THE COST OF PUBLIC MISTRUST: THE INDIRECT IMPACT OF MASS SHOOTINGS ON HOME VALUES

by

Austin Dey

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Austin Dey

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The following individuals read and discussed the thesis submitted by student Austin Dey, and they evaluated the student's presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

Samia Islam Ph.D.	Chair, Supervisory Committee
Rafael Ribas Ph.D.	Member, Supervisory Committee
Lee Parton Ph.D.	Member, Supervisory Committee

The final reading approval of the thesis was granted by Samia Islam Ph.D., Chair of the Supervisory Committee. The thesis was approved by the Graduate College.

DEDICATION

I dedicate this paper to my wonderful parents, Brian and Karleen. Their unconditional support and love have made me the person I am today. Thank you for always encouraging me to follow my dreams. I love you.

ACKNOWLEDGMENTS

I want to express my utmost gratitude to my committee member, Dr. Rafael Ribas, for his help throughout the process of creating this thesis. Dr. Ribas provided insightful feedback on countless drafts, offered expert advice on research methods, and shared his vast knowledge of econometrics and economic theory, without which this paper would not have been possible. I am also grateful to my remaining committee members, Dr. Samia Islam and Dr. Lee Parton, whose expertise and guidance have been indispensable in shaping my growth as a scholar. Their feedback and constructive criticism helped me improve my research and produce a thesis I am proud of.

ABSTRACT

This thesis examines how mass shootings indirectly impact residential home values across the United States. I hand-collected data on internet search interests around 15 mass shooting events from 2012 to 2019 to measure public concern over mass shootings. Using an event study, I estimate the causal effects of shootings on home values in outlying areas over three years. The results indicate a significant negative relationship between mass shootings and home values two years after an event. This thesis demonstrates that the consequences of mass shootings are not confined to affected areas but have lasting nationwide impacts that reduce economic outcomes across the country.

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LIST OF ABBREVIATIONS

ATF Bureau of Alcohol, Tobacco, Firearm and Explosives

BEA Bureau of Economic Analysis

CBSA Core-Based Statistical Area

FFL Federal Firearm License

TVP The Violence Project

ZHVI Zillow Home Value Index

CHAPTER 1:
INTRODUCTION

The most fundamental role of any form of government is to implement policies that protect the health and well-being of its citizens. When policy fails, public mistrust and fear will soon follow (Delhey & Newton, 2003; Kasperson *et al.*, 1992). Heightened risk perceptions result in an array of public responses that lead to reductions in social cohesion, compliance, and predictability (Breakwell, 2020; Beatty *et al.*, 2019; Aghion *et al.*, 2010). A disastrous policy failure can lead to significant localized social and economic consequences (Davis, 2004; Owens & Ba, 2021; Anderson *et al.*, 2022; Daly *et al.*, 2008). However, when public safety failures repeatedly happen in various locations, how is risk perception impacted nationwide? Moreover, how does the increased risk perception influence people's migration decisions, affecting the residential values of at-risk communities?

A growing risk factor in the minds of suburban families is mass shootings. Mass shootings are extreme acts of gun violence that receive ample nationwide media attention. The frequency of these events has increased considerably over the last three decades; however, they are objectively rare compared to other general gun violence (Lin *et al.*, 2018). While mass shootings account for a small fraction of gun-related deaths in the United States, public risk perceptions of these events are high, with a recent survey indicating that a top fear for Americans is to be a victim of a mass shooting (Bader, 2016).

This thesis studies the economic consequences of the fear of mass shootings. The primary goal is to assess the indirect effects of risk perception triggered by mass shootings on home values in outlying locations. However, the problem with this approach is public fear needs to be identified. Without a measure of risk perception change after events, home value changes cannot be directly attributed to mass shootings.

This issue is addressed using internet search interest one week before and after an event to identify the level of risk perception change of a mass shooting. A causal relationship between search interest and home value is established, allowing an estimation of how search changes affect home value changes. Interaction effects between the changes in search interest and location-specific characteristics are estimated to identify the types of areas and people that show the most significant concern and impact on home prices. This interaction creates location-specific signals which determine the extent of the relationship between fear of shootings and home values in varying locations.

Results show areas with high levels of concern experience decreases in home values two years after a mass shooting event. The effect of mass shootings on home values is heterogeneous; for instance, areas with higher incomes show more significant reductions in home values. High densities of federal firearm licenses in locations show evidence of a mitigating effect on fear and its impact on residential values.

These findings suggest that the impacts of mass shootings are not localized. The consequences of these tragedies have significant effects nationwide. Awareness of distant disasters is wide-reaching, and the high information saturation of mass shootings incites a collective risk perception that may cause people to move locations out of fear, regardless of geographic proximity to the event's origin. These findings suggest that the actual cost of mass shootings may be underestimated in prior literature that only estimates the local effects of these incidents.

The present work is closely related to two other studies in which Muñoz-Morales & Singh (2023) and Brodeur & Yousaf (2022) investigate the impact of mass shootings on property values and house prices in the area where the shooting occurred. These studies consistently found that mass shootings significantly decrease home and property values within a one-mile radius of the shooting location. This paper contributes to the prior economic literature by assessing the impact of a mass shooting on home values in outlying areas.

This thesis relates to the work of Bailey *et al.* (2018) in which the authors investigate the economic effects of social interaction online. They find that housing price experiences seen by individuals within their social network can significantly alter their perception and purchasing behaviors of residential property. These changes in perception and behavior can cause nationwide effects in the housing market. This thesis contributes to this literature by showing that mass shooting experiences seen by distant individuals can influence risk perceptions and impact home values nationwide.

This paper is related to literature estimating the effects of crime on property values. The negative relationship between crimes and property values in localized areas is well established (Gibbons, 2004; Linden & Rockoff, 2008; Lynch & Rasmussen, 2001; Pope, 2008; Pope & Pope, 2012; Hellman & Naroff, 1979; Thaler, 1978, 1977). Repeated policy failures and high public fear have clear economic consequences in communities. Long-lasting community costs are shown in many public safety catastrophes, including environmental, natural, or health crises (Christensen *et al.*, 2023;

Daly *et al.*, 2008; Davis, 2004). This thesis contributes to the broad literature on estimating the costs of disastrous policy failures.

The remainder of this thesis is organized as follows. Chapter 2 reviews relevant literature surrounding mass shootings. Chapter 3 describes this paper's data collection and variable construction. Chapter 4 presents the empirical methods used. Chapter 5 reports the results of this paper. Chapter 6 discusses the finding and limitations of this thesis.

CHAPTER 2:
RELEVANT LITERATURE

From 1966 to 2019, 168 mass shootings occurred in the United States. Over this period, only two events have happened in the same ZIP Code in Las Vegas, separated by an 18-year gap. Mass shootings are rare anomalies that are unpredictable and highly unlikely to repeat in the exact location twice. These heinous acts receive immense media attention, sparking fear and uncertainty nationwide.

The frequency of mass shooting events increased over the last 30 years, from 1982 to 2018. Increases in shooting decrease the time between events suggesting contagion effects in incidents (Lin *et al.*, 2018). Nugent *et al.* (2021) finds a 12-month periodicity of the mass shooting events between 2014 to 2019. This periodicity explains 51 percent of the variation in events and suggests a correlation between mass shootings and generalized imitation. Evidence of contagion and imitation effects shows the indirect consequences of high media saturation of mass shootings.

Semenza & Bernau (2020) finds that the deadliness, weapon type, location, and media coverage of a mass shooting significantly affect the public interest in it. Internet search interest after an event in topics such as gun control and rights shows a slight variation in frequency over the last two decades. People are not desensitized to mass shootings over time; these events continue to incite a collective threat perception in public. High doses of media on mass shootings cause individuals to perceive them as possible future threats to themselves. While these tragedies are perceived as a public collective, individual responses are fragmented.

Jetter & Walker (2022) test the causal relationship between media attention and subsequent mass shootings from 2006 to 2017. Their results indicate media attention around an event positively correlates with the likelihood and deadliness of future shootings. Shootings with high awareness are triggering, showing a significant correlation between the levels of publicity and the number of future mass shootings.

These events cause significant reductions in educational and health outcomes in affected areas. Mass shootings are associated with a 27 percentage-point decline in the likelihood of having excellent community well-being and a thirteen percentage-point reduction in the probability of having excellent emotional health four weeks following the incident (Soni & Tekin, 2020). The effects are more robust and longer-lasting among individuals exposed to deadlier mass shootings. These events cause reductions in high school enrollments and are found to decrease test scores significantly (Beland & Kim, 2016). In the wake of these violent acts, public fear increases and perceived safety decreases resulting in immense adverse mental health effects (Lowe & Galea, 2017; Levine & McKnight, 2021).

Mass shootings are increasing in frequency in the United States. Evidence of contagion and imitation effects suggest a causal link between mass shootings and high media attention. High publicity increases the likelihood and deadliness of future shootings. These tragedies significantly impact public well-being, emotional health, and perceived safety. Further research is needed to inform general preparedness, preventative policy, and post-incident health interventions.

CHAPTER 3:

SAMPLE AND DATA SOURCES

In this chapter, I describe the data collection and sample creation for this study. Each section of this chapter details the subset of data collected from each source and the construction of variables. Variable descriptives are presented in a table at the end of this chapter.

3.1 Mass Shooting Events

Mass shooting event data is collected from The Violence Project (TVP) (Peterson & Densley., 2022). The TVP is a non-profit organization that collects data and conducts empirical research on mass shootings to improve policy and practice. The National Institute of Justice funds the organization.

The TVP defines mass shootings under the Congressional Research Service definition for a mass shooting as: "A multiple homicide incident in which four or more victims are murdered with firearms—not including the offender(s)—within one event, and at least some of the murders occurred in a public location or locations in close geographical proximity, and the murders are not attributable to any other underlying criminal activity or commonplace circumstance."

This paper uses a sample of 15 mass shootings[1] from April 2012 to May 2019.

[1] Events and their specifics can be seen in Table A.1 of the Appendix.

Events in the sample are incredibly deadly, ranging from 9 to 82 victims (killed and injured). The shootings occur in a wide range of geographical areas, including the West Coast (California and Oregon), the East Coast (Connecticut, Washington D.C., Florida, and Virginia), and the Midwest (Pennsylvania and Texas). Events take place in eight location categories: K-12 schools, universities and colleges, workplaces, retail establishments, entertainment venues, government buildings, and places of worship.

The 15 events within the sample are representative of the average characteristics of shooting locations over the last 25 years. The 15 events are selected due to being the deadliest shootings from 2012 to 2019, excluding the 2016 Orlando and 2017 Vegas shootings. Vegas and Orlando are excluded from the selected events due to being extreme outliers. These two events collectively account for over a thousand victims (killed and injured) and are not seen as representative of average events.

In order to select a subset of events to include in this study, I use the community characteristics of all mass shooting locations from 2012 to 2019 to compare all events to the 15 selected events and the two dropped events. Table 3.1 below shows the average and standard deviations of community characteristics across the different events. The chosen events show higher averages of killed and injured individuals; however, the community characteristics are close to that of all events over the period.

