtained results show that the economic impact of mass shootings is more evident when census tracts are considered as the spatial unit of analysis, and when they are perpetrated in public spaces. Furthermore, mass shootings affect to a greater extent the employment of those sectors that are more reliant on face-to-face interactions.

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1 Introduction

Gun violence is a relentless issue in the United States (U.S.), with a staggering death-toll of 21,009 in 2021 alone[1]. Among the different types of gun violence, mass shootings stand out as one of its most prominent and attention-grabbing forms. Although it is difficult to assert that these incidents are experiencing an increasing trend[2], and even though they account for a relatively small percentage of overall gun-related deaths (Duwe, 2020), mass shootings are receiving a significant media coverage as compared to other kinds of gun violence (Schildkraut, Elsass, and Meredith, 2018). Furthermore, 47.4% of U.S. citizens reported being "afraid or very afraid" of "random/mass shootings" in 2019 (Sheth, 2019). Remarkably, and despite the occurence of the COVID-19 pandemic, this level of dread has persisted at 36.7% in subsequent years (Amirazizi, 2022).

In parallel to this societal concern regarding mass shootings, it has appeared a growing body of academic literature that explores the impact of these violent incidents beyond the loss of human lives. Lowe and Galea (2017) review the studies about the mental health consequences of mass shootings, concluding that they are related to adverse psychological outcomes in survivors, and to a decline in the perceived safety of indirectly exposed individuals. Rossin–Slater, Schnell, Schwandt, Trejo, and Uniat (2020) find that these attacks increase the use of antidepressants among the youth, especially when they occur in schools. Luca, Malhotra, and Poliquin (2020) conclude that these events increase firearm bills in a 15%, indicating a disproportionate effect with respect to other forms of gun deaths. At the county level, Yousaf (2021) shows that the attacks influence electoral outcomes.

Notwithstanding the foregoing, the literature that deals with the economic effects of mass shootings is rather scarce. Sakariyahu, Lawal, Yusuf, and Olatunji (2023) analyze their influence on investor sentiment in the stock market. These authors show that the attacks adversely affect market indices during the following days, but in a heterogeneous manner across economic sectors. Using a sample of eleven mass shootings perpetrated at schools, Muñoz–Morales and Singh (2023) find that the incidents exerted an adverse

[1] Together with 26,328 firearm-related suicides, and 40,603 injuries (*Gun Violence Archive* 2023).

[2] Smart and Schell (2021) review how the consideration of alternative definitions, data sources, and sample periods leads to different claims about the dynamics of mass shootings.

effect on property values and school enrollment rates in neighboring areas. To the best of our knowledge, only Brodeur and Yousaf (2022) conduct a broad study about the impact of mass shootings on local economies (counties). Applying difference-in-differences (DiD) estimation techniques, they show that the attacks lead to lower levels of both earnings and employment, mainly in the goods production, manufacturing, and services sectors. These authors also suggest that mass shootings are related to negative mental health outcomes and reductions in the wealth of households, through lower housing prices.

In this paper, we adhere to the Federal Bureau of Investigation's (FBI) definition of mass shootings, setting the casualty threshold at four. Additionally, we exclude cases related to felonies. Our primary aim is to further illuminate the economic effects of these violent incidents. To accomplish this, we have constructed a comprehensive dataset using sources that provide detailed information about their locations. This endeavor allows us to delve into the geographical extent of the economic impact of the attacks by encompassing the analysis for counties, zip codes, and census tracts. We employ the extension of the Rosen-Roback model developed by Moretti (2011) – that integrates mobility frictions – to posit that mass shootings lessen both the amenity level and the productivity of workers in affected areas. This theoretical framework predicts that the magnitude of the adverse effects depends on the extent of worker mobility. Leveraging the latest advancements in DiD estimation techniques – which consider the presence of heterogeneous effects and variation in treatment dates – we provide evidence that census tracts are the spatial units most affected by mass shootings. Our analysis reveals a persistent and self-reinforcing decline in employment levels as well as a consistent decrease in housing prices within these areas.

Furthermore, we elucidate the differential effects of mass shootings across economic sectors, observing that those relying more heavily on face-to-face interactions are disproportionately affected. Making use of data on employment by wage and educational attainment, we also investigate whether these attacks exert heterogeneous effects on workers with different skills. Our results provide limited evidence that mass shootings alter the employment composition. As another contribution, we study the potential influence of the 'fear hypothesis' (Becker and Rubinstein, 2011) in shaping the behavior of economic agents after the attacks. In this regard, we find that those attacks occurring in public spaces – inherently characterized by a heightened level of indiscriminate violence – are found to have more pronounced effects.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature on the impact of crime and violent incidents on local economies. It also introduces the theoretical model used as the framework for analyzing the economic impact of mass shootings. Section 3 explains the construction of our dataset, and details the sources of information from which the data of employment, housing prices, and other control variables have been extracted. Section 4 presents the estimation methods that have been implemented. While Section 5 delves into the impact of mass shootings on employment, Section 6 shows the corresponding analysis for housing prices. Finally, Section 7 concludes.

2 Background

2.1 Literature review

The study of the economic effects of mass shootings differs from those of other violent incidents, such as common crime or terrorism, due to their higher degree of randomness. While common crime tends to be concentrated in specific areas, and terrorism targets specific political, social, or religious objectives, the occurence of mass shootings is much less predictable. Nonetheless, all these violent incidents influence the behavior of economic agents within their respective areas of influence, hence prompting comparable impacts that are transmitted through similar mechanisms. In this regard, an outcome commonly found in the related literature is that these events make the places where they occur to be less desirable for living. For instance, Dugan (1999) reveals that personal crime victimization is directly associated with a higher probability of household relocation. Additionally, Tita, Petras, and Greenbaum (2006) show that crime has an adverse effect on house values in U.S. census tracts, that varies across income levels. However, homicides exert a more homogeneous and greater impact. This result is in line with Klimova and Lee (2014) who, taking into consideration asymmetric information between buyers and sellers, find that murders decrease the value of nearby houses.

The inverse relationship between violence and housing prices extends beyond ordinary crime. Besley and Mueller (2012) estimate that areas with higher killing incidence experienced more significant increases in housing values as a result of the peace process in Northern Ireland. Hazam and Felsenstein (2007) show that terrorism exerts a negative effect on housing prices. This study also finds that the more random and violent the attack the greater its effects, giving support to the 'fear hypothesis' (Becker and Rubinstein, 2011) which states that there are two main forces affecting the (heterogeneous) behavior of individuals in the face of terror: the objective risk of being a victim, and the related subjective fear. Notably, such kind of events can also lead to demographic impacts; see Sanso-Navarro, Sanz-Gracia, and Vera-Cabello (2019) for the case of terrorism in the Basque country and Navarre (Spain).

Violent shocks also erode economic activity, as shown by Greenbaum and Tita (2004), who claim that, on the one hand, businesses may choose not to locate in or to leave those neighborhoods with high crime rates due to the associated security costs. On the other hand, both customers and employees may fear becoming victims, thus reducing business activity in affected areas. At the census tract level in Southern California, Hipp, Williams, Kim, and Kim (2019) find that criminality increases business closures and/or relocations. They also show that property crimes have a greater impact on the retail sector, whereas violent crimes tend to affect white-collar businesses. Moreover, Rosenthal and Ross (2010) develop a theoretical model where the retail and wholesale sectors make their location decisions taking into account the presence of crime. In addition, these authors provide empirical evidence that the shares of total activity and employment of the retail sector are lower in those areas that suffer violent crimes. From the point of view of consumers, Fe and Sanfelice (2022) combine mobile device data on customer visits to venues and geolocated crime data from the Chicago Police Department, showing an inverse relationship between these two variables.

In the same line, but focusing on violence, Brodeur (2018) investigated the influence of terror in U.S. counties, considering that related incidents lead to higher consumer uncertainty and business security costs. This author finds that counties experiencing successful terrorist attacks displayed subsequent lower levels of employment and earnings. Rozo (2018) develops a theoretical framework linking violence with the costs faced and prices set by firms. This author tests the model predictions by examining abrupt security improvements in Colombia, concluding that firms located in more violent municipalities experience larger reductions in output prices compared to input costs, leading to market exits. Fich, Nguyen, and Petmezas (2023) show that terror drive away inventors and reduce productivity of firms located in attacked areas.

2.2 Conceptual framework

The empirical analysis of the economic impact of mass shootings can be framed within the extension of the Rosen-Roback model for local labor markets proposed by Moretti (2011) to include mobility frictions[3]. According to the standard version of this theoretical framework, the utility that a worker obtains for living in location a is given by the function $U_a(w_a, r_a, A_a, s)$, where w_a denotes nominal wages, r_a refers to housing prices, A_a represents the available level of amenities, and s embodies the idiosyncratic preferences of workers for living in each location. These preferences reflect the connections of each worker with a given place – such as being born there or having family and friends – and, in turn, represent the mobility degree of workers between locations. For simplicity, we assume that there are two locations, a and b, and adopt the perspective of the place experiencing the shock caused by the mass shooting, say b.

Given that, in equilibrium, the marginal worker would be indifferent between living in any location, it implies that $U_a(w_a, r_a, A_a, s) = U_b(w_b, r_b, A_b, s)$. If there are $N = N_a + N_b$ workers, the local labor supply curve for location b would be a function $N_b = f(w_a, w_b, r_a, r_b, A_a, A_b, s)$. The elasticity of this labor supply depends on the mobility degree of workers, such that $\frac{\partial N_b}{\partial s} > 0$. In the extreme case of $s = 0$, where workers are perfectly mobile, the labor supply curve will be flat.

Firms in each location are price-takers and operate according to a Cobb-Douglas production function with constant returns to scale. Both labor and capital are compensated according to their marginal products, that depend on a parameter $X_{a,b}$ capturing the location-specific productivity. Therefore, we can simplify the expression for labor demand in location b as $N_b = f(w_b, K_b, X_b)$.

[3] See also Ahlfeldt, Bald, Roth, and Seidel (2020) for a similar theoretical model that includes mobility frictions and non-tradable goods.

Each worker consumes one unit of housing, $H_b = N_b$, making its demand to be equal to the supply of labor: $H_b = N_b = f(w_a, w_b, r_a, r_b, A_a, A_b, s)$. Finally, it is considered a simple functional form for housing supply: $r_b = \phi + k_b N_b$, where k_b reflects the elasticity of the housing supply in location b. This parameter will be large in the presence of geographical or regulatory restrictions that make it difficult to build new houses. In the extreme case where $k_b = \infty$, it would be impossible to modify the size of the housing stock, as reflected by a vertical housing supply curve.

2.2.1 Shocks to labor and housing markets

The utility of the theoretical framework discussed above for analyzing the economic effects of mass shootings lies in its disregard for the influence they may have on other locations. In particular, the attacks can be interpreted as a negative shock to the level of local amenities, A_b, that captures a myriad of characteristics making this place (dis-)attractive for living, such as the weather, the level of air pollution, the number of trees, or the presence of museums, monuments, and heritage sites. From the literature reviewed previously, we know that crime, terrorism, and other violent shocks make the places where they occur less attractive for living; thus, we are assuming that this is also the case of mass shootings.

The adverse shock induced by a mass shooting would shift the labor supply towards the left, reducing the level of employment in location b. Furthermore, wages will increase in order to compensate for the amenity loss. A virtue of the theoretical framework adopted is that the magnitude of the decrease in N_b depends on the elasticity of the labor supply. To illustrate this, Panel (a) of Figure 1 represents the effect of the labor supply shift with imperfect mobility (N'), as compared to the extreme case where the labor supply is flat (N''), showing that the displacement of workers will be higher in the latter. We incorporate this notion by assuming that workers are more prone to move between census tracts than between counties.

[Insert Figure 1 about here]

It can also be considered that mass shootings make workers in affected locations to be less productive, both due to mental health issues and more strict security protocols at the workplace. By denoting the adverse productivity shock derived from an attack as ∇X_b, it shifts labor demand towards the left, lowering wages and, consequently, displacing workers from location b. As shown in Panel (b) of Figure 1 for both an increasing and a flat labor supply, the magnitude of these effects, again, depends of the degree of workers mobility. It is also worth noting that we are considering a scenario without agglomeration economies. The presence of spillovers would imply $X_b = h(N_b)$, with $h' > 0$, making the productivity loss induced by an attack to magnify itself because the expelled workers will further decrease productivity, lowering wages and making more workers to move until the decrease in housing prices offsets that of wages. If the two shifts occur simultaneously – what can be expected to be the case after a mass shooting – the outflow of workers from location b would be even greater, as shown in Panel (c). Nonetheless, the effect on wages is not clearly defined, as it depends on both the degree of mobility and the relative importance of each kind of shock.

[Insert Figure 2 about here]

The shock provoked by a mass shooting on amenities and productivity (wages) will induce a reduction in housing demand in location b equivalent to that in the labor supply. This would make housing prices to be lower, to an extent that also depends on the mobility degree of the labor force; see Panel (a) of Figure 2. Another factor that influences the magnitude of the price reduction in the housing market is the supply elasticity. For illustrative purposes, as in the case of perfectly mobile workers, Panel (b) displays the impact of the shock when housing supply is rigid ($k_b = \infty$), showing that there is an inverse relationship between the elasticity of housing supply and the magnitude of price reduction[4]. In our context, it can be assumed that the elasticity is lower is smaller geographical units as their size correspond to tighter markets.

2.2.2 Heterogeneous labor and non-tradable goods

Moretti (2011) extends his theoretical framework to account for heterogeneous labor, and to introduce the presence of both tradable and non-tradable goods. Without delving too deeply into the details of the model, the main idea is that the employment composition of location b, in terms of skilled (N_b^H) and unskilled workers (N_b^L), would change

[4] $k_b = \infty$ implies that no new housing can be built in location b, what might be realistic in the short run. However, it also means that no housing can become vacant. In this extreme case, landowners are forced to fully adjust the prices to accommodate the shock.

after the shock if their mobility degrees – s_H and s_L, respectively – differ and/or if the productivity decrease for each group is different[5]. Assuming that $s_H > s_L$, as well as that the shock affects the productivity of both groups of workers equally ($\nabla X_b^H = \nabla X_b^L$), the outflow of skilled workers would be greater than that of unskilled ones, hence altering the labor composition of location b. Alternatively, if $s_H = s_L$ and $\nabla X_b^H > \nabla X_b^L$, the shock will disproportionately affect the productivity of skilled labor, leading to an outflow of this type of workers, together with an inflow of unskilled ones attracted by lower housing prices[6].

The distinction between tradable and non-tradable goods is linked with the concept of local multipliers (Moretti, 2010). In the present context, the impact of a mass shooting on the non-tradable sector could be twofold. Firstly, it encompasses services that are consumed locally, such as retail, restaurants, or theaters; hence, their demand might be adversely affected after an attack as it exacerbates the fear of victimization. Secondly, the shocks on amenities and productivity imply a reduction in the number of workers in affected locations. In addition, if the reduction in productivity exceeds that in amenities ($\nabla X_b > \nabla A_b$), wages would also be lower. These two effects will further decrease the demand for non-tradable goods in location b.

3 Data

3.1 Mass shootings

There is no standard definition of what constitutes a mass shooting, partly due to the lack of a legislation considering this type of attack as a distinct crime in the U.S. Consequently, there exist various definitions of mass shootings that, in practical terms, differ on the criteria established, such as the threshold for the number of victims, the motivation behind the attack, or the type of place where it is perpetrated. As a result, there are different figures regarding the number of mass shootings and their related victims. Smart and Schell (2021) provide a review of the databases that track mass shootings, and show that the differences are significant, ranging from 6 to 502 mass shootings, and from 60 to 628 victims, in the year 2019. As noted in the introductory section, by adopting the FBI's

[5]It can also be assumed that their amenities change differently with analogous results.

[6]This rules out the existence of different housing markets for each group at location b.

definition of mass shootings, we set the casualty threshold at four victims, excluding the perpetrator(s) (Krouse and Richardson, 2015). Additionally, we exclude felony-related mass shootings, such as armed robberies or those associated with gangs and organized crime.

There are two main sources of information that can be exploited to study issues related to mass shootings. One alternative is to filter the Supplementary Homicide Report (SHR), elaborated by the FBI, to identify those cases that match the above-mentioned criteria. Although this report is a voluntary program for law enforcement agencies that suffers some coverage limitations (Duwe, 2020), it is an official source and one of the most comprehensive databases of homicides commited in the U.S. However, the SHR lacks information regarding the particulars of the incidents, especially those concerning their location. For this reason, we have relied on the second alternative, which involves the use of databases from media and academic institutions containing more detailed information. It is important to acknowledge that media-based data sets may also have restrictions, missing less notorious incidents or those occurring at the same time that other prominent events, particularly when accounting for older attacks only reported in print media or on television. In order to reduce this potential missing information, we have exploited four data sets.

The first of them is the Violence Project Mass Shooter Database (Peterson and Densley, 2022), which focuses on mass public shootings – defined as indiscriminate attacks taking place at public spaces – and establishes a threshold of four victims. Given that both criteria match our adopted definition, all incidents included in this database have been taken into account. The Mother Jones Database (Follman, Aronsen, and Pan, 2020) also centers on mass public shootings, but it changed its criterion in 2013, setting a threshold of three victims. Therefore, these cases have been excluded from our sample. Besides, the Associated Press and USA Today Mass Killing Database (Fox, 2022) establishes a threshold of four victims and rules out those events not involving a firearm or felony-related. Finally, the Stanford Mass Shootings in America Database (Peterson and Densley, 2022), that ends in 2016, leaves incidents related with gangs or organized crime out[7], but

[7] Although the criterion regarding the motivation of the assailant is similar to ours, there were three cases associated with robberies that have not been included in our sample.

the threshold of victims is set to three people injured, including the attacker(s). Hence, we have disregarded those attacks with less than four victims fatally injured.

[Insert Figure 3 about here]

It should be pointed out that the four databases cover events considered as 'spree' – i.e., committed in various locations but within a short period of time – that have been included in our sample. After merging the information from these data sets that fulfill our criteria, we cover a sample of 399 mass shootings from 1966 to 2021, that entailed 2,277 fatalities and 2,113 persons injured. Figure 3 represents a chloropleth map with the geographical distribution of these incidents and population density at the county level. It can be observed that the spatial distribution of mass shootings aligns with that of population, with denser areas experiencing a higher number of attacks. The data on employment, one of our indicators of economic conditions as described in the next subsection, constrains our analysis to the period 2003–2019. This time span includes 274 mass shootings, that resulted in 1,567 fatalities and 1,610 persons injured.

3.2 Employment, housing prices and control variables

As pointed out in the introduction, beyond counties, we are interested in analyzing more granular data at the zip code[8] and census tract levels. To do so, we have exploited data from the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census Bureau. In particular, we have drawn upon the Origin-Destination Employment Statistics (LODES) dataset (U.S. Census Bureau, 2022), that provides information on both residence (RAC) and workplace (WAC) area characteristics. We put the focus on the WAC data, which includes the number of jobs – excluding federal employment – by blocks. WAC files have been extracted from the Urban Institute, that aggregates the information for both ZCTAs (Urban Institute, 2022a) and census tracts (Urban Institute, 2022b). Given that the latter have been designed to align within county boundaries, we are able to further aggregate the information of census tracts to obtain that for counties. These data cover the period from 2002 to 2019, and provide comprehensive information including

[8] Zip codes are primarily designed as routing tools for the U.S. Postal Service, hence not being considered as proper spatial units. In order to facilitate the analysis at this geographic level, the U.S. Census Bureau created ZIP Code Tabulation Areas (ZCTAs) in the year 2000, which are areal representations of zip codes and serve as a practical way to examine data.