Table 3.1: Event Community Characteristics

	All Events		Selected Events		Vegas and Orlando	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Killed	7.8	(5.2)	12.5	(6.1)	53.5	(4.5)
Injured	7.9	(12.6)	16.6	(17.8)	470	(417.0)
Total Population	29029	(21712)	39484	(12687)	25877	(15608)
Median Age	36.5	(6.5)	36.6	(2.1)	36.5	(7.2)
% White Alone	69.1	(25.1)	68.2	(15.7)	73.1	(21.9)
% Female Household	14.2	(7.9)	11.7	(0.7)	12.0	(6.3)
% Rental Units	42.2	(17.5)	57.2	(21.3)	39.4	(18.6)
% Employed	56.0	(12.7)	63	(1.9)	58.8	(7.7)
% HS Graduate	76.4	(22.8)	53.6	(25.1)	77.3	(25.8)
% College Graduate	25.7	(19.7)	19.3	(2.1)	33.6	(21.9)
Gun Stores	0.9	(1.2)	1	(1.0)	1.3	(1.4)
Homicide Rate	9.8	(8.5)	6.9	(1.1)	9.9	(7.7)
N Events	45		15		2	

*N*otes: This table lists the average and standard deviations for community characteristics for mass shooting locations. Values are at the Zip Code level. Each of the three primary columns represents a different sample of mass shootings, with the first consisting of all events from April 2012 to May 2019 and the second being this paper's sample. The third is the two outliers that meet the criteria for being in the top 15 deadliest events but were purposely not included in the event selection. Killed and Injured represents the number of killed and injured individuals within the event; values do not include the assailant.

3.2 Home Values

Data for monthly home values are collected from the Zillow Home Value Index (ZHVI) (Zillow, 2022). Home values in the 35th through 65th percentile range are included to reflect the typical value for homes at the county level, and all values are seasonally adjusted. The initial data set consists of monthly home values for 2,831 individual counties from April 2009 to May 2022.

All counties with populations over 300,000 residents are dropped from the sample. The exclusion of counties with large populations makes the data sample more representative of home values in suburban-like areas within metropolitan areas. County-level data is aggregated by weighted average into Core-Based Statistical Area (CBSA) level. The final sample for this paper consists of monthly home values for 919 CBSA locations across the United States over 13 years.

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3.3 Search Interest

Internet search data is collected from Google Trends (Google, 2022). Searches are represented by interest by metro sub-region in the United States. Search interest is an index for interest scaled from 0 to 100. This number is calculated as the fraction of topic searches over the exhaustive searches in that area over a seven-day window.

This paper investigates three search topics to gauge interest in mass shooting events: “gun violence”, “gun control”, and “shooting”. These topics are chosen due to their popularity, each showing a relatively high search volume year around. While these topics exhibit frequent search activity, they spike considerably after a mass shooting event.

Search data is collected one week before and after an event for every metro subregion in the country. The seven-day values are aggregated by average to their respective CBSA, and the difference between the pre-event and post-event values is taken and logged. The final search variables directly measure the one-week percent change in interest for each mass shooting and CBSAs in the sample.

Out of the three search topics, the primary search topic chosen for identification is “shooting”. This topic shows the most significant average uptick after events and offers a higher saturation of searches across more areas. As seen in Table A.2 in Appendix A, the topic “shooting” consistently shows a more significant average change and standard deviation for each event and CBSA compared to the search topics of “gun violence”, “gun control”.

Figure 3.1 illustrates the nationwide change in searches across all events and locations for the topic of ”shooting” one week before and after the events. Nationwide search interest increases by over 80 percent within two days after a mass shooting and shows a steep downward trend for the following five days.

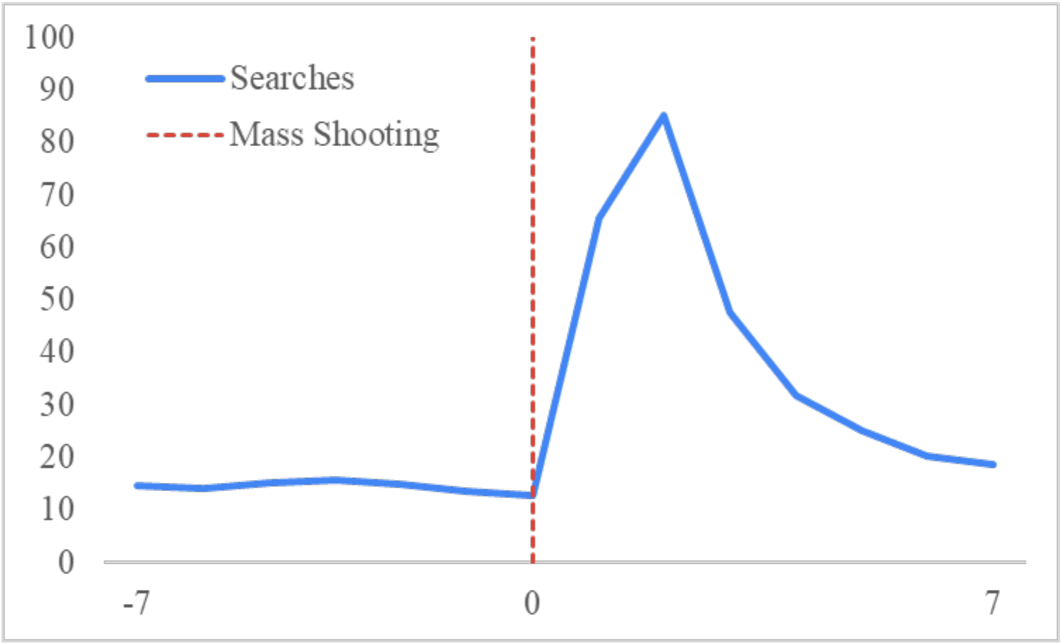


Figure 3.1: Mass Shootings Search Interest

Notes: This graph shows the average one-week change in relative search interest for the topic of "shooting" for all CBSAs and mass shootings events in the sample from 2012-2019. The y-axis can be interpreted as a scale of nationwide interest in the topic from 0 to 100. The x-axis represents days with (0) representing one day before the mass shooting events.

3.4 Homicides

Data for homicides is collected at a yearly-county level from the FBI Uniform Crime Reporting system from 2012 to 2019 (FBI, 2023). The technical specification of homicides is the number of murder and negligent manslaughter offenses known by law enforcement at the county level.

For this study, the number of homicides per county is aggregated to the CBSA level and divided by the total population. This variable is then put into terms of homicides per 100,000 residents. The log of this value is taken to limit the influence of outliers in the sample.

3.5 Federal Firearm Licences

A critical, independent variable of interest in this mass shooting research is the gun culture within CBSA locations. However, reliable and comprehensive data for personal gun ownership is not collected across the United States. While firearm ownership in the country is not well documented, the federal licenses to sell them are. This research uses federal firearm licenses (FFL) as a proxy for gun culture seeing the density of FFLs as representative of the firearm culture of an area.

Federal firearm licenses are collected from theBureau of Alcohol, Tobacco, Firearm and Explosives (ATF) by ZIP Code across all 50 states (ATF, 2023). The license classification is “Dealer in Firearms Other Than Destructive Devices (Includes Gunsmiths).” The ATF only offers this data back until 2014.

I collect all addresses of FFLs in the country from 2014 to 2019. Using the ZIP Code of the addresses of these licenses, counts are aggregated to the county level using a ZIP Code crosswalk. There is no perfect one-to-one ratio between ZIP Codes and counties, so ZIP Codes are placed in counties where over half of the residents live. County values are then aggregated to their respective CBSA, divided by total area population, and put into terms per 1,000 people. The final independent variable is FFL density for all CBSA areas in the sample.

3.6 Demographics

Data on age demographics are collected from the Census 2012-2019 at the county-level (Census, 2022). Census reports age groups in intervals of 5 years; groups are summed to create groups 0-19, 20-34, 35-59, and 60 and over. Counties with total populations greater than 300,000 are dropped, and the remaining is aggregated to the

CBSA level and divided by the total population of all groups to give a percentage.

U.S. Census Bureau provides population counts for race groups: White, Black, Asian, Native American, Hawaiian, and Hispanic. Counts for Asian, Native, American, and Hawaiian are combined to create a general minority group referred to as *other*. The sample variable construction is the same approach for age in which counties with total populations greater than 300,000 are dropped, and the remaining were aggregated to the CBSA level. The values are then divided by the total population of all races to show a percentage of residents in each metro level fitting within the race category.

County per capita personal income is collected from the Bureau of Economic Analysis (BEA) from 2012 through 2019 (BEA, 2023). The BEA reports these values as the total income for residents in a county divided by the county's total population. This metric also includes residents that work outside of their respective counties.

County income values are aggregated by average to CBSA level. The log of this value is taken. The resulting variable is the log of per capita personal income for all CBSAs in the sample from 2012 to 2019.

County presidential election results are collected for the 2012 and 2016 presidential elections from the Harvard Dataverse (Data & Lab, 2018). Vote counts are the county votes for each presidential candidate in the two elections. Votes are summed to the CBSA level, and three groups are made for total Republican, Democratic, and Other votes. Total CBSA votes per group are divided by CBSA total votes to give a percentage of votes per group.

Table 3.2: Variable Summary Statistics: 2012-2019

Variable	Description	Count	Mean	Std. Dev.	Min.	Max.
HV 12 mos.	Log change of home values 12 months after shooting.	8507	0.020	0.053	-0.840	0.604
HV 24 mos.	Log change of home values 34 months after shooting.	8507	0.044	0.091	-0.430	0.796
HV 30 mos.	Log change of home values 30 months after shooting.	8507	0.065	0.107	-0.463	0.939
HV 36 mos.	Log change of home values 36 months after shooting.	8507	0.091	0.125	-0.491	1.109
Searches	One-week percent change in Google Search Interest.	8507	0.093	0.188	-0.990	0.870
Rep. Votes	Percentage of Republican votes per CBSA.	8507	0.570	0.130	0.130	0.908
Dem. Votes	Percentage of Democratic votes per CBSA.	8507	0.391	0.127	0.074	0.863
Other Votes	Percentage of Other Votes per CBSA.	8507	0.038	0.033	0.000	0.349
Log Income	The log of per capita personal income.	8506	10.588	0.199	10.043	11.995
Pop. 0 to 19	Percentage of the population between ages 0 to 19.	8507	0.256	0.030	0.077	0.387
Pop. 20 to 34	Percentage of the population between ages 20 to 34.	8507	0.199	0.039	0.082	0.396
Pop. 35-59	Percentage of the population between ages 34 to 59.	8507	0.315	0.026	0.176	0.409
Pop. 60 +	Percentage of the population between ages 60 and up.	8507	0.231	0.049	0.105	0.664
Hispanic	Percentage of the Hispanic population.	8507	0.103	0.141	0.008	0.963
Black	Percentage of the Black population.	8507	0.088	0.117	0.002	0.640
White	Percentage of the white population.	8507	0.857	0.120	0.167	0.990
Other	Percentage of all other races population.	8507	0.034	0.044	0.004	0.802
FFL Density	Federal firearm license density: Number of licenses per 1,000 residents	6136	0.234	0.152	0.007	1.272
Homicides	Log number of homicides per 100,000 residents.	7759	0.129	0.785	-3.470	3.129
Unique CBSA	Unique Core-Based Statistical Areas.	751	-	-	-	-
N	Total observations	8507	-	-	-	-

*N*otes: This table lists all variables used in the pooled event sample. Events are from April 2012 to May 2019. All values are at the CBSA level. Observations are made up of 15 mass shooting events. The sample includes data for 751 CBSA in the Continental US.