2-digit NAICS codes, and the educational attainment as well as earnings of workers in each job.

The information about housing prices has been extracted from the Federal Housing Finance Agency (FHFA), that elaborates an index (HPI) using a weighted, repeated-sales methodology from mortgage data about transactions all over the U.S. (Bogin, Doerner, and Larson, 2019). Among other geographical levels, the HPI is calculated for counties, 5-digit zip codes[9], and census tracts. Descriptive statistics for the level of employment, its composition, and housing prices in counties, ZCTAs, and census tracts, distinguishing the data for those units that have experienced a mass shooting, are provided in Table A1 in the Appendix.

We have used the National Historical Geographic Information System (NHGIS; Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2022) as the source of information for control variables. For each unit of analysis and covariate, we have extracted the latest available data prior to a mass shooting. Given that the census is elaborated on a decennial basis, this implies that for those attacks between 2003 and 2010 we have used information referred to the year 2000, and data for the year 2010 for those incidents in the 2010s have been considered. The control variables used depend on the economic outcome that is being analyzed.

In the case of employment, we are controlling for factors related to population, the urban/rural status, and other socio-economic characteristics. These variables reflect the size – measured as the number of residents – and density of each geographical unit, an indicator variable of whether the majority of the population lives in urban areas, its ethnographic, age and educational attainment composition, per capita income, and the poverty rate. To deal with the influence of mass shootings on the HPI, we are considering variables that capture the urban/rural status, the housing stock, and commuting times. These variables reflect the size – using the total housing stock – and density, as well as the share of vacant housing. We also include the indicator variable about the urban character of the area, and the share of people divided by commuting times. At this point, it is important to note that census tracts are defined using 2010 boundaries when employment

[9]These data have been aggregated to ZCTAs using the crosswalk file provided by the Uniform Data System Mapper site, see https://udsmapper.org/zip-code-to-zcta-crosswalk/.

is the outcome variable under scrutiny, while the data for the HPI is based on 2020 limits. Therefore, to ensure compatibility, the data for the control variables in each analysis have been standardized to the correct boundaries using the crosswalk files provided by the NHGIS. Table A2 in the Appendix reports definitions for all covariates along with its descriptive statistics for both attacked and non-attacked areas.

4 Methodology

The geographic entities affected by a mass shooting can be considered as having received an adverse 'treatment'; i.e., being attacked. Therefore, and given the potential randomness and exogenous character of these events, a DiD estimation setup can be adopted to conduct an empirical analysis of their economic effects. Under a staggered treatment framework, and in a panel data context, let us follow Callaway and Sant'Anna (2021a) and consider $\{Y_{i,1}, Y_{i,2}, ..., Y_{i,\tau}, X_i, D_{i,1}, D_{i,2}, ..., D_{i,\tau}\}_{i=1,...,n}$; where $Y_{i,t}$ is the outcome of interest, and X_i is a vector of pre-treatment covariates associated with the outcome. $D_{i,t} = 1$ implies that $D_{i,t+1} = 1$ for $t = 1, 2, ..., \tau$. The starting time of the treatment is modelled using dummies, G_{ig}, which are equal to one if the unit i experienced the treatment (shock, in our context) at period g, zero otherwise. In the case where the not-yet-treated units are used as the comparison group, the conditional parallel trends assumption, in a simplified way, takes the form:

$$E\left[Y_t(0) - Y_{t-1}(0)|X, G_g = 1\right] = E\left[Y_t(0) - Y_{t-1}(0)|X, D_s = 0, G_g = 0\right] \qquad (1)$$

for each $g \in G$ and $(s, t) \in \{2, ..., \tau\}\text{x}\{2, ..., \tau\}$, such that $g \leq t \leq s$.

Callaway and Sant'Anna (2021a) set a further overlap assumption stating that, for each $t \in \{2, ..., \tau\}$, there exist some $\varepsilon > 0$ such that $P(G_g = 1) > \varepsilon$, and that $p_{g,t}(X) < 1 - \varepsilon$. This means that, at least, a positive fraction of the units starts treatment at period g. Moreover, for all g and t, the propensity score is uniformly bounded away from one, thus ruling out 'irregular indentification' (Khan and Tamer, 2010). The authors propose three alternative methods to recover the average treatment effect on the treated (ATT), our main parameter of interest. Among them, we have opted for the doubly robust estimation (Sant'Anna and Zhao, 2020), because it is consistent if, at least, one of the other alternative methods is correctly specified.

When the comparison group is made up by those units that have not been treated yet, the DR estimator takes the form:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E\left[G_g\right]} - \frac{\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}}{E\left[\frac{p_{g,t}(X)(1-D_t)(1-G_g)}{1-p_{g,t}(X)}\right]}\right)(Y_t - Y_{t-1} - m^{ny}_{g,t}(X))\right] \quad (2)$$

where $m^{ny}_{g,t}(X) = E\left[Y_t - Y_{g-1}|X, D_T = 0, G_g = 0\right]$ is the outcome of a regression for the not-yet-treated group.

Our sample includes 274 mass shootings that were perpetrated in a time span of 17 years. Although this might result in difficult to interpret ATTs, Callaway and Sant'Anna (2021a) have foreseen this type of situations, providing the researchers four grouping schemes:

$$\theta = \sum_{g \in G} \sum_{\tau}^{t=2} \omega(g,t) ATT(g,t) \quad (3)$$

with $\omega(g,t)$ denoting a weighting function set by the researcher.

The first grouping scheme corresponds to a simple average, that calculates the mean effect of all events across all periods. This provides an overall estimate of the ATT. Second, the group average effect is obtained as the mean effect of each group of events occuring in a given period. This allows us to examine the mean effects of the events as different 'cohorts' in each year. Third, the calendar average effect, that can be considered as the reciprocal of the group average effect. This scheme calculates the mean effect in each period based on all previous events. Fourth, the dynamic scheme estimates the effects for each period relative to that when the treatment took place. This allows researchers to define a time window and calculate pre- and post-treatment effects during the corresponding interval. Consequently, dynamic average effects can provide insights of long-run impacts, as well as mean effects before the treatment, which may serve as a test for the presence of pre-existing trends. In the present paper, we are setting the time window to span 10 years before and after a mass shooting, and calculating pre-treatment effects by using the preceding period to the mass shooting, $g-1$, as the reference point.

This approach aligns with the calculation method in the dynamic TWFE specification, where the omitted dummy corresponds to $g-1$.

Lastly, in order to maintain consistency with the staggered treatment approach, we find it more rigorous from a methodological point of view to exclude those units that experienced a mass shootings before the start of our sample period. Although the number of these units is relatively small, their inclusion could potentially distort the analysis by considering repeatedly affected units as if they were treated for the first time. As mentioned in Section 3, our sample period covers the years 2003 to 2019, comprising 274 incidents. Therefore, we are excluding those units that suffered an attack between 1966 and 2003, resulting in 171 counties, 265 ZCTAs, and 271 census tracts suffering their first mass shooting during our sample period[10].

5 The impact of mass shootings on employment

Our primary objective is to analyze how mass shootings affect employment at different levels of geographical disaggregation. With this aim, we employ the natural logarithm of total employment as the dependent variable. In what follows, we present two specifications for the estimation of the effects: (i) an unconditional approach, that involves conducting raw comparisons between affected and non-affected areas; and (ii) a conditional specification, grounded on the comprehensive set of variables detailed in Section 5, in order to conduct a more restricted and targeted assessment.

[Insert Table 1 about here]

Table 1 presents the average estimation results from each grouping scheme outlined in the previous section, for the three spatial units analyzed, and both the unconditional and conditional specifications. One notable finding is that, in the case of counties, the use of the unconditional specification appears to be inappropriate due to the presence of pre-existing trends, as reflected by the significant value of the average effects before the attacks. Moreover, results for ZCTAs and census tracts show a more pronounced effect

[10] The estimation has been carried out using the 'csdid' Stata module developed by Rios–Avila, Sant'Anna, and Callaway (2021) that, compared to the 'did' R package (Callaway and Sant'Anna, 2021b), has the advantage of not requiring a balanced sample. To do so, 'csdid' considers all possible 2x2 specific combinations for each estimation procedure, thereby minimizing the loss of information when panels are not strongly balanced.

in the context of the conditional specification than in the unconditional one. This implies that the impact of mass shootings becomes more evident when areas with similar characteristics are compared. However, despite the influence of mass shootings on employment is negative in all geographic entities, estimated ATTs are only statistically significant in census tracts. This finding is in line with the theoretical framework developed in Section 2.2, as workers are expected to be more mobile at this level of geographical disaggregation.

[Insert Figure 4 about here]

The group average effect – representing the mean impact by year of occurrence – shows that mass shootings lead to an approximate 9.5% employment reduction at the census tract level. Calendar effects indicate a yearly mean reduction of 10.6%. The simple average effect, interpreted as the gross mean impact across all shootings and years, estimates a 13.4% employment reduction in affected census tracts[11]. The dynamic effects, considering a ten-year window before and after incidents, show an average yearly reduction of 14.8%. As shown in Figure 4, the pre-attack employment evolution shows significant differences between unconditional and conditional specifications at the county level. Furthermore, dynamic effects indicate persistent and cumulative employment reductions in census tracts. According to the theoretical framework, this suggests that agglomeration economies play a significant role in transmitting the negative effects of mass shootings on employment. The initial job displacements, although moderate, appear to reduce local economic activity, thereby triggering subsequent reductions.