CHAPTER 4:
EMPIRICAL METHODS

This chapter describes the empirical methods applied in this study. CBSA locations contain underlying home value trends that are caused by unobserved factors. I present the detrending method of home values over the estimation periods to control for these trends. Observed CBSA characteristics may influence home value changes. To control for these factors, I present a triple-difference model, which combines web searches, location characteristics, and their interactions to estimate the indirect causal effects of mass shootings on home values.

The intuition of using web searches to estimate the indirect effects of mass shootings is that search interest measures individuals' risk perception of events. High fear in areas can incite public migration responses which impact home values nationwide. Using an event study approach, I examine the relationship between high-frequency search data and low-frequency housing data to assess the impact incidents have on home values across the country. Interaction effects between searches and CBSA characteristics act as locational and demographic signals, which describe the extent of the relationship between search interest and home values among different kinds of people and areas.

4.1 Detrending Home Values

This paper uses an event study as described by Kothari & Warner (2004) to investigate the event's impacts on home values where an estimation window of three years is established around each mass shooting. Home values are detrended and value changes after their occurrence are investigated.

Detrending home values is essential in estimating the causal impacts of mass shootings because it separates the underlying CBSA trends from the event effect. This limits the influence of confounding locational trends resulting from other unobservable factors. This allows the impact of mass shootings to be more clearly identified in value changes after their occurrence.

For each event and CBSA, a simple linear-trend regression is conducted on pre-event home values three years leading up to the shooting:

$$\log(y_{ik,t}) = \beta_{0_{ik}} + \beta_{1_{ik}} t + \epsilon_{ik,t} \tag{4.1}$$
$$\text{with } t \in [-36, -1]$$

where $y_{ik,t}$ represents median home value in CBSA i, t months before the event k. $\beta_{0_{ik}}$ represents the predicted median home value in the month of the event k, and $\beta_{1_{ik}}$ represents the monthly growth rate in home values before event k.

The estimated coefficients detrend home values before and after the events. Subtracting pre-event trend components from post-event home values:

$$\hat{e}_{ik,t} = log(y_{ik,t}) - \hat{\beta}_{0_{ik}} - \hat{\beta}_{1_{ik}} t \tag{4.2}$$
$$\text{with } t \in [-36, 36]$$

4.2 Difference-in-Difference Model

A difference-in-difference model measures the effect mass shootings have on home values relative to changes in home values in the absence of a mass shooting. However, the problem with just using this approach is that if home values change partly due to location characteristics that are present regardless of a mass shooting, the average event effect could be biased. Thus, I use a triple difference approach by including an interaction term between web searches and CBSA characteristics to control for location factors. This approach allows a comparison of multiple reactions across different characteristics and search interests. I also further control for possible bias by including home value pre-trends and pre-levels and their interactions with covariates.

The primary model specification to estimate the causal effects of mass shootings' on home values is a cross-sectional regression described in the following:

$$\begin{aligned}\Delta\hat{e}_{ik,t} = \alpha_1 \Delta S_{ik} + \alpha_2[\Delta S_{ik} \times X_{ik,-12}] + \alpha_3 X_{ik,-12} + \gamma_1 \hat{\beta}_{1_{ik}} + \phi_1 \hat{\beta}_{0_{ik}} \\ + \omega_1[\hat{\beta}_{0_{ik}} \times X_{ik,-12}] + \omega_2[\hat{\beta}_{1_{ik}} \times X_{ik,-12}] + u_{ik,t} \\ \text{with } t = 12,\ 24,\ 30,\ 36\end{aligned} \tag{4.3}$$

where $\Delta\hat{e}_{ik,t} = \hat{\epsilon}_{ik,t} - \hat{\epsilon}_{ik,0}$ represents the difference in log home values in CBSA i, t months after the event k, variable ΔS_{ik} represents the difference in search interest one week before and after event k, and $u_{ik,t}$ is the error term. $X_{ik,-12}$ is a vector of pre-event CBSA characteristics of the number of homicides, per capita personal income, the population percentage of white individuals, the population percentage of individuals ages 0 to 19, FFL density, and the percentage of Democratic votes for the presidential election.

CBSA characteristics and home value pre-trends may be correlated. For example, the number of homicides in a CBSA would likely decrease the home values of the location. High personal income could indicate a prospering area promoting an upward trend in home values. Controlling for observable factors affecting home values is necessary to isolate the impact of mass shooting events. The model includes $\hat{\beta}_{0_{ik,t}}$ and $\hat{\beta}_{1_{ik,t}}$ and their interactions with covariates to control the relationship between home value pre-trends and CBSA characteristics.

My coefficients of interest are α_1 and α_2. These coefficients represent the causal effect of searches on home values. Coefficient α_1 is the effect a one-percent increase in search interest after an event has on the percent change in post-event home values. Coefficient α_2 is interpreted as the effect a percent change in search interest has on post-event home values in CBSA areas with specific demographics. They are measuring the extent of the relationship between search interest changes, and home value changes across different groups of people.

However, to claim coefficients α_1 and α_2 represent causal effects, necessary identification assumptions are required. The first assumption is that some variations in web searches are related to fear. This assumption is needed to make the link between how search changes are representative of changes in risk perception in which mass shooting impacts can be inferred. This assumption is violated when individuals search for mass shootings solely out of curiosity because they do not see them as dangerous or applicable to themselves. Thus, no reactionary choices are made after events.

The second assumption is there is conditional independence. Controlling for search interest is unrelated to home value changes if there were no mass shootings. The hypothesis holds if the model is conducted on pre-event home values and the coefficient

α_1 takes a zero value. A zero coefficient value would indicate that the search interest solely represents mass shooting concerns and does not influence home values without an event. However, this assumption is violated if events such as gang violence or serial killer spark concern for mass shootings and impact home values.

The second assumption is also violated when observed or unobserved CBSA characteristics impact home values and event concerns. This would result in a non-zero coefficient value for estimating pre-event home values for α_2. For instance, if a CBSA location has persistent factors such as crime, poverty, or demographics that impact home values and concern of mass shootings regardless of an event happening. The interaction between CBSA pre-trends and CBSA characteristics is included to mitigate this possibility by controlling for location specifics trends such as their homicide rates or political identity. .

CHAPTER 5:

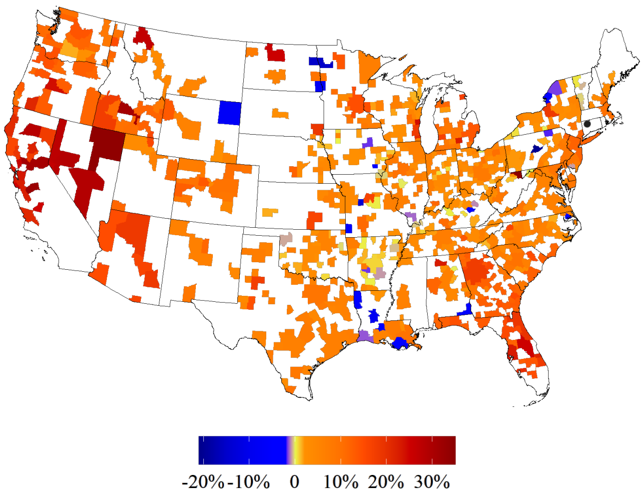
RESULTS

The main results are presented in three parts of this chapter. The first is a descriptive analysis of internet searches to address a background question of this paper: What groups of people show the most concern for mass shootings? The second section reports results on the primary question of this thesis: What are the indirect impacts of mass shootings on home values? The third section reports the results of robustness checks in which the primary model is run across different samples with varying county size restrictions. Furthermore, a placebo regression model is run on pre-event home values to test identification assumptions and the validity of the main findings.

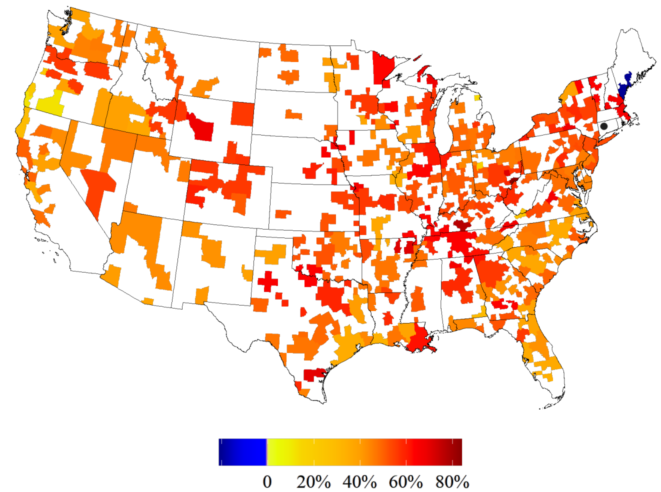
5.1 Descriptive Analysis

This paper hypothesizes economic consequences of a mass shooting are not localized. A highly publicized event has nationwide impacts across many regions. Figure 5.1 below shows internet search interest changes and home value changes after the infamous Sandy Hook Elementary School Shooting on December 14, 2012.

Map (a) shows home value changes one year after the event. Map (b) shows the change in search interest on the topic of "shooting" one week after the event. A clear causal link between the two maps is not identifiable; however, the maps clearly show nationwide variation in the variables of interest after the incident.



(a) **Home Value: One Year**



(b) **Google Search: One Week**

Figure 5.1: Home Value and Search Interest change: Newtown, CT 12/14/2012

*N*otes: This figure shows the change in log home values and internet search interest for CBSA locations after Sandy Hook Elementary School Shooting on December 14, 2012. A black dot on both maps represents the shooting location. Map (a) shows the change in log home values one year after the event. Positive home value change is depicted in red, and negative is in blue. Map (b) shows the percent change in search interest one week after the event. Values yellow to red show the increase in searches. Values in red represent areas with a higher-than-average search volume. Blue represents a decrease in search interest.

Nationwide variation in searches and home values raises a background question in the paper. What kind of people and locations shows the most concern and interest in mass shootings? To explore this question, a series of regressions are run with *Searches* as the dependent variable and CBSA characteristics as the independent variables. Characteristics include population densities of ages 0-19, 20-34, 60 plus, and races Black, Hispanic, and other. Also, per capita personal income, the number of homicides, FFL density, and the percentage of Democratic votes for the presidential election. Note information for FFLs is unavailable for 2012 and 2013, so two different event pools are made from 2012 to 2019 and from 2014 to 2019.

Estimated results are shown in Table 5.1. The first column of the table shows results for all events from 2012 to 2019 and all covariates, except Federal Firearm License (FFL) density. Column two displays results for all events and includes only age and race demographics as explanatory variables. Column three shows the results of events and all covariates from 2014 to 2019. Finally, column four shows results using only voter, income, homicide, and FFL characteristics.

An unexpected result of this descriptive analysis is search interest in young populations ages 0 to 19 years old shows a negative coefficient across all models. This is interpreted as CBSAs with high proportions of children, teenagers, and young adults indicate less concern for mass shootings than that of areas with middle-aged demographics. This result is surprising, given young populations are the primary targets for many mass shootings.

Personal income indicates a negative relationship with searches. The more money individuals make, the less concerned they are about a mass shooting event. This result is expected; higher income gives greater ability to live in low crimes areas and to take precautionary steps, which would like lower risk perception of events.

Areas with greater numbers of black and minority populations show more significant concern for mass shootings than white demographics. This is consistent with the results of personal income showing negative values across all models. These results suggest that the risk perception of regions with larger populations of poor and minority individuals is significantly higher than that of wealthy and white people.

FFL density in a CBSA negatively correlates with search interest. Areas with large gun cultures are assumed to be predominantly conservative. However, the results of column three show a conflicting effect with democratic votes, which also offers a negative correlation. This result is considered an estimation error, given the number of demographic variables included in the model. When population age and race demographics are dropped, as shown in column four, FFL density continues to offer a negative correlation. At the same time, the coefficient of democratic votes reverses to a small nonsignificant positive value. These results suggest areas with high FFL density, regardless of political identity, show less concern for mass shootings.

In conclusion, lower-income areas and high minority populations are more concerned about mass shootings. Areas with higher populations of children, white people, income, and larger gun culture have less concern about mass shootings. This descriptive analysis sheds a fascinating light on the risk perception of different population groups and gives an insight into the background of the primary results of this research.

Table 5.1: Regression of Searches on CBSA Demographics

Events	2012-2019	2012-2019	2014-2019	2014-2019
	Searches	Searches	Searches	Searches
Pop. 0-19	**-0.502*** **	**-0.428*** **	**-0.554*** **	–
	(0.101)	(0.098)	(0.124)	
Pop. 20-34	-0.074	-0.048	-0.061	–
	(0.052)	(0.050)	(0.066)	
Pop. 60+	**-0.145***	-0.103	-0.072	–
	(0.062)	(0.062)	(0.077)	
Black	0.004	0.018	**0.032***	–
	(0.013)	(0.011)	(0.015)	
Hispanic	0.006	0.003	0.003	–
	(0.0101)	(0.010)	(0.012)	
Other	**0.071***	**0.069** **	**0.085** **	–
	(0.029)	(0.026)	(0.027)	
Voter Dem.	-0.018	**-0.023***	**-0.036***	0.003
	(0.012)	(0.010)	(0.015)	(0.013)
Income	**-0.020** **	–	**-0.028** **	**-0.020***
	(0.007)		(0.009)	(0.009)
Homicides	-0.002	–	0.000	0.003
	(0.002)		(0.002)	(0.002)
FFL Density	–	–	**-0.041** **	**-0.032***
			(0.013)	(0.012)
N	7758	8507	5542	5542

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All regressions include event-fixed effects and robust standard errors. All covariates are time-varying lagged values. Events 1-15 include all events of the sample 2012-2019. Events 5-15 include mass shootings from 2014-2019. FFL data is only available for 2014 onward which results in events 1-4 being dropped from models that include the variable *FFL Density*. The variable *Pop.∗* represents the proportion of the CBSA population within the given age ranges. *Black*, *Hispanic* , and *Other* represent population race demographics. The variable *Other* includes all races other than white, black, and Hispanic. *Voter Dem.* is the proportion of Democratic voters in CBSA. *Income* represents per capita personal income. *Homicides* is the number of homicides and non-negligent manslaughter per area. *FFLDensity* represents the density of FFLs per CBSA.

5.2 Estimated Effects on Home Values

This section reports the main results of this paper which aim to answer the question, what are the indirect impacts of mass shootings on home values? To accomplish this, regressions are run using the model specification 4.3 for all events and CBSAs[1]. Values reported are the coefficients of searches and their interaction with CBSA characteristics. Estimated effects are seen in Table 5.2 below which each letter represents a separate cross-sectional regression. Regressions (A) through (G) only include variables and interactions for searches and the given CBSA characteristic, and Model (H) includes all covariates and interactions within the same model.

This research finds a significant negative correlation between search interest and mass shootings. Estimated results indicate CBSAs with considerable concern for events see decreases in home values within two years of shootings. Negative impacts continue to increase three years after an event. On average, holding everything else constant, a one standard deviation increase in search interest is responsible for a 1.2 percent reduction in median home values of a CBSA three years after an event.

The negative effect of searches on home values is increased when interacting with income. Results show that areas with high personal income and concern see more significant home value reductions than searches alone. On average, holding everything else constant, a one standard deviation increase in per capita personal income is responsible for a two and four percent reduction in median home values two and three years after an event. Decreases in home values of affluent locations are significant and intuitively make sense. Wealthy individuals have a greater ability to move out of areas they believe to be dangerous.

[1]Estimated results for individual events can be seen in Appendix B.

FFL density is shown to have a mitigating effect on the negative impact of concern on home values. The results of Model (G) indicate that for concerned areas, with every one additional FFL per 1,000 residents', home values increase by eight percent within three years of an event, holding all else constant.

As explained in the descriptive analysis, a reasonable assumption would be areas with large gun cultures consist of primarily conservative demographics. However, the mitigating effects of gun culture shouldn't be attributed to voter characteristics. Interaction effects with Democratic votes show little impact on home values, and the interaction gives conflicting results between the estimation periods.

Consistent with the descriptive analysis, larger proportions of young people between zero and 19 years have an unexpected result. This interaction, as seen in Model (D), shows that areas with large proportions of young demographics significantly mitigate the effects of searches on home values. This result is counter-intuitive; it is assumed that areas with high proportions of families and young children would be highly reactive to these events; however, the results indicate the opposite. The mitigating effect of young demographics becomes less significant when controlling for other interactions between CBSA characteristics, seen in Model (H). There is a negative correlation[2] between young populations and personal income, which may explain the magnitude decrease when controlling for other covariate interactions.

Results suggest the number of homicides of CBSAs have little effect on the reaction to mass shootings and their impact on home values. Results are not statistically significant, and coefficients show opposite signs between models controlling and not controlling for other covariates. The number of homicides and searches for shootings

[2]Table A.3 of Appendix A shows the correlation matrix of all CBSA characteristic indicators.

have nearly zero correlation, and homicides are strongly negatively correlated with income, which may explain the lack of magnitude and significance. However, no causal inferences are made, given conflicting results and a lack of statistical significance.

Table 5.2: Regression of Home Value Impacts: Searches

		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
(A)	Searches	**0.021*****	**-0.014*****	**-0.048*****	**-0.066*****
		(0.002)	(0.004)	(0.005)	(0.007)
(B)	Voter Dem. × Searches	0.025	-0.048	-0.075	0.012
		(0.020)	(0.031)	(0.042)	(0.056)
(C)	White × Searches	-0.022	-0.054	-0.023	-0.016
		(0.020)	(0.033)	(0.042)	(0.053)
(D)	Pop. 0-19 × Searches	-0.152	0.219	**0.492****	**0.502***
		(0.084)	(0.127)	(0.191)	(0.245)
(E)	Income × Searches	0.006	**-0.120*****	**-0.195*****	**-0.199*****
		(0.016)	(0.024)	(0.035)	(0.045)
(F)	Homicides × Searches	-0.002	0.005	0.009	0.009
		(0.003)	(0.005)	(0.006)	(0.008)
(G)	FFL Density × Searches	**-0.032***	0.028	**0.078***	0.078
		(0.013)	(0.024)	(0.030)	(0.041)
(H)	Voter Dem. × Searches	-0.009	0.018	0.032	-0.000
		(0.024)	(0.035)	(0.048)	(0.063)
	White × Searches	-0.020	-0.022	0.032	0.048
		(0.022)	(0.037)	(0.045)	(0.056)
	Pop. 0-19 × Searches	-0.161	0.112	0.373	0.455
		(0.086)	(0.130)	(0.197)	(0.258)
	Income × Searches	0.005	**-0.115*****	**-0.194*****	**-0.207*****
		(0.017)	(0.026)	(0.037)	(0.047)
	Homicides × Searches	-0.002	-0.003	-0.004	-0.004
		(0.003)	(0.005)	(0.007)	(0.009)
	FFL Density × Searches	-0.027	0.040	**0.086****	**0.096***
		(0.015)	(0.026)	(0.033)	(0.045)

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable *FFL Density* is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable *FFL Density* is included, the resulting sample covers 2014 to 2019. The variable *Searches* represents CBSA search interest on the topic of "shootings". The variable $Pop. 0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. *Voter Dem.* is the proportion of Democratic voters in CBSA. *Income* represents per capita personal income. *Homicides* is the number of homicides and non-negligent manslaughter per CBSA. *FFL Density* represent the density of FFLs per CBSA.

5.3 Robustness Checks

5.3.1 County Population

The main results use a sample including counties with less than 300,000 residents. To check the robustness of results, the model is run across samples varying in county sizes, seen in Appendix B tables B.1 to B.4. I include all counties, counties less than 100,000 and less than 500,000. Also, the average population size of counties within the 15 mass shooting events is 866,893, so a sample includes counties within 100,000 more or less than the average size of events. The robustness checks show similar results for searches across all sample variations.

Across all different sample sizes, results remained relatively consistent. Searches remain statistically significant, with a negative coefficient occurring two years after events with a growing magnitude out to 36 months. All results show the negative coefficient of income and the positive coefficient for FFL density. With no substantial changes across sample specifications, it is concluded that the main results regarding county size restrictions are robust.

5.3.2 Placebo Test

A placebo model is conducted on pre-event home values to check the robustness of the main results further. This specification tests if the critical assumption of conditional independence holds investigating the presence of pre-event trends. Using the exact model specification, regressions are run over five sequential periods 6, 12, 18, 24, and 30 months before the mass shooting events. The results of the placebo model can be seen below in Table 5.3.

The results show coefficients for internet search are close to zero across all estimation periods. This is a good sign indicating that the causal impacts of searches are tied directly to mass shooting events. These results provide evidence that the identification assumptions are met in internet searches for CBSA locations.

However, red flags are raised in other explanatory variables. The most significant signs of bias are shown in FFL density and income, seen in models (E),(G), and (H). Both show evidence of persistent pre-trends across nearly all estimation periods. The estimated coefficients for these variables indicate the identification assumption does not hold, and there is likely estimation bias in the results of these variables. Pre-existing trends for per capita personal income do intuitively make sense; higher income would result in increased home values. When other covariates are controlled for in model (H), bias within income becomes less significant. However, the presence of pre-trends regarding FFL density is less intuitive.

Negative coefficients across all estimation periods for FFL density are interesting. These results suggest that home values are decreasing in areas with large gun cultures regardless of events occurring. When controlling for other covariates, the results remain the same; this suggests a constant underlying factor about firearm culture affecting home values of CBSA areas.

An argument can be made for the remaining covariates meeting the common trends assumption. While coefficients for democratic votes, white, and population ages do not take exact values of zero, they are relatively small across estimation periods. Small coefficients for these indicators suggest evidence that their estimated results are valid.