5.1 Economic activities

Section 2.1 provides evidence indicating that some economic activities are particularly vulnerable to violent shocks. Additionally, theoretical discussions on the response of the non-tradable sector to such events imply that services heavily dependent on direct interaction with the public are likely to be more adversely affected. Taking advantage of the disaggregation of employment data at the 2-digits NAICS code, we are checking whether

[11] A rough estimation of these figures considers that the mean number of employed persons in census tracts is $1,805$; see Table 1. Thus, a mass shooting occurring in a random census tract would result in a loss – or relocation – of, approximately, 242 jobs.

this is the case in the present context by conducting a separate analysis for the employment in the retail trade (NAICS 44-45); arts, entertainment, and recreation (NAICS 71); and accomodation and food services (NAICS 72) sectors. While the public character of the retail trade sector is evident, it also encompasses subsectors like grocery stores or supermarkets, which provide essential goods that remain necessary even after violent events. NAICS codes 71 and 72 include businesses related to museums or artistic events, sport events, or restaurants and hotels, that are expected to be more vulnerable to massive shootings.

[Insert Table 2 about here]

Estimation results are reported in Table 2, both for the unconditional and conditional specifications. It is worth noting that the latter incorporates employment share per sector to capture specialization and control for the potential existence of employment clusters. The first noteworthy result is that the negative effect of mass shootings is statistically significant for the retail trade and arts, entertainment, and recreation sectors in ZCTAs, indicating a higher vulnerability of these economic activities. Specifically, the retail trade sector shows a 3.8% employment reduction on simple average, with a slightly higher calendar effect of 5.3%, also displaying persistence as shown by the post-treatment average effects. The arts, entertainment, and recreation sector shows a more pronounced reduction, being negative and significant independently of the grouping scheme, estimating an 8.7% reduction on a simple average basis. At the census tract level, the retail sector does not show significant effects and, strikingly, affected units exhibit a positive pre-trend in employment when using the conditional specification. However, the accommodation and food services sector shows a greater adverse effect than the estimation for overall employment, regardless of the grouping scheme. The arts, entertainment, and recreation sector shows a pronounced decrease, reaching a simple average reduction of 17.5% and exceeding 19% in calendar and post-treatment averages. In summary, these results show that sectors involving close public interaction are particularly sensitive to mass shootings.

5.2 Employment composition

As outlined in Section 2.2, there exists the possibility that different groups of workers exhibit varying degrees of mobility and/or their productivity may be distinctly impacted by adverse shocks. Moreover, some studies reviewed in Section 2.1 suggest that the most skilled or qualified workers are particularly susceptible to violent attacks. We have investigated these issues by analyzing the changes in the shares of employment by wage and educational attainment levels after massive shootings. To do so, we have considered the share of workers that belong to three wage ranks – less than 1,250$/month, between 1,250 and 3,333$/month, and more than 3333$/month – and to three categories of education: less than high school, with high school or associate's degree, and with bachelor's degree or higher.

[Insert Tables 3 and 4 about here]

Table 3 reports the results for changes in the composition of employment by wages. These figures show that, besides a modest increase in the proportion of lower-paid jobs at the county level, there appears to be no significant effect of mass shootings on the wage employment composition. Table 4 provides the insights about the changes induced by the attacks on employment by educational attainment. The presence of pre-existing trends in the shares of workers with different levels of education cannot be entirely ruled out in counties, even when those with similar characteristics are compared. There is a slight increase (decrease) in the share of workers with no high school completion (bachelor's or higher degree) in ZCTAs. If we consider the group average effect in census tracts, we observe a small reduction in the proportion of highly educated workers. In summary, both sets of results indicate that changes in the composition of employment prompted by mass shootings, although taking place at broader levels than employment reductions, are minor. This complicates the interpretation of differences in mobility among worker groups, and the relative reduction in their productivity due to the shock.

5.3 Mass public shootings

The 'fear hypothesis' (Becker and Rubinstein, 2011) establishes that the more random and violent is an attack, the greater should be its influence on the behavior of individuals.

In order to test this prediction in the present context, we have focused on a subsample of 118 mass shootings[12] that occurred in public spaces; i.e., 'mass public shootings' (Duwe, 2020). While our definition encompasses a range of incidents, including 'familicides', mass public shootings are characterized by their indiscriminate nature, that typically results in a higher number of fatalities. On average, the mass public shootings included in our sample involve more than seven victims, compared to an overall mean of less than five. Therefore, if the 'fear hypothesis' applies in this type of violent attack, we should find greater effects than those estimated using the full sample.

[Insert Table 5 about here]

The figures reported in Table 5 corroborate the lack of significance of the effects of mass shootings on employment at the county and ZCTA levels. However, and regardless of the grouping scheme applied, the estimated impact in census tracts is larger than those obtained from the analysis with the entire sample. Focusing on the conditional specification, the average group effect is 11.2% (compared to 9.4%), the average calendar effect is 12.1% (10.6%), and the simple average effect is 16.6% (13.4%). Furthermore, the average dynamic effect ten years after the attacks is 19.3% (14.8%), indicating a higher persistence of the impact. These findings back up our initial idea that the more indiscriminate and violent is a mass shooting, the more adverse its effect on employment.

6 Mass shootings and housing prices

The limited avalability of population data with a yearly frequency restricts our understanding of the demographic response to mass shootings. Nevertheless, we are able to analyze the potential effects of these incidents on the residential attractiveness of the areas where they are perpetrated. A decline in housing prices does not necessarily entail a reduction in total population. Indeed, according to the theoretical framework, this effect acts as an equalizer mechanism to the utility derived from living in these areas. As described in Section 3.2, the HPI that is being analyzed has been calculated through repeated sales, including transactions that involve the same property within the same time period. This methodology boasts the advantage of incorporating both housing stock

[12] This figure increases to 216 if the period from 1996 to 2021 is considered.

quality and neighborhood externalities that influence prices. However, this data source presents a limitation with regards to the number of complete panels that it provides, because the HPI computation is not possible when there is an insufficient number of repeated sales. As a consequence, the analysis carried out in this section refers to 187 mass shootings. The conditional specification controls for the urban/rural character of the unit, the housing stock, as well as its density and vacant share, and the commuting time of the residents. This last variable seems pertinent given that mass shootings influence the location of employment, which is a factor correlated with housing prices.

[Insert Table 6 about here]

Table 6 shows the results for the estimated response of the HPI to the occurence of mass shootings. Once again, the conditional specification appears to better capture their effects – especially in the case of counties – as it mitigates the pre-existing trends observed in the unconditional analysis. The attacks exert a modest negative average effect at the county level when grouped by calendar time, whereas no discernible impact is found when alternative grouping schemes are employed. This outcome is consistent with the dynamics plotted in graphic (d) of Figure 5, where cumulative effects become statistically different from zero at the end of the 10-year window. No significant impact is obtained at the ZCTA level and, in line with the results presented in Section 5, the most pronounced influence is found in census tracts. Taking into account the conditional specification that tries to control for employment reductions, the simple average effect induced by mass shootings on the HPI implies a reduction of 6.6. This effect is also persistent, as the average annual HPI decrease after an attack is 7.9. Unlike the estimation result for employment, the impact of mass shootings on census tracts – depicted in graphics (e) and (f) of Figure 5 – is persistent but not cumulative. The academic literature on 'filtering' explains that declining housing prices lead to properties being occupied by lower-income families (Rosenthal, 2014). Given that the HPI is a repeated sales index, derived from transactions of properties that have actually been sold, this results suggests that this type of process is at play in our context. Consequently, the reduced aggregate income in census tracts after experiencing a mass shooting may be precipitating negative externalities that elucidate the persistent and, in the case of employment, cumulative estimated effects.

[Insert Figure 5 about here]

7 Concluding remarks

This paper deals with the impact of mass shootings in three U.S. geographic entities: counties, ZCTAs, and census tracts. With this aim, we establish a theoretical framework using an extension of the Rosen-Roback model that accounts for mobility frictions in local labor markets. This framework predicts that violent shocks reduce amenities and labor productivity, leading to workers displacements and housing prices reductions, in an extent that depends on the degree of labor force mobility. Furthermore, these reductions could be cumulative if agglomeration economies are influential, and there may be heterogeneous impacts on different types of workers and economic sectors.

Using recent advances in DiD estimation methods, we have obtained evidence that mass shootings lead to significant and persistent employment reductions in attacked census tracts. We also find that those economic activities that rely more heavily on face-to-face interactions experience a greater number of job losses after a mass shooting, and that these incidents slightly affect the composition of employment by wage and educational attainment levels. Furthermore, those attacks that are conducted in public spaces, characterized by their indiscriminate and violent nature, seem to exert more pronounced impacts. In addition, we have explored whether mass shootings affect the desirability for living in the affected areas, finding a negative effect on housing prices at the census tract level. The adverse economic effects of mass shootings are concentrated in the vicinity of their occurence, consistent with the hypothesis that workers are more mobile with respect to these smaller areas. Our study also suggests that agglomeration economies and externalities significantly influence how these effects translate across local economies, causing the initial impact to cumulate over time.

To conclude, it is worth noting that our study is not without limitations. The primary restriction is data availability, such that the lack of yearly residential information limits our ability to determine whether the scale of population movements compares to those of employment. A second limitation is the impossibility to track where displaced jobs relocate. If employment shifts from a census tract to another location within the same county, this could explain the lack of significant effects observed at this level of geographical disaggregation. Further research is needed to explore the possible presence of spillovers in this context. The implementation of DiD techniques accounting for spatial effects could provide valuable insights in this regard.

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Tables and figures

Table 1: Mass shootings average effects on employment.