Table 5.3: Regression of Home Value Impacts: Placebo Test

		HV -30 mos.	HV -24 mos.	HV -18 mos.	HV -12 mos.	HV -6 mos.
(A)	Searches	0.001	0.001	-0.001	**0.004***	0.002
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
(B)	Voter Dem. × Searches	0.005	**0.038****	0.026	**0.030***	0.004
		(0.009)	(0.014)	(0.016)	(0.015)	(0.010)
(C)	White × Searches	0.002	0.014	0.017	0.006	-0.011
		(0.012)	(0.015)	(0.021)	(0.019)	(0.013)
(D)	Pop. 0-19 × Searches	**-0.077***	-0.026	-0.055	-0.085	-0.070
		(0.038)	(0.059)	(0.068)	(0.062)	(0.044)
(E)	Income × Searches	0.007	**0.022***	**0.032****	**0.022***	**0.015***
		(0.007)	(0.009)	(0.011)	(0.010)	(0.007)
(F)	Homicides × Searches	-0.002	-0.005	**-0.006***	-0.004	-0.004
		(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
(G)	FFL Density × Searches	**-0.023****	**-0.044*****	**-0.057*****	**-0.044*****	**-0.033*****
		(0.008)	(0.012)	(0.013)	(0.012)	(0.009)
(H)	Voter Dem. × Searches	-0.016	0.017	-0.014	-0.000	**-0.032***
		(0.011)	(0.016)	(0.019)	(0.018)	(0.013)
	White × Searches	-0.000	0.023	0.018	0.009	-0.021
		(0.012)	(0.017)	(0.022)	(0.019)	(0.014)
	Pop. 0-19 × Searches	**-0.095***	-0.000	-0.055	-0.080	**-0.104***
		(0.043)	(0.065)	(0.075)	(0.068)	(0.050)
	Income × Searches	0.008	0.018	**0.031***	0.020	**0.020***
		(0.007)	(0.010)	(0.012)	(0.011)	(0.009)
	Homicides × Searches	-0.001	-0.001	-0.002	-0.001	-0.003
		(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
	FFL Density × Searches	**-0.028****	**-0.043*****	**-0.065*****	**-0.047*****	**-0.039*****
		(0.009)	(0.012)	(0.014)	(0.013)	(0.010)

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. The change of pre-event home values are constructed by $\Delta\hat{\epsilon}_{ik,-t} = \hat{\epsilon}_{ik,0} - \hat{\epsilon}_{ik,-t}$. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable $FFL\,Density$ is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable $FFL\,Density$ is included, the resulting sample covers 2014 to 2019. The variable *Searches* represents CBSA search interest on the topic of "shootings". The variable $Pop.\,0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. $Voter\,Dem.$ is the proportion of Democratic voters in CBSA. $Income$ represents per capita personal income. $Homicides$ is the number of homicides and non-negligent manslaughter per CBSA. $FFL\,Density$ represent the density of FFLs per CBSA.

CHAPTER 6:

DISCUSSION

This research finds evidence that mass shootings have a nationwide effect, impacting home values in outlying areas. The estimation methods directly create a causal link between high-risk perception and a decrease in home values. Public concern for these events suggests evidence of a population movement within three years following a shooting incident. The results of this estimation are similar to that of Muñoz-Morales & Singh (2023); Brodeur & Yousaf (2022); Christensen *et al.* (2023) in which a negative correlation between mass shootings or other highly publicized crises inflicts adverse effects on home values over an extended period.

While the methods used in this analysis are statistically sound, limitations exist. This study uses a relatively small sample of 15 mass shooting events. While I argue the sampled events used accurately represent all mass shootings within the sample period, investigating more events would only add to the estimation accuracy. Additionally, the results of search interactions may underestimate the effect of mass shootings on home values. Search interest is an accurate metric to measure event awareness; however, searches only make up a portion of total media exposure. Also, a one-week sample period for internet searches may be too long to capture the full magnitude of public concern. Other highly publicized events within the period may contribute to noise in the estimation.

The demographic indicators in this study capture the general make-up of CBSA locations; however, more extensive indicators of political affiliation and income distribution would hone estimation results. Pre-existing trends in FFL density and income suggest evidence of some bias within the sample. However, data limitations are uncontrollable. This paper uses the best available data and methods to mitigate limitations and estimation bias.

Overall, the findings of this paper are robust and offer a contribution to mass shooting literature. The costs of mass shootings are not localized; these events incite a high public risk perception that has nationwide consequences. This paper finds a response in home values from mass shooting concerns. However, it can not claim value changes are solely triggered by individual events. Mass shootings may have a compounding effect influencing home values over a much extended period.

A sensible next step to this research should investigate the relationship between mass shootings and home values through a panel model. This framework could account for variations in the impact of mass shootings over time and location. Additionally, an instrumental variable method interacting with web searches and FFL density could be applied to the panel model to address endogeneity concerns. FFL density is a valid explanatory variable to measure locational gun culture, and it does not correlate with home values.

In conclusion, this research provides evidence that mass shootings affect home values nationwide, impacting outlying areas. The estimation methods establish a causal link between high-risk perception and decreased home values. These findings align with previous studies that have reported a negative correlation between mass shootings or other highly publicized crises and adverse effects on home values. Although there are limitations in the study, the results are statistically sound and contribute to the existing literature on the economic consequences of mass shootings.

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APPENDIX A:

SUMMARY STATISTICS

Table A.1: Mass Shooting Events: 2012-2019

Shooting Location Address	Date	Region	Area Type	Location Type	Killed	Injured
7900 Oakport St, Oakland, CA 94621	4/2/2012	West	Urban	University	7	3
14300 E Alameda Ave, Aurora, CO 80012	7/20/2012	West	Urban	Retail	12	70
12 Dickenson Dr, Sandy Hook, CT 06482	12/14/2012	Northeast	Suburban	K-12	27	1
601 M Street SE, Washington, DC 20003	9/16/2013	South	Urban	Gov. Building	12	8
839 Embarcadero del Norte, Isla Vista, CA 93117	5/23/2014	West	Suburban	University	6	14
110 Calhoun St, Charleston, SC 29401	6/17/2015	South	Urban	House of Worship	9	0
1139 Umpqua College Rd Roseburg, OR 97470	10/1/2015	West	Rural	University	9	7
1365 S Waterman Ave, San Bernardino, CA 92408	12/2/2015	West	Urban	Office	14	22
100 Terminal Dr, Fort Lauderdale, FL 33315	1/6/2017	South	Urban	Retail	5	43
216 4th St, Sutherland Springs, TX 78161	11/5/2017	South	Rural	House of Worship	25	20
5901 Pine Island Rd, Parkland, FL 33076	2/14/2018	South	Suburban	K-12	17	17
16000 Hwy 6, Santa Fe, TX 77517	5/18/2018	South	Suburban	K-12	10	13
5898 Wilkins Ave, Pittsburgh, PA 15217	10/27/2018	Northeast	Urban	House of Worship	11	6
99 Rolling Oaks Dr., Thousand Oaks, CA 91361	11/7/2018	West	Suburban	Rest/Bar/NC	12	21
Municipal Center Building 10, 2425 Nimmo Pkwy, Virginia Beach, VA 23456	5/31/2019	South	Urban	Office	12	4

*N*otes: This table lists all mass shooting events investigated in this research. Events are from April 2012 to May 2019. Census geographic designations define event region and area type. Location type describes the shooting locations where the university includes all higher education locations, retail represents all public commerce locations, and office represents any place of business. Rest/Bar/NC represents restaurants bars and nightclubs. Data used for this table was collected from the TVP mass shooter database. https://www.theviolenceproject.org/

Table A.2: Summary Statistics: Google Search Interest

Event	Google Topic	Mean	Std. Dev.	Min	Max
Oakland, CA	Shooting	8.7%	16.6%	-47%	84%
4/2/2012	Gun Violence	1.9%	10.3%	-83%	72%
	Gun Control	0.9%	10.2%	-100%	91%
Aurora, CO	Shooting	8.8%	9.5%	-81%	48%
7/20/2012	Gun Violence	-1.0%	11.0%	-93%	100%
	Gun Control	4.4%	12.3%	-64%	67%
Newtown, CT	Shooting	49.9%	10.7%	-20%	84%
12/14/2012	Gun Violence	3.8%	11.7%	-56%	100%
	Gun Control	12.2%	8.2%	-34%	53%
Washington D.C., DC	Shooting	2.1%	3.1%	-37%	14%
9/16/2013	Gun Violence	-0.2%	10.7%	-100%	58%
	Gun Control	2.5%	11.4%	-54%	100%
Isla Vista , CA	Shooting	-0.9%	8.0%	-73%	28%
5/23/2014	Gun Violence	-1.6%	10.7%	-81%	100%
	Gun Control	0.1%	6.8%	-44%	100%
Charleston , SC	Shooting	4.0%	12.9%	-69%	84%
6/17/2015	Gun Violence	2.2%	16.0%	-71%	100%
	Gun Control	-3.7%	9.6%	-65%	68%
Roseburg , OR	Shooting	-15.7%	14.0%	-82%	21%
10/1/2015	Gun Violence	3.7%	11.3%	-63%	100%
	Gun Control	5.5%	7.4%	-100%	50%
San Bernardino, CA	Shooting	7.7%	3.3%	-15%	30%
12/2/2015	Gun Violence	4.1%	12.2%	-33%	100%
	Gun Control	-0.8%	11.5%	-94%	100%
Fort Lauderdale, FL	Shooting	23.8%	6.6%	0%	59%
1/6/2017	Gun Violence	0.0%	6.5%	-44%	100%
	Gun Control	-0.8%	16.4%	-100%	100%
Sutherland Springs, TX	Shooting	19.2%	14.7%	-44%	63%
11/5/2017	Gun Violence	1.6%	11.0%	-100%	100%
	Gun Control	2.1%	13.8%	-100%	100%
Parkland, FL	Shooting	24.6%	7.7%	-18%	47%
2/14/2018	Gun Violence	11.6%	16.4%	-100%	90%
	Gun Control	20.0%	14.5%	-58%	100%
Santa Fe, TX	Shooting	5.4%	12.5%	-99%	74%
5/18/2018	Gun Violence	1.5%	9.7%	-86%	71%
	Gun Control	-2.0%	7.0%	-45%	86%
Pittsburgh, PA	Shooting	3.7%	12.1%	-69%	84%
10/27/2018	Gun Violence	2.3%	15.9%	-71%	100%
	Gun Control	-3.7%	9.6%	-65%	68%
Thousand Oaks, CA	Shooting	11.4%	5.2%	-36%	31%
11/7/2018	Gun Violence	4.2%	14.0%	-100%	63%
	Gun Control	-2.6%	8.8%	-65%	100%
Virginia Beach, VA	Shooting	-11.3%	9.0%	-53%	19%
5/31/2019	Gun Violence	-1.1%	13.0%	-69%	100%
	Gun Control	1.0%	8.1%	-100%	54%

*N*otes: This table shows the summary statistics for search topics by event. Topics include shooting, gun violence, and gun control.

Table A.3: Correlation Matrix of CBSA Characteristics

	Searches	Voter Dem.	White	Pop. 0-19	Income	Homicides	Gun Shops
Searches	1						
Voter Dem.	-0.077	1					
White	-0.038	-0.216	1				
Pop. 0-19	-0.086	-0.169	-0.106	1			
Income	0.006	0.174	0.233	-0.212	1		
Homicides	0.000	-0.192	-0.171	-0.038	-0.213	1	
FFL Density	-0.006	-0.377	0.213	-0.060	0.024	0.146	1

*N*otes: This table is a correlation matrix for explanatory variables used in the final model specification.

APPENDIX B:

ESTIMATED RESULTS

Table B.1: Regression of Home Value Impacts: All Counties

		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
(A)	Searches	**0.019*** **	**-0.017*** **	**-0.054*** **	**-0.073*** **
		(0.002)	(0.004)	(0.005)	(0.006)
(B)	Voter Dem. × Searches	0.002	**-0.058***	-0.057	0.030
		(0.018)	(0.028)	(0.038)	(0.050)
(C)	White × Searches	-0.029	**-0.065***	-0.046	-0.025
		(0.019)	(0.032)	(0.040)	(0.051)
(D)	Pop. 0-19 × Searches	**-0.161***	0.053	0.215	**0.416***
		(0.066)	(0.100)	(0.152)	(0.187)
(E)	Income × Searches	0.012	**-0.083*** **	**-0.150*** **	**-0.169*** **
		(0.013)	(0.023)	(0.031)	(0.038)
(F)	Homicides × Searches	-0.003	0.009*	0.014*	0.010
		(0.003)	(0.005)	(0.006)	(0.007)
(G)	FFL Density × Searches	**-0.028***	0.029	**0.075** **	**0.077***
		(0.012)	(0.021)	(0.028)	(0.038)
(H)	Voter Dem. × Searches	0.015	0.054	0.065	0.004
		(0.022)	(0.032)	(0.043)	(0.056)
	White × Searches	-0.036	-0.049	-0.011	0.024
		(0.021)	(0.035)	(0.042)	(0.053)
	Pop. 0-19 × Searches	**-0.168***	-0.047	0.062	0.282
		(0.069)	(0.106)	(0.159)	(0.200)
	Income × Searches	0.011	**-0.071** **	**-0.138*** **	**-0.160*** **
		(0.015)	(0.024)	(0.033)	(0.040)
	Homicides × Searches	-0.004	0.001	0.003	0.001
		(0.003)	(0.005)	(0.006)	(0.008)
	FFL Density × Searches	-0.026	0.024	**0.064***	0.080
		(0.014)	(0.023)	(0.031)	(0.041)

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. This model uses a sample of all county population sizes. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable *FFL Density* is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable *FFL Density* is included, the resulting sample covers 2014 to 2019. The variable *Searches* represents CBSA search interest on the topic of "shootings". The variable $Pop. 0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. *Voter Dem.* is the proportion of Democratic voters in CBSA. *Income* represents per capita personal income. *Homicides* is the number of homicides and non-negligent manslaughter per CBSA. *FFL Density* represent the density of FFLs per CBSA.

Table B.2: Regression of Home Value Impacts: Counties Smaller than 500k

		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
(A)	Searches	**0.019***** (0.002)	**-0.017***** (0.004)	**-0.053***** (0.005)	**-0.073***** (0.006)
(B)	Voter Dem. × Searches	-0.004 (0.019)	**-0.062*** (0.028)	-0.069 (0.038)	0.024 (0.051)
(C)	White × Searches	-0.029 (0.019)	**-0.064*** (0.032)	-0.039 (0.040)	-0.025 (0.051)
(D)	Pop. 0-19 × Searches	**-0.182**** (0.068)	0.021 (0.102)	0.237 (0.147)	**0.390*** (0.190)
(E)	Income × Searches	0.011 (0.013)	**-0.084***** (0.023)	**-0.152***** (0.031)	**-0.169***** (0.038)
(F)	Homicides × Searches	-0.001 (0.003)	**0.010*** (0.005)	**0.014*** (0.006)	0.011 (0.007)
(G)	FFL Density × Searches	**-0.025*** (0.012)	0.030 (0.022)	**0.075**** (0.028)	**0.080*** (0.038)
(H)	Voter Dem. × Searches	0.019 (0.022)	0.057 (0.032)	0.065 (0.043)	0.007 (0.056)
	White × Searches	-0.035 (0.021)	-0.048 (0.035)	-0.004 (0.042)	0.022 (0.053)
	Pop. 0-19 × Searches	**-0.190**** (0.071)	-0.085 (0.108)	0.077 (0.159)	0.252 (0.205)
	Income × Searches	0.010 (0.015)	**-0.073**** (0.025)	**-0.141***** (0.033)	**-0.161***** (0.040)
	Homicides × Searches	-0.003 (0.003)	0.002 (0.005)	0.003 (0.006)	0.001 (0.008)
	FFL Density × Searches	-0.025 (0.014)	0.024 (0.023)	**0.063*** (0.031)	**0.081*** (0.041)

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. This model uses a sample of counties with a population of less than 500,000. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable *FFL Density* is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable *FFL Density* is included, the resulting sample covers 2014 to 2019. The variable *Searches* represents CBSA search interest on the topic of "shootings". The variable $Pop. 0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. *Voter Dem.* is the proportion of Democratic voters in CBSA. *Income* represents per capita personal income. *Homicides* is the number of homicides and non-negligent manslaughter per CBSA. *FFL Density* represent the density of FFLs per CBSA.

Table B.3: Regression of Home Value Impacts: Counties Smaller than 100k

		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
(A)	Searches	**0.013*****	**-0.018*****	**-0.045*****	**-0.069*****
		(0.003)	(0.004)	(0.005)	(0.007)
(B)	Voter Dem. × Searches	-0.034	**-0.092****	**-0.085***	-0.004
		(0.022)	(0.031)	(0.039)	(0.051)
(C)	White × Searches	-0.014	**-0.060***	-0.042	-0.024
		(0.019)	(0.030)	(0.035)	(0.045)
(D)	Pop. 0-19 × Searches	**-0.238****	0.003	0.108	0.006
		(0.080)	(0.119)	(0.174)	(0.216)
(E)	Income × Searches	-0.007	**-0.091*****	**-0.131*****	**-0.132****
		(0.017)	(0.025)	(0.034)	(0.046)
(F)	Homicides × Searches	0.002	**0.013***	0.014	**0.016***
		(0.004)	(0.006)	(0.007)	(0.008)
(G)	FFL Density × Searches	-0.005	0.040	**0.067***	**0.079***
		(0.013)	(0.023)	(0.028)	(0.037)
(H)	Voter Dem. × Searches	0.030	**0.073***	0.060	0.028
		(0.024)	(0.031)	(0.042)	(0.054)
	White × Searches	-0.013	-0.045	-0.018	0.005
		(0.021)	(0.033)	(0.037)	(0.047)
	Pop. 0-19 × Searches	**-0.268****	-0.065	0.060	0.025
		(0.083)	(0.120)	(0.178)	(0.226)
	Income × Searches	-0.006	**-0.079****	**-0.126*****	**-0.136****
		(0.017)	(0.026)	(0.034)	(0.047)
	Homicides × Searches	0.000	0.004	0.002	0.005
		(0.004)	(0.006)	(0.007)	(0.008)
	FFL Density × Searches	-0.016	0.035	**0.069***	**0.082***
		(0.015)	(0.024)	(0.030)	(0.041)

*N*otes: Standard errors in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. This model uses a sample of counties with a population of less than 100,000. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable *FFL Density* is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable *FFL Density* is included, the resulting sample covers 2014 to 2019. The variable *Searches* represents CBSA search interest on the topic of "shootings". The variable $Pop.\,0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. *Voter Dem.* is the proportion of Democratic voters in CBSA. *Income* represents per capita personal income. *Homicides* is the number of homicides and non-negligent manslaughter per CBSA. *FFL Density* represent the density of FFLs per CBSA.

Table B.4: Regression of Home Value Impacts: Counties Average Event Size

		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
(A)	Searches	**0.024***	**-0.062****	**-0.130*****	**-0.153*****
		(0.010)	(0.023)	(0.035)	(0.042)
(B)	Voter Dem. × Searches	**0.203***	0.274	0.236	0.319
		(0.101)	(0.203)	(0.284)	(0.352)
(C)	White × Searches	**-0.248***	-0.339	-0.119	-0.015
		(0.122)	(0.289)	(0.408)	(0.495)
(D)	Pop. 0-19 × Searches	-0.657	-0.880	-1.739	-2.714
		(0.441)	(0.966)	(1.376)	(1.598)
(E)	Income × Searches	0.060	0.061	0.034	0.001
		(0.056)	(0.089)	(0.104)	(0.115)
(F)	Homicides × Searches	-0.005	-0.012	-0.034	-0.055
		(0.009)	(0.019)	(0.026)	(0.030)
(G)	FFL Density × Searches	**-0.813*****	**-0.953***	-0.761	-0.710
		(0.227)	(0.475)	(0.657)	(0.817)
(H)	Voter Dem. × Searches	0.108	0.306	0.642	0.854
		(0.149)	(0.274)	(0.391)	(0.506)
	White × Searches	**-0.300***	-0.455	-0.397	-0.421
		(0.144)	(0.323)	(0.439)	(0.526)
	Pop. 0-19 × Searches	-0.697	-1.280	-2.691	**-4.399***
		(0.617)	(1.224)	(1.788)	(2.100)
	Income × Searches	-0.033	-0.049	-0.093	-0.183
		(0.071)	(0.117)	(0.142)	(0.168)
	Homicides × Searches	0.000	-0.005	-0.018	-0.025
		(0.011)	(0.023)	(0.030)	(0.035)
	FFL Density × Searches	**-0.782***	-1.168	-1.485	-1.946
		(0.370)	(0.693)	(0.909)	(1.142)

*N*otes: Standard errors in parentheses. * p<0.05 ** p<0.01 *** p<0.001. This model uses a sample of counties with a population within 100,000 of the average population size of event counties. All covariates are time-varying lagged values and symbol × represents the interaction. All models include linear time trends and levels. All horizontal lines indicate a different cross-sectional regression model. Model (A) includes only searches as an explanatory variable, (B)-(G) includes searches and the specified covariate and their interaction, and (H) includes all covariates and their interactions within the same model. All models include all events of the sample 2012-2019 except when variable $FFLDensity$ is included. FFL data is only available for 2014 onward which results in events 1-4 being dropped when variable $FFL\ Density$ is included, the resulting sample covers 2014 to 2019. The variable $Searches$ represents CBSA search interest on the topic of "shootings". The variable $Pop. 0-19$ represents the proportion of the CBSA population within the given age of zero to 19 years old. $Voter\ Dem.$ is the proportion of Democratic voters in CBSA. $Income$ represents per capita personal income. $Homicides$ is the number of homicides and non-negligent manslaughter per CBSA. $FFL\ Density$ represent the density of FFLs per CBSA..