	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	0.0133 **	0.0016	-0.0050	-0.0104	-0.0968 ***	-0.0993 ***
	(0.0057)	(0.0055)	(0.0131)	(0.0125)	(0.0254)	(0.0262)
Calendar	0.0052	-0.0009	-0.0184	-0.0170	-0.1153 ***	-0.1114 ***
	(0.0066)	(0.0064)	(0.0168)	(0.0158)	(0.0300)	(0.0319)
Simple	0.0080	-0.0024	-0.0178	-0.0224	-0.1404 ***	-0.1434 ***
	(0.0077)	(0.0072)	(0.0190)	(0.0183)	(0.0348)	(0.0364)
Dynamic:						
Pre-treatment	-0.0204 **	-0.0074	0.0164	0.0125	0.0050	0.0115
	(0.0082)	(0.0076)	(0.0160)	(0.0156)	(0.0260)	(0.0257)
Post-treatment	0.0055	-0.0050	-0.0188	-0.0247	-0.1555 ***	-0.1601 ***
	(0.0088)	(0.0082)	(0.0216)	(0.0215)	(0.0397)	(0.0417)

Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002 - 2019. *p<0.1, **p<0.05, ***p<0.01.

Table 2: Mass shootings average effects on employment by NAICS code.

	44-45		71		72	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0046	0.0031	0.0177	-0.0096	0.0357 ***	0.0084
	(0.0072)	(0.0093)	(0.0225)	(0.0218)	(0.0080)	(0.0083)
Calendar	-0.0012	-0.0038	-0.0031	-0.0245	0.0369 ***	0.0129
	(0.0108)	(0.0105)	(0.0251)	(0.0218)	(0.0124)	(0.0119)
Simple	0.0005	-0.0042	0.0201	-0.0152	0.0393 ***	0.0038
	(0.0100)	(0.0102)	(0.0270)	(0.0257)	(0.0108)	(0.0107)
Dynamic:						
Pre-treatment	-0.0123	-0.0057	-0.0285	0.0043	-0.0509 ***	-0.0124
	(0.0106)	(0.0102)	(0.0216)	(0.0212)	(0.0133)	(0.0128)
Post-treatment	0.0006	-0.0038	0.0203	-0.0179	0.0404 ***	0.0028
	(0.0103)	(0.0108)	(0.0271)	(0.0264)	(0.0110)	(0.0112)
ZCTAs						
Group	0.0042	-0.0110	-0.0363	-0.0613 **	-0.0115	-0.0177
	(0.0161)	(0.0141)	(0.0277)	(0.0284)	(0.0180)	(0.0168)
Calendar	-0.0322	-0.0540 **	-0.0835 *	-0.1005 **	-0.0002	-0.0165
	(0.0296)	(0.0264)	(0.0428)	(0.0425)	(0.0504)	(0.0397)
Simple	-0.0164	-0.0394 *	-0.0618	-0.0915 **	-0.0254	-0.0316
	(0.0242)	(0.0201)	(0.0418)	(0.0427)	(0.0299)	(0.0265)
Dynamic:						
Pre-treatment	0.0070	0.0123	0.0215	0.0244	-0.0511 **	-0.0304
	(0.0166)	(0.0172)	(0.0469)	(0.0462)	(0.0218)	(0.0212)
Post-treatment	-0.0111	-0.0362 *	-0.0695	-0.0977 **	-0.0260	-0.0323
	(0.0247)	(0.0215)	(0.0458)	(0.0464)	(0.0292)	(0.0274)
Census tracts						
Group	0.0007	-0.0214	-0.0703	-0.1245 ***	-0.0871 ***	-0.1115 ***
	(0.0272)	(0.0277)	(0.0454)	(0.0450)	(0.0310)	(0.0295)
Calendar	0.0202	-0.0061	-0.1443 ***	-0.2125 ***	-0.1063 ***	-0.1372 ***
	(0.0530)	(0.0563)	(0.0553)	(0.0551)	(0.0385)	(0.0364)
Simple	-0.0128	-0.0413	-0.1148 *	-0.1935 ***	-0.1250 ***	-0.1584 ***
	(0.0403)	(0.0413)	(0.0594)	(0.0597)	(0.0415)	(0.0382)
Dynamic:						
Pre-treatment	0.0425	0.0728 **	0.0269	0.0739	-0.0102	0.0134
	(0.0330)	(0.0337)	(0.0648)	(0.0643)	(0.0351)	(0.0348)
Post-treatment	-0.0128	-0.0423	-0.1308 **	-0.2166 ***	-0.1377 ***	-0.1716 ***
	(0.0445)	(0.0454)	(0.0643)	(0.0626)	(0.0443)	(0.0416)

Notes: 44-45: Retail trade; 71: Arts, entertainment and recreation; 72:Accomodation and food services. (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002 - 2019. *p<0.1, **p<0.05, ***p<0.01.

Table 3: Mass shootings average effects on employment composition by wage level.

	Low		Medium		High	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0053 ***	0.0017	0.0003	-0.0008	-0.0056 ***	-0.0008
	(0.0011)	(0.0011)	(0.0014)	(0.0015)	(0.0017)	(0.0017)
Calendar	0.0068 ***	0.0018	-0.0021	-0.0018	-0.0046 **	-0.0001
	(0.0017)	(0.0014)	(0.0022)	(0.0022)	(0.0019)	(0.0020)
Simple	0.0091 ***	0.0033 **	-0.0017	-0.0026	-0.0074 ***	-0.0007
	(0.0016)	(0.0015)	(0.0021)	(0.0022)	(0.0023)	(0.0023)
Dynamic:						
Pre-treatment	-0.0067 ***	-0.0006	0.0047 **	0.0025	0.0020	-0.0018
	(0.0017)	(0.0014)	(0.0020)	(0.0020)	(0.0026)	(0.0026)
Post-treatment	0.0101 ***	0.0037 **	-0.0014	-0.0024	-0.0087 ***	-0.0012
	(0.0016)	(0.0017)	(0.0022)	(0.0023)	(0.0025)	(0.0026)
ZCTAs						
Group	0.0046 *	0.0016	-0.0034	-0.0035	-0.0012	0.0019
	(0.0025)	(0.0024)	(0.0028)	(0.0027)	(0.0027)	(0.0026)
Calendar	0.0024	-0.0012	-0.0030	-0.0012	0.0006	0.0024
	(0.0059)	(0.0058)	(0.0059)	(0.0058)	(0.0029)	(0.0027)
Simple	0.0064 *	0.0014	-0.0046	-0.0032	-0.0018	0.0018
	(0.0037)	(0.0036)	(0.0043)	(0.0042)	(0.0035)	(0.0033)
Dynamic:						
Pre-treatment	-0.0051 *	0.0001	0.0044	0.0034	0.0007	-0.0035
	(0.0026)	(0.0027)	(0.0028)	(0.0028)	(0.0027)	(0.0026)
Post-treatment	0.0070 *	0.0016	-0.0041	-0.0028	-0.0029	0.0012
	(0.0038)	(0.0038)	(0.0043)	(0.0042)	(0.0037)	(0.0035)
Census tracts						
Group	0.0034	0.0040	-0.0014	0.0013	-0.0020	-0.0053
	(0.0035)	(0.0036)	(0.0033)	(0.0033)	(0.0044)	(0.0044)
Calendar	-0.0017	-0.0008	-0.0017	0.0024	0.0033	-0.0016
	(0.0056)	(0.0060)	(0.0057)	(0.0059)	(0.0047)	(0.0048)
Simple	0.0035	0.0052	-0.0036	-0.0002	0.00005	-0.0051
	(0.0049)	(0.0051)	(0.0048)	(0.0049)	(0.0058)	(0.0058)
Dynamic:						
Pre-treatment	-0.0018	-0.0034	0.0048	0.0037	-0.0030	-0.0003
	(0.0042)	(0.0042)	(0.0039)	(0.0039)	(0.0042)	(0.0043)
Post-treatment	0.0044	0.0065	-0.0030	0.0004	-0.0014	-0.0068
	(0.0054)	(0.0057)	(0.0050)	(0.0052)	(0.0066)	(0.0067)

Notes: Low: <1250$/month; Medium: 1250-3333$/month; High: >3333$/month. (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002 - 2019. *p<0.1, **p<0.05, ***p<0.01

Table 4: Mass shootings average effects on employment composition by educational attainment.