Table B.5: Single Event Home Value Impacts: Search Interest

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	Searches	0.000781	0.00628	0.0119	-0.00133
4/2/2012		(0.0108)	(0.0141)	(0.0136)	(0.0157)
Aurora, CO	Searches	0.0124	0.00848	0.0131	0.0155
7/20/2012		(0.0181)	(0.0286)	(0.0320)	(0.0374)
Newtown, CT	Searches	-0.0669**	-0.0915**	-0.110***	-0.127***
12/14/2012		(0.0205)	(0.0281)	(0.0327)	(0.0368)
Washington D.C., DC	Searches	-0.0552	-0.178*	-0.199	-0.227
9/16/2013		(0.0484)	(0.0859)	(0.109)	(0.122)
Isla Vista , CA	Searches	0.0170	0.0359	0.0512	0.0659
5/23/2014		(0.0133)	(0.0217)	(0.0278)	(0.0362)
Charleston , SC	Searches	-0.00560	-0.0185	-0.00435	-0.00298
6/17/2015		(0.00766)	(0.0117)	(0.0143)	(0.0163)
Roseburg , OR	Searches	-0.00108	-0.00563	0.00488	0.00772
10/1/2015		(0.00876)	(0.0150)	(0.0161)	(0.0195)
San Bernardino, CA	Searches	0.0675	0.136	0.189*	0.204*
12/2/2015		(0.0377)	(0.0753)	(0.0907)	(0.102)
Fort Lauderdale, FL	Searches	0.0138	0.0132	0.0235	0.0216
1/6/2017		(0.0157)	(0.0231)	(0.0255)	(0.0298)
Sutherland Springs, TX	Searches	-0.0123	-0.0241	-0.0214	-0.0348
11/5/2017		(0.00903)	(0.0148)	(0.0173)	(0.0232)
Parkland, FL	Searches	-0.0000393	-0.00117	-0.00733	0.0227
2/14/2018		(0.0173)	(0.0243)	(0.0285)	(0.0359)
Santa Fe, TX	Searches	0.00133	0.0291	0.0209	0.0179
5/18/2018		(0.00797)	(0.0179)	(0.0198)	(0.0226)
Pittsburgh, PA	Searches	0.0157	0.0291	0.0313	0.0321
10/27/2018		(0.0149)	(0.0192)	(0.0263)	(0.0323)
Thousand Oaks, CA	Searches	0.0311	0.0708*	0.109*	0.113*
11/7/2018		(0.0228)	(0.0331)	(0.0430)	(0.0547)
Virginia Beach, VA	Searches	0.00317	0.0365	0.0746*	0.108*
5/31/2019		(0.0124)	(0.0254)	(0.0341)	(0.0439)

Standard errors are in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.6: Single Event Home Value Impacts: Search Interest and Dem. Votes

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	Voter Dem. × Searches	-0.0814	-0.137	-0.126	-0.103
4/2/2012		(0.0818)	(0.122)	(0.138)	(0.157)
Aurora, CO	Voter Dem. × Searches	0.0488	0.0271	0.0465	0.0354
7/20/2012		(0.148)	(0.221)	(0.241)	(0.288)
Newtown, CT	Voter Dem. × Searches	0.0785	0.174	0.189	0.164
12/14/2012		(0.160)	(0.211)	(0.244)	(0.279)
Washington D.C., DC	Voter Dem. × Searches	0.170	0.0277	0.206	0.329
9/16/2013		(0.381)	(0.698)	(0.921)	(1.050)
Isla Vista , CA	Voter Dem. × Searches	0.0210	0.152	0.0400	-0.0130
5/23/2014		(0.136)	(0.215)	(0.262)	(0.321)
Charleston , SC	Voter Dem. × Searches	0.00507	0.0514	0.0505	0.0822
6/17/2015		(0.0609)	(0.0976)	(0.118)	(0.135)
Roseburg , OR	Voter Dem. × Searches	0.0528	0.0212	-0.00858	0.00478
10/1/2015		(0.0657)	(0.129)	(0.146)	(0.164)
San Bernardino, CA	Voter Dem. × Searches	0.165	0.329	0.183	0.233
12/2/2015		(0.353)	(0.705)	(0.864)	(1.024)
Fort Lauderdale, FL	Voter Dem. × Searches	0.176	0.382	0.438	0.360
1/6/2017		(0.123)	(0.201)	(0.230)	(0.258)
Sutherland Springs, TX	Voter Dem. × Searches	-0.0614	-0.0942	-0.138	-0.186
11/5/2017		(0.0559)	(0.0950)	(0.106)	(0.157)
Parkland, FL	Voter Dem. × Searches	-0.0351	-0.0573	-0.0779	-0.141
2/14/2018		(0.139)	(0.204)	(0.222)	(0.293)
Santa Fe, TX	Voter Dem. × Searches	0.146	0.213	0.0804	0.191
5/18/2018		(0.0797)	(0.178)	(0.207)	(0.241)
Pittsburgh, PA	Voter Dem. × Searches	0.130	-0.126	-0.434	-0.173
10/27/2018		(0.244)	(0.187)	(0.253)	(0.344)
Thousand Oaks, CA	Voter Dem. × Searches	0.0537	0.193	0.259	0.517
11/7/2018		(0.186)	(0.288)	(0.355)	(0.464)
Virginia Beach, VA	Voter Dem. × Searches	-0.0498	-0.229	-0.397	-0.495
5/31/2019		(0.0899)	(0.172)	(0.227)	(0.272)

Standard errors are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.7: Single Event Home Value Impacts: Search Interest and Homicides

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	Homicides × Searches	-0.00467	-0.00980	-0.0182	-0.0198
4/2/2012		(0.0157)	(0.0233)	(0.0266)	(0.0292)
Aurora, CO	Homicides × Searches	0.00594	0.0212	0.0119	0.00184
7/20/2012		(0.0259)	(0.0434)	(0.0472)	(0.0528)
Newtown, CT	Homicides × Searches	0.0217	0.0203	0.0302	0.0477
12/14/2012		(0.0270)	(0.0364)	(0.0421)	(0.0484)
Washington D.C., DC	Homicides × Searches	-0.165*	-0.187	-0.176	-0.186
9/16/2013		(0.0694)	(0.111)	(0.135)	(0.163)
Isla Vista , CA	Homicides × Searches	-0.00936	-0.0112	-0.0307	-0.0495
5/23/2014		(0.0142)	(0.0213)	(0.0250)	(0.0299)
Charleston , SC	Homicides × Searches	-0.00609	0.00841	-0.00162	-0.00716
6/17/2015		(0.00913)	(0.0167)	(0.0196)	(0.0232)
Roseburg , OR	Homicides × Searches	0.0179	0.0415*	0.0492*	0.0611*
10/1/2015		(0.0104)	(0.0187)	(0.0200)	(0.0250)
San Bernardino, CA	Homicides × Searches	0.0426	0.112*	0.159*	0.188*
12/2/2015		(0.0312)	(0.0556)	(0.0651)	(0.0752)
Fort Lauderdale, FL	Homicides × Searches	-0.0192	-0.00355	-0.00729	0.00760
1/6/2017		(0.0189)	(0.0326)	(0.0374)	(0.0432)
Sutherland Springs, TX	Homicides × Searches	0.00999*	0.0137	0.0208	0.0292*
11/5/2017		(0.00471)	(0.00900)	(0.0114)	(0.0121)
Parkland, FL	Homicides × Searches	0.0327	0.0145	0.0533	0.0605
2/14/2018		(0.0235)	(0.0385)	(0.0334)	(0.0549)
Santa Fe, TX	Homicides × Searches	0.00423	-0.000543	0.00958	0.0157
5/18/2018		(0.0144)	(0.0265)	(0.0324)	(0.0386)
Pittsburgh, PA	Homicides × Searches	0.0130	0.0126	0.0180	0.0718*
10/27/2018		(0.00854)	(0.0262)	(0.0295)	(0.0345)
Thousand Oaks, CA	Homicides × Searches	0.0113	0.0602	0.0675	0.0309
11/7/2018		(0.0353)	(0.0553)	(0.0679)	(0.0946)
Virginia Beach, VA	Homicides × Searches	0.0395	0.0704	0.110	0.0954
5/31/2019		(0.0324)	(0.0482)	(0.0567)	(0.0796)

Standard errors are in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.8: **Single Event Home Value Impacts: Search Interest and Income**

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	Income × Searches	-0.0206	-0.0248	-0.00678	0.0314
4/2/2012		(0.0634)	(0.0729)	(0.0791)	(0.0855)
Aurora, CO	Income × Searches	-0.440**	-0.580*	-0.611*	-0.656*
7/20/2012		(0.168)	(0.242)	(0.252)	(0.283)
Newtown, CT	Income × Searches	-0.0370	0.0803	0.116	0.0730
12/14/2012		(0.143)	(0.189)	(0.217)	(0.244)
Washington D.C., DC	Income × Searches	-0.705	-1.529*	-1.993**	-2.647***
9/16/2013		(0.439)	(0.607)	(0.656)	(0.667)
Isla Vista , CA	Income × Searches	-0.0397	-0.0329	-0.00849	0.0271
5/23/2014		(0.0393)	(0.0954)	(0.147)	(0.204)
Charleston , SC	Income × Searches	-0.0109	-0.0296	-0.0176	-0.0236
6/17/2015		(0.0426)	(0.0913)	(0.110)	(0.124)
Roseburg , OR	Income × Searches	-0.109	-0.123	-0.138	-0.226
10/1/2015		(0.0634)	(0.105)	(0.116)	(0.125)
San Bernardino, CA	Income × Searches	-0.360	-0.765	-0.842	-0.840
12/2/2015		(0.243)	(0.451)	(0.521)	(0.529)
Fort Lauderdale, FL	Income × Searches	0.0653	-0.100	-0.175	-0.299
1/6/2017		(0.0966)	(0.148)	(0.165)	(0.189)
Sutherland Springs, TX	Income × Searches	0.0168	0.0259	0.0696	0.155*
11/5/2017		(0.0264)	(0.0464)	(0.0475)	(0.0622)
Parkland, FL	Income × Searches	-0.201*	-0.332**	-0.280*	-0.395*
2/14/2018		(0.0912)	(0.115)	(0.119)	(0.162)
Santa Fe, TX	Income × Searches	-0.0167	0.0594	-0.0309	-0.000269
5/18/2018		(0.0722)	(0.137)	(0.143)	(0.179)
Pittsburgh, PA	Income × Searches	-0.0646	-0.284**	-0.507**	-0.379*
10/27/2018		(0.177)	(0.103)	(0.158)	(0.174)
Thousand Oaks, CA	Income × Searches	0.0793	-0.272	-0.0871	-0.245
11/7/2018		(0.129)	(0.236)	(0.282)	(0.356)
Virginia Beach, VA	Income × Searches	0.0696	0.0657	0.173	0.123
5/31/2019		(0.0606)	(0.138)	(0.173)	(0.202)

Standard errors are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.9: Single Event Home Value Impacts: Search Interest and White