	(A)		(B)		(C)	
	(1)	(2)	(1)	(2)	(1)	(2)
Counties						
Group	0.0028 ***	0.0013 **	0.0002	0.0001	-0.0030 ***	-0.0014 *
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Calendar	0.0025 ***	0.0012 **	0.0002	0.0001	-0.0028 ***	-0.0012
	(0.0006)	(0.0006)	(0.0009)	(0.0010)	(0.0010)	(0.0010)
Simple	0.0033 ***	0.0015 **	0.0006	0.0004	-0.0039 ***	-0.0020 *
	(0.0007)	(0.0006)	(0.0010)	(0.0010)	(0.0011)	(0.0012)
Dynamic:						
Pre-treatment	-0.0052 ***	-0.0017 **	-0.0020 *	-0.0012	0.0072 ***	0.0029 ***
	(0.0009)	(0.0007)	(0.0012)	(0.0011)	(0.0009)	(0.0009)
Post-treatment	0.0043 ***	0.0020 ***	0.0007	0.0004	-0.0050 ***	-0.0024
	(0.0009)	(0.0007)	(0.0012)	(0.0013)	(0.0015)	(0.0015)
ZCTAs						
Group	0.0040 ***	0.0016 *	-0.00001	0.0006	-0.0040 ***	-0.0021
	(0.0008)	(0.0008)	(0.0014)	(0.0015)	(0.0014)	(0.0014)
Calendar	0.0040 ***	0.0020	0.0007	0.0007	-0.0047 **	-0.0027
	(0.0012)	(0.0013)	(0.0024)	(0.0025)	(0.0024)	(0.0023)
Simple	0.0049 ***	0.0020 *	0.0010	0.0014	-0.0059 ***	-0.0034 *
	(0.0010)	(0.0010)	(0.0022)	(0.0022)	(0.0021)	(0.0021)
Dynamic:						
Pre-treatment	-0.0039 **	-0.0001	0.0012	0.0017	0.0028	-0.0016
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0017)	(0.0017)
Post-treatment	0.0061 ***	0.0025 *	0.0016	0.0023	-0.0077 ***	-0.0048 *
	(0.0013)	(0.0013)	(0.0028)	(0.0028)	(0.0026)	(0.0025)
Census tracts						
Group	0.0031	0.0031	0.0033	0.0032	-0.0064 **	-0.0062 **
	(0.0022)	(0.0022)	(0.0034)	(0.0034)	(0.0028)	(0.0028)
Calendar	0.0021	0.0023	0.0028	0.0030	-0.0049	-0.0052
	(0.0021)	(0.0021)	(0.0039)	(0.0039)	(0.0040)	(0.0040)
Simple	0.0033	0.0033	0.0026	0.0026	-0.0059	-0.0060
	(0.0024)	(0.0024)	(0.0044)	(0.0043)	(0.0039)	(0.0039)
Dynamic:						
Pre-treatment	0.0015	0.0017	0.0021	0.0024	-0.0036	-0.0041
	(0.0024)	(0.0025)	(0.0042)	(0.0042)	(0.0038)	(0.0039)
Post-treatment	0.0052	0.0053	-0.0005	-0.0003	-0.0047	-0.0050
	(0.0037)	(0.0038)	(0.0077)	(0.0077)	(0.0056)	(0.0056)

Notes: : (A) Less than high school; (B) High school or associate's degree; and (C) Bachelor degree or higher. (1) Unconditonal especification. (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,686 census tracts during the period 2009 -2019. *p<0.1, **p<0.05, ***p<0.01.

Table 5: Mass public shootings average effects on employment.

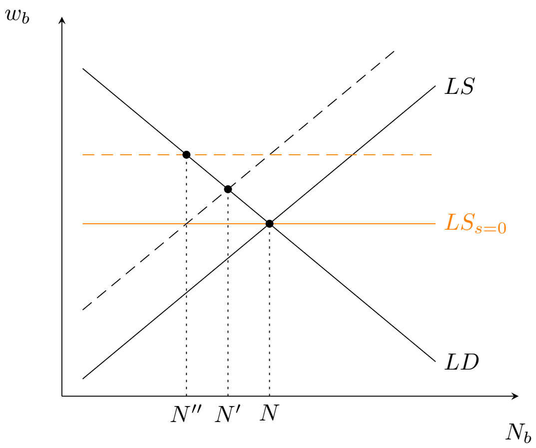
	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	0.0258 ***	0.0036	-0.0008	-0.0221	-0.1078 ***	-0.1192 ***
	(0.0089)	(0.0085)	(0.0253)	(0.0247)	(0.0359)	(0.0400)
Calendar	0.0178 *	0.0036	-0.0047	-0.0214	-0.1238 ***	-0.1290 **
	(0.0100)	(0.0085)	(0.0314)	(0.0302)	(0.0446)	(0.0511)
Simple	0.0239 *	0.0027	-0.0051	-0.0322	-0.1643 ***	-0.1818 ***
	(0.0124)	(0.0113)	(0.0376)	(0.0368)	(0.0553)	(0.0626)
Dynamic:						
Pre-treatment	-0.0296 **	-0.0084	-0.0006	0.0038	-0.0205	-0.0030
	(0.0130)	(0.0149)	(0.0209)	(0.0208)	(0.0395)	(0.0404)
Post-treatment	0.0205	-0.0002	-0.0051	-0.0338	-0.1938 ***	-0.2154 ***
	(0.0144)	(0.0130)	(0.0434)	(0.0440)	(0.0638)	(0.0732)

Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 3,145 counties, 32,817 ZCTAs, and 72,698 census tracts during the period 2002 -2019. *p<0.1, **p<0.05, ***p<0.01.

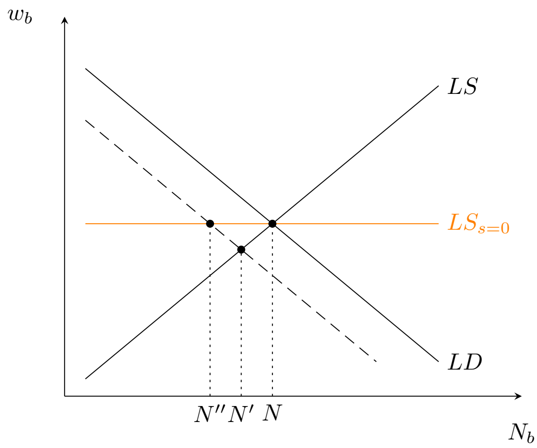
Table 6: Mass shootings average effects on housing prices.

	Counties		ZCTAs		Census tracts	
	(1)	(2)	(1)	(2)	(1)	(2)
Group	3.5065	-0.5464	9.3597 **	1.1565	-5.5529 **	-2.8585
	(5.1668)	(5.9658)	(4.4792)	(4.0258)	(2.3587)	(2.1976)
Calendar	-12.0485 *	-7.4777	-4.3903	-9.3781 *	-9.0213 ***	-6.5239 **
	(6.9372)	(6.9854)	(5.2186)	(4.8848)	(3.0244)	(2.8925)
Simple	-7.4039	-5.7386	4.7788	-1.8398	-9.1340 ***	-6.6226 **
	(8.0106)	(8.2151)	(6.1173)	(5.6819)	(3.3530)	(3.1855)
Dynamic:						
Pre-treatment	-7.8290 *	-0.4801	-8.7035	-0.7818	1.0356	0.6265
	(4.5960)	(4.3884)	(5.4185)	(5.2142)	(2.7158)	(2.5883)
Post-treatment	-9.6050	-7.1062	7.9992	0.8244	-10.2959 ***	-7.9462 **
	(8.6114)	(8.7128)	(7.2541)	(6.8742)	(3.5739)	(3.4266)

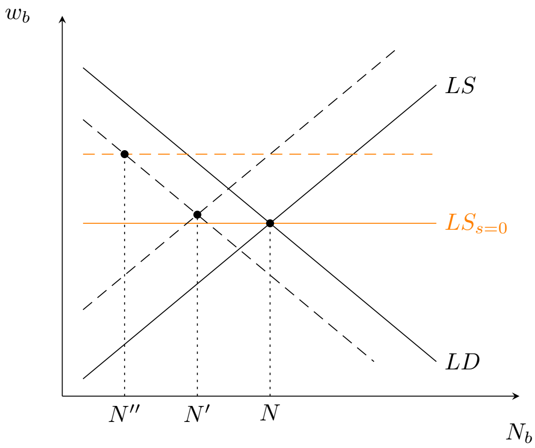
Notes: (1) Unconditonal especification; (2) Conditional especification. The sample covers 2,773 counties, 18,891, ZCTAs and 63,747 census tracts during the period 2002 - 2019. *p<0.1, **p<0.05, ***p<0.01.



(a) Amenity shock (∇A_b)

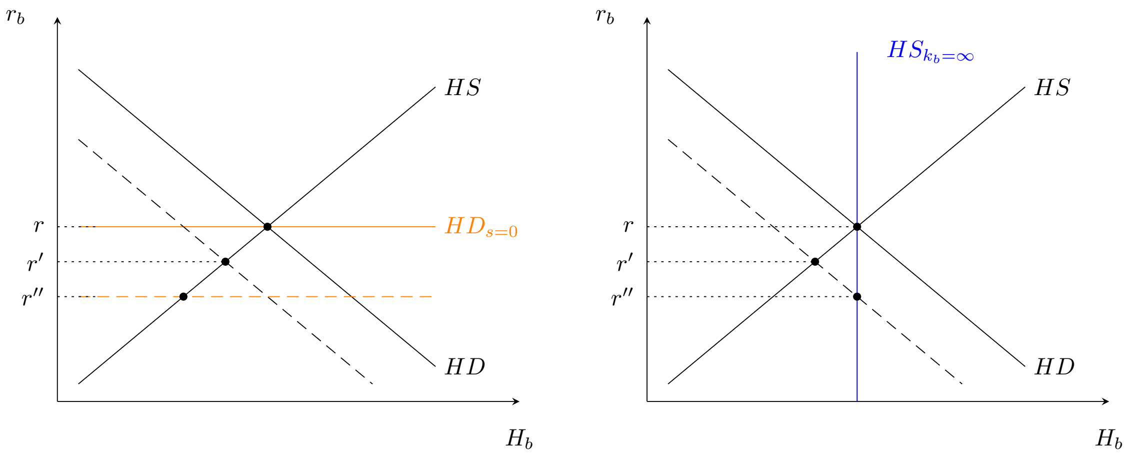


(b) Productivity shock (∇X_b)



(c) Both shocks ($\nabla A_b + \nabla X_b$)

Figure 1: Shocks to the local labor market



(a) Perfect vs. imperfect mobility of workers **(b)** Elastic vs. inelastic housing supply

Figure 2: Shock to the local housing demand

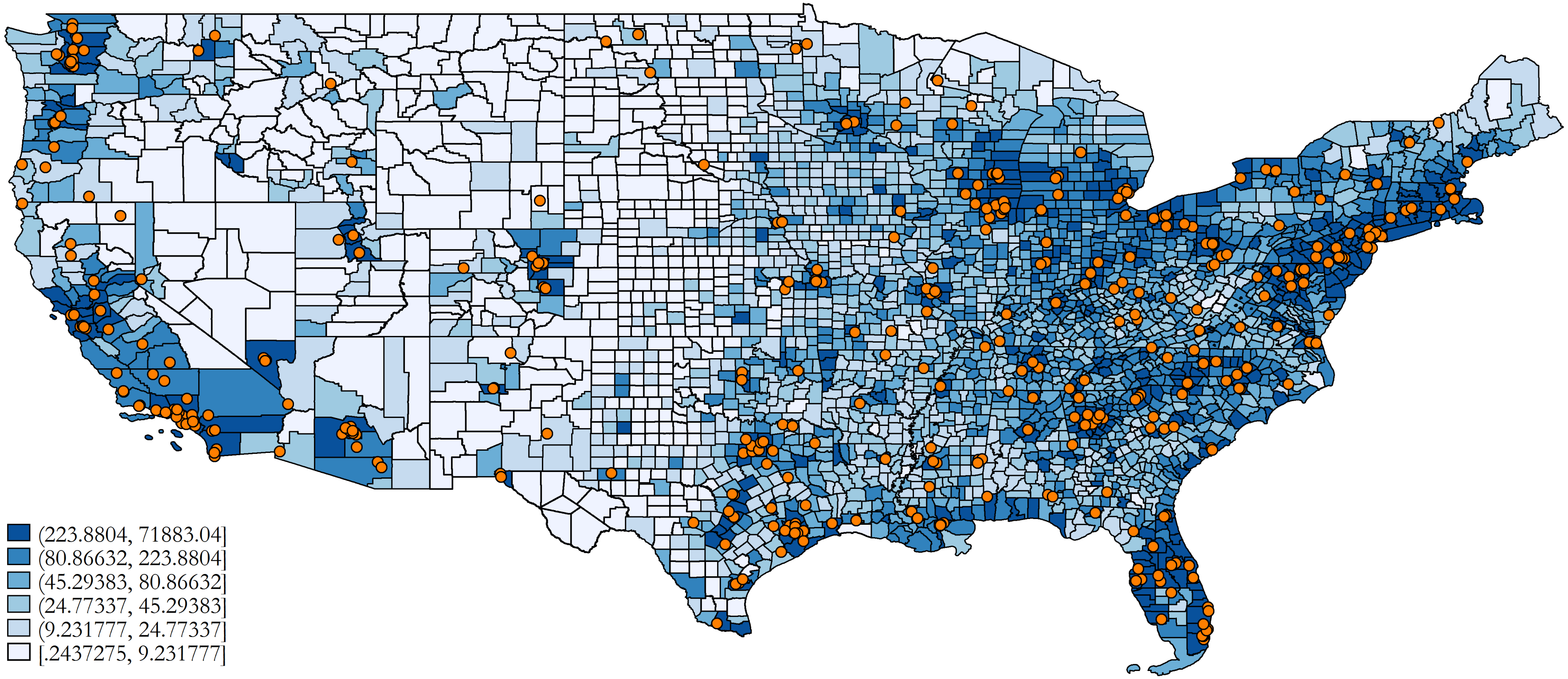
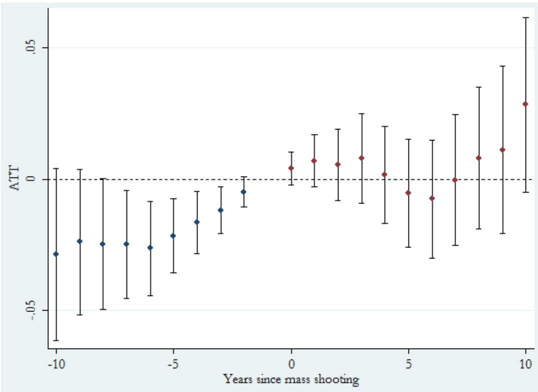
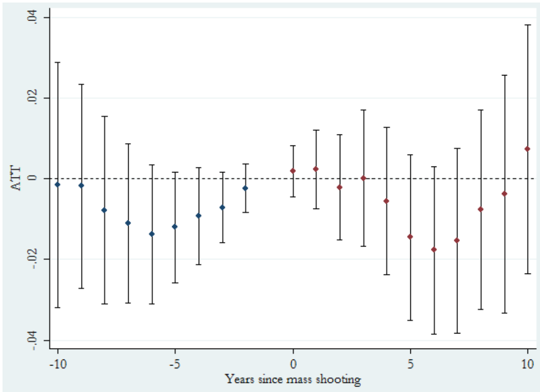


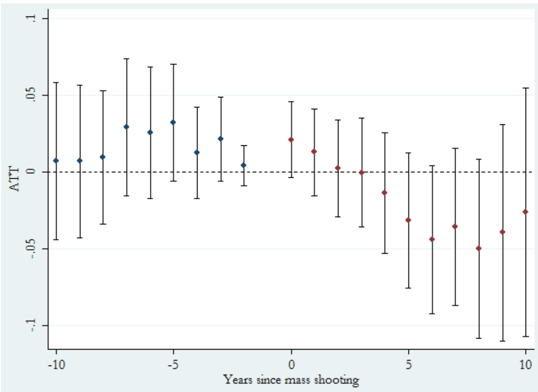
Figure 3: Mass shootings location (dots) and population density. U.S. counties, 1966–2021.



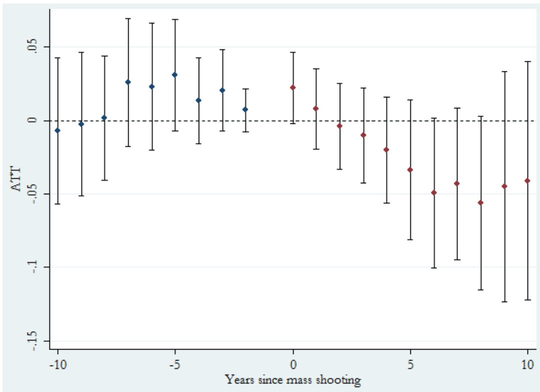
(a) Counties - Unconditional



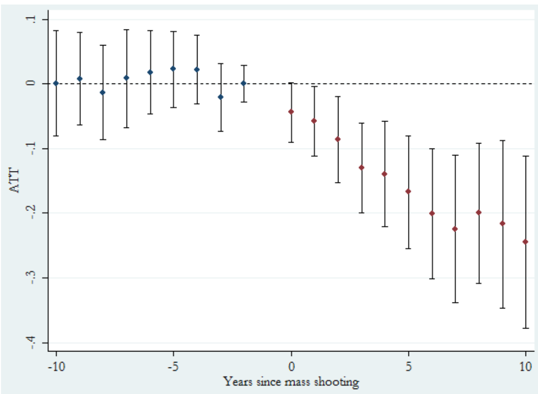
(b) Counties - Conditional



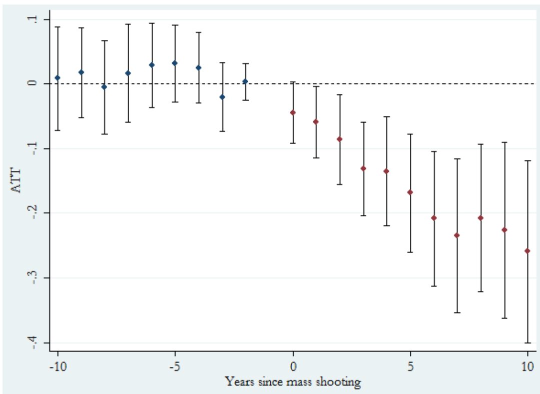
(c) ZCTAs - Unconditional



(d) ZCTAs - Conditional

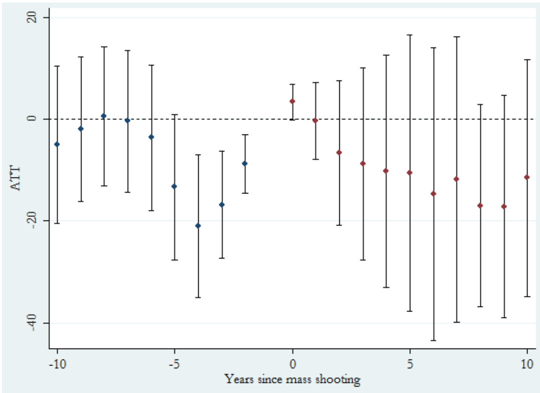


(e) Census tracts - Unconditional

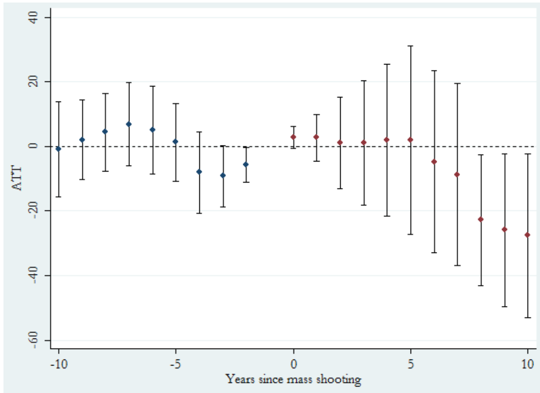


(f) Census tracts - Conditional

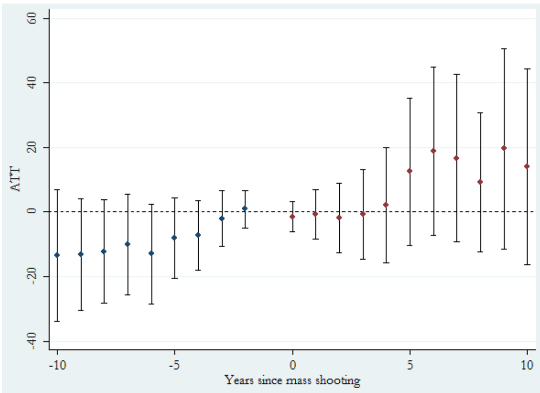
Figure 4: Dynamic average effects of mass shootings on employment.



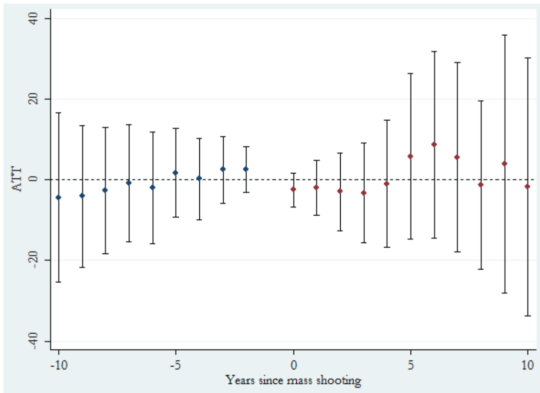
(a) Counties - Unconditional



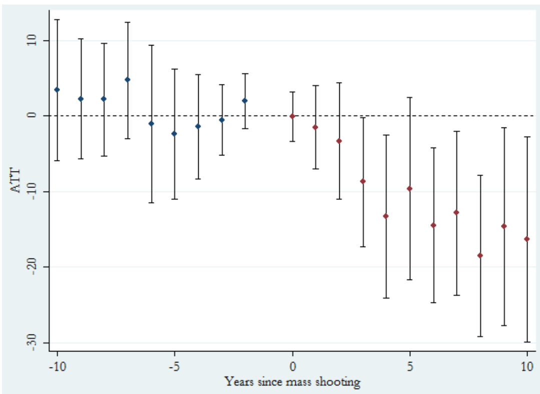
(b) Counties - Conditional



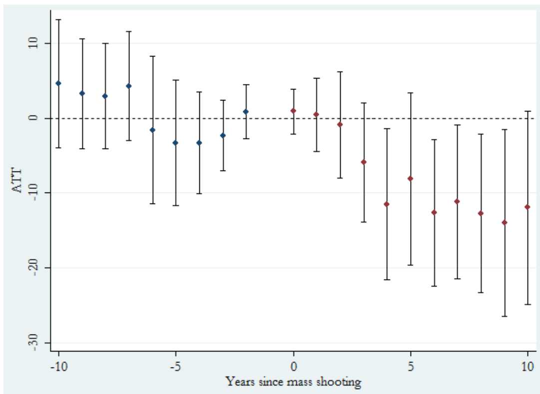
(c) ZCTAs - Unconditional



(d) ZCTAs - Conditional



(e) Census tracts - Unconditional



(f) Census tracts - Conditional

Figure 5: Dynamic average effects of mass shootings on housing prices.

Appendix

Table A1: Descriptive statistics for employment and housing prices, 2003–2019.

	Counties		ZCTAs		Census tracts	
	All	Affected	All	Affected	All	Affected
Total employment	41,471.86	161,434.70	4,133.61	15,450.15	1,805.17	6,486.34
	(149,565.80)	(195,857.40)	(8,587.62)	(19,989.05)	(3,718.51)	(15,138.97)
NAICS:						
44-45: Retail trade	4,733.03	18,302.56	471.75	1,442.55	206.02	366.7
	(15,406.89)	(21,075.49)	(979.10)	(1,755.01)	(403.10)	(626.82)
71: Arts, entertainment, and recreation	717.11	3,032.79	71.48	338.12	31.21	215.26
	(3,281.71)	(6,229.46)	(370.01)	(1,342.66)	(224.42)	(1,293.35)
72: Accomodation and food services	3,699.26	14,116.56	368.71	1,716.58	161.02	547.84
	(13,706.53)	(17,794.33)	(1,048.85)	(6,479.38)	(489.64)	(1,699.83)
Wage level (%):						
Low (<1250$/month)	30.64	28.34	32.5	27.91	31.66	29.14
	(6.92)	(5.55)	(15.64)	(9.51)	(12.32)	(12.10)
Medium (1250–3333$/month)	41.12	39.08	39.17	38.87	38.79	39.07
	(6.65)	(5.81)	(13.15)	(7.90)	(9.40)	(9.62)
High (>3333$/month)	28.24	32.59	28.33	33.22	29.55	31.8
	(10.28)	(9.71)	(16.47)	(13.74)	(14.57)	(16.05)
Educational attainment[1] (%):						
Less than high school	12.26	12.83	12.83	14.05	14.27	14.38
	(4.20)	(4.52)	(7.93)	(5.82)	(6.62)	(6.80)
High school or associate's degree	66.02	62.28	64.76	60.61	60.52	60.9
	(4.97)	(5.24)	(10.93)	(6.59)	(8.12)	(7.63)
Bachelor degree or higher	21.73	24.88	22.41	25.34	25.21	24.72
	(4.92)	-5.55	(10.21)	(7.63)	(8.55)	(8.49)
House price index	261.72	375.08	274.16	347.71	224.24	211.88
	(169.44)	(209.36)	(221.90)	(262.21)	(133.08)	(122.66)

Notes: This table reports average values and their corresponding standard deviations in parentheses. [1] This data is only available for the period 2009 - 2019.

Table A2: Descriptive statistics for control variables, 2003–2019.

	Counties		ZCTAs		Census tracts	
	All	Affected	All	Affected	All	Affected
Population:						
Total population	94,439.06 (304,949.80)	345,604.90 (398,692.30)	9,350.10 (13354.65)	24,395.19 (17476.76)	4,085.61 (1819.41)	4,442.25 (2,257.84)
Population density[1]	248.61 (1714.38)	703.50 (1,599.10)	1,231.72 (4,829.31)	2,425.64 (3,723.31)	5,181.56 (11,657.09)	3,295.83 (5,178.85)
Urban/rural status:						
Urbanized area[2] (%)	21.75 (41.26)	64.16 (47.96)	30.56 (46.06)	69.89 (45.88)	69.67 (45.97)	67.62 (46.80)
Urban cluster[3] (%)	17.69 (38.16)	12.02 (32.53)	10.11 (30.14)	11.38 (31.76)	10.06 (30.08)	9.49 (29.31)
Rural area (%)	60.56 (48.87)	23.82 (42.60)	59.06 (49.17)	18.74 (39.02)	20.12 (40.09)	22.89 (42.01)
Socio-economic characteristics:						
Whites (%)	83.93 (16.29)	77.79 (13.80)	84.09 (20.24)	70.95 (23.98)	66.27 (30.03)	62.65 (29.53)
Blacks (%)	8.73 (14.35)	11.53 (12.12)	7.58 (15.77)	15.50 (21.83)	13.77 (22.37)	15.36 (23.35)
Hispanics (%)	7.38 (12.77)	11.44 (14.82)	7.68 (14.54)	15.48 (20.79)	13.81 (20.18)	16.23 (23.04)
<21 years old (%)	29.70 (4.02)	30.71 (3.67)	27.28 (6.80)	28.77 (7.65)	29.99 (7.93)	29.81 (9.32)
22-64 years old (%)	51.70 (3.39)	52.87 (3.20)	57.47 (5.88)	58.52 (7.21)	56.76 (6.89)	57.68 (8.81)
>65 years old (%)	18.61 (4.78)	16.42 (4.68)	15.25 (6.46)	12.71 (5.48)	13.25 (7.36)	12.51 (6.21)
Less than high school (%)	19.31 (8.46)	17.39 (7.40)	17.16 (11.30)	18.81 (11.58)	17.31 (12.87)	20.20 (13.27)
High scool or associate degree (%)	62.79 (7.20)	59.37 (6.71)	62.33 (12.46)	57.21 (11.18)	57.08 (13.08)	57.25 (12.35)
Bachelor degree or higher (%)	17.90 (8.37)	23.24 (9.61)	20.51 (14.84)	23.98 (15.61)	25.61 (17.82)	22.56 (16.38)
Per capita income	20,762.14 (5,635.86)	23,148.82 (6,104.04)	23,123.63 (11,337.50)	23,162.71 (9,820.92)	24,738.56 (13,083.82)	22,498.96 (11,181.62)
Poverty rate (%)	15.32 (6.50)	14.50 (5.76)	13.50 (9.55)	16.91 (11.26)	14.59 (12.07)	19.07 (14.13)
Housing stock:						
Total housing units	45,003.69 (124,847.40)	145,566.10 (164,225.30)	6,176.74 (5,839.43)	11,119.18 (6,411.21)	1,571.99 (583.39)	1,658.09 (592.97)
Housing density[4]	123.60 (862.20)	316.29 (738.37)	659.17 (1612.40)	1,065.11 (1,539.14)	1,363.03 (1963.22)	1,147.95 (1,760.82)
Vacant housing units (%)	14.33 (9.45)	11.50 (7.75)	11.26 (11.12)	9.88 (6.54)	8.65 (8.88)	8.91 (6.20)
Commuting times:						
Less than 30 min. to work (%)	69.66 (11.76)	68.80 (11.09)	64.56 (14.83)	67.40 (13.68)	65.72 (15.56)	66.79 (14.65)
30 - 60 min. to work (%)	22.91 (9.10)	23.99 (8.47)	27.29 (11.78)	25.00 (10.72)	26.51 (12.22)	25.30 (11.81)
More than 60 min. (%)	7.43 (4.46)	7.20 (4.42)	8.15 (6.03)	7.60 (5.09)	7.77 (6.55)	7.91 (6.04)

Notes: This table reports average values and their corresponding standard deviations in parentheses. [1]Population per square mile. [2]Most people living in an area with a population greater than 50,000. [3]Most people living in an area with a population between 2,500 and 50,000. [4]Housing units per square mile.