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	White × Searches	0.0236	0.242**	0.247***	0.259**
4/2/2012		(0.0542)	(0.0807)	(0.0742)	(0.0913)
Aurora, CO	White × Searches	-0.320**	-0.536**	-0.656***	-0.728**
7/20/2012		(0.111)	(0.187)	(0.197)	(0.223)
Newtown, CT	White × Searches	-0.0307	-0.0335	-0.0917	-0.102
12/14/2012		(0.195)	(0.261)	(0.309)	(0.358)
Washington D.C., DC	White × Searches	0.134	0.495	0.474	0.316
9/16/2013		(0.432)	(0.729)	(0.987)	(1.146)
Isla Vista , CA	White × Searches	-0.0721	-0.151	-0.137	-0.240
5/23/2014		(0.155)	(0.210)	(0.241)	(0.285)
Charleston , SC	White × Searches	-0.0271	-0.0449	-0.0366	-0.0382
6/17/2015		(0.0521)	(0.0725)	(0.0870)	(0.102)
Roseburg , OR	White × Searches	0.0598	0.254	0.247	0.276
10/1/2015		(0.0602)	(0.144)	(0.149)	(0.162)
San Bernardino, CA	White × Searches	-0.157	0.110	-0.0712	0.0149
12/2/2015		(0.264)	(0.563)	(0.640)	(0.678)
Fort Lauderdale, FL	White × Searches	-0.0591	-0.0297	-0.0338	-0.0299
1/6/2017		(0.100)	(0.165)	(0.183)	(0.220)
Sutherland Springs, TX	White × Searches	0.0140	-0.0299	0.0971	0.520
11/5/2017		(0.100)	(0.268)	(0.273)	(0.311)
Parkland, FL	White × Searches	0.152	0.212	0.175	-0.0272
2/14/2018		(0.139)	(0.188)	(0.242)	(0.274)
Santa Fe, TX	White × Searches	0.0718	0.186	0.300*	0.225
5/18/2018		(0.0645)	(0.112)	(0.132)	(0.156)
Pittsburgh, PA	White × Searches	-0.362	-0.484*	-0.845**	-1.397***
10/27/2018		(0.223)	(0.236)	(0.276)	(0.346)
Thousand Oaks, CA	White × Searches	0.164	-0.0646	0.145	-0.265
11/7/2018		(0.162)	(0.264)	(0.312)	(0.443)
Virginia Beach, VA	White × Searches	-0.0786	-0.295*	-0.168	-0.348
5/31/2019		(0.0918)	(0.149)	(0.204)	(0.258)

Standard errors are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.10: Single Event Home Value Impacts: Search Interest and FFL Density

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Isla Vista , CA 5/23/2014	FFL Density × Searches	-0.0403 (0.0619)	-0.00470 (0.110)	0.0263 (0.139)	0.0812 (0.179)
Charleston , SC 6/17/2015	FFL Density × Searches	0.0655 (0.0551)	0.0567 (0.0822)	0.102 (0.107)	0.150 (0.115)
Roseburg , OR 10/1/2015	FFL Density × Searches	-0.0882 (0.0465)	-0.132 (0.0932)	-0.143 (0.104)	-0.184 (0.113)
San Bernardino, CA 12/2/2015	FFL Density × Searches	-0.393 (0.216)	-0.583 (0.438)	-0.651 (0.506)	-0.660 (0.549)
Fort Lauderdale, FL 1/6/2017	FFL Density × Searches	-0.00739 (0.0721)	-0.0721 (0.109)	-0.0895 (0.121)	-0.184 (0.157)
Sutherland Springs, TX 11/5/2017	FFL Density × Searches	-0.0191 (0.0430)	-0.0250 (0.0630)	-0.0319 (0.0748)	0.0194 (0.0963)
Parkland, FL 2/14/2018	FFL Density × Searches	0.110 (0.0956)	0.110 (0.134)	0.0943 (0.157)	0.176 (0.190)
Santa Fe, TX 5/18/2018	FFL Density × Searches	0.0592 (0.0399)	0.125 (0.113)	0.208 (0.107)	0.222 (0.118)
Pittsburgh, PA 10/27/2018	FFL Density × Searches	0.0104 (0.0783)	0.0568 (0.140)	0.157 (0.172)	0.0760 (0.217)
Thousand Oaks, CA 11/7/2018	FFL Density × Searches	0.219 (0.339)	0.0247 (0.375)	0.0787 (0.409)	-0.106 (0.538)
Virginia Beach, VA 5/31/2019	FFL Density × Searches	-0.0488 (0.0436)	-0.106 (0.0752)	-0.0768 (0.102)	-0.203 (0.188)

Standard errors are in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.11: Single Event Home Value Impacts: Search Interest and Age

Event		HV 12 mos.	HV 24 mos.	HV 30 mos.	HV 36 mos.
Oakland, CA	Pop. 0-19 × Searches	-0.196	-0.238	-0.240	-0.225
4/2/2012		(0.309)	(0.491)	(0.543)	(0.638)
Aurora, CO	Pop. 0-19 × Searches	-0.823*	-1.260	-1.464*	-1.727*
7/20/2012		(0.418)	(0.672)	(0.719)	(0.811)
Newtown, CT	Pop. 0-19 × Searches	0.543	1.249	1.892	2.207
12/14/2012		(0.678)	(0.937)	(1.107)	(1.253)
Washington D.C., DC	Pop. 0-19 × Searches	-0.0207	0.430	-0.862	-0.895
9/16/2013		(1.866)	(3.221)	(3.911)	(4.442)
Isla Vista , CA	Pop. 0-19 × Searches	-1.239*	-1.733*	-1.910*	-2.289*
5/23/2014		(0.482)	(0.771)	(0.836)	(1.003)
Charleston , SC	Pop. 0-19 × Searches	0.0211	-0.306	-0.329	-0.432
6/17/2015		(0.277)	(0.466)	(0.581)	(0.664)
Roseburg , OR	Pop. 0-19 × Searches	0.252	0.565	0.851	0.964
10/1/2015		(0.232)	(0.493)	(0.543)	(0.727)
San Bernardino, CA	Pop. 0-19 × Searches	0.917	2.122	2.901	3.255
12/2/2015		(0.855)	(1.698)	(2.049)	(2.353)
Fort Lauderdale, FL	Pop. 0-19 × Searches	0.776	0.193	0.144	0.461
1/6/2017		(0.716)	(1.110)	(1.295)	(1.452)
Sutherland Springs, TX	Pop. 0-19 × Searches	-0.0971	-0.0857	-0.107	-0.162
11/5/2017		(0.153)	(0.240)	(0.270)	(0.374)
Parkland, FL	Pop. 0-19 × Searches	-0.573	-0.451	-0.822	-0.901
2/14/2018		(0.510)	(0.716)	(0.792)	(1.039)
Santa Fe, TX	Pop. 0-19 × Searches	-0.625*	-1.225	-1.410	-1.583
5/18/2018		(0.312)	(0.655)	(0.760)	(0.905)
Pittsburgh, PA	Pop. 0-19 × Searches	-0.485	-0.111	-0.797	-1.164
10/27/2018		(0.396)	(0.405)	(0.825)	(0.827)
Thousand Oaks, CA	Pop. 0-19 × Searches	0.697	2.183	2.569	4.841
11/7/2018		(0.930)	(1.552)	(1.957)	(2.835)
Virginia Beach, VA	Pop. 0-19 × Searches	-0.0375	0.791	1.097	1.683
5/31/2019		(0.382)	(0.949)	(1.324)	(1.583)

Standard errors are in parentheses. * $p<0.05$ ** $p<0.01$ *** $p<0.001$. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.

Table B.12: Single Event Home Value Impacts: All Interactions

Event		HV 12 mos.		HV 24 mos.		HV 30 mos.		HV 36 mos.	
Oakland, CA	Voter Dem. × Searches	-0.0888	(0.104)	-0.0275	(0.142)	-0.00585	(0.157)	0.0119	(0.172)
4/2/2012	White × Searches	0.00744	(0.0880)	0.312*	(0.121)	0.309**	(0.110)	0.312*	(0.124)
	Pop. 0-19 × Searches	-0.222	(0.404)	-0.0500	(0.639)	0.0269	(0.682)	0.0893	(0.813)
	Income × Searches	-0.0245	(0.0835)	-0.0932	(0.0860)	-0.0832	(0.0971)	-0.0423	(0.110)
	Homicides × Searches	-0.00378	(0.0171)	0.00821	(0.0240)	0.000278	(0.0259)	0.00252	(0.0275)
Aurora, CO	Voter Dem. × Searches	-0.205	(0.229)	-0.466	(0.337)	-0.590	(0.351)	-0.676	(0.380)
7/20/2012	White × Searches	-0.154	(0.168)	-0.365	(0.265)	-0.508	(0.277)	-0.546	(0.310)
	Pop. 0-19 × Searches	-2.383**	(0.806)	-4.252**	(1.466)	-4.640**	(1.617)	-5.136**	(1.733)
	Income × Searches	-0.418*	(0.192)	-0.501	(0.277)	-0.494	(0.294)	-0.552	(0.327)
	Homicides × Searches	0.0850*	(0.0403)	0.163*	(0.0692)	0.169*	(0.0753)	0.174*	(0.0809)
Newtown, CT	Voter Dem. × Searches	0.215	(0.190)	0.349	(0.242)	0.404	(0.281)	0.463	(0.319)
12/14/2012	White × Searches	0.108	(0.215)	0.153	(0.280)	0.146	(0.332)	0.205	(0.388)
	Pop. 0-19 × Searches	0.530	(0.731)	1.303	(1.009)	1.909	(1.184)	2.150	(1.333)
	Income × Searches	-0.135	(0.168)	-0.0677	(0.214)	-0.0420	(0.247)	-0.112	(0.278)
	Homicides × Searches	0.0165	(0.0294)	0.0189	(0.0381)	0.0252	(0.0433)	0.0380	(0.0500)
Washington D.C., DC	Voter Dem. × Searches	0.235	(0.464)	0.170	(0.765)	0.402	(0.994)	0.566	(1.063)
9/16/2013	White × Searches	0.0345	(0.470)	0.396	(0.785)	0.246	(1.055)	0.138	(1.186)
	Pop. 0-19 × Searches	1.002	(1.974)	2.281	(3.458)	0.788	(4.151)	1.442	(4.538)
	Income × Searches	-0.742	(0.473)	-1.657**	(0.639)	-2.116**	(0.697)	-2.809***	(0.727)
	Homicides × Searches	-0.159*	(0.0757)	-0.194	(0.111)	-0.171	(0.129)	-0.179	(0.153)
Isla Vista , CA	Voter Dem. × Searches	-0.109	(0.117)	0.162	(0.212)	0.116	(0.252)	0.177	(0.305)
5/23/2014	White × Searches	-0.0402	(0.181)	-0.0263	(0.248)	0.0151	(0.268)	-0.0736	(0.306)
	Pop. 0-19 × Searches	-1.240*	(0.561)	-1.463	(0.820)	-1.500	(0.919)	-1.773	(1.116)
	Income × Searches	-0.0178	(0.0501)	0.0135	(0.106)	0.0400	(0.147)	0.0836	(0.197)
	Homicides × Searches	0.00226	(0.0165)	0.00857	(0.0293)	-0.00846	(0.0386)	-0.0163	(0.0500)
	FFL Density × Searches	-0.0680	(0.0769)	0.00504	(0.122)	0.00870	(0.149)	0.0527	(0.171)
Charleston , SC	Voter Dem. × Searches	0.0596	(0.0637)	0.179	(0.116)	0.203	(0.158)	0.292	(0.175)
6/17/2015	White × Searches	-0.0405	(0.0672)	0.0153	(0.101)	-0.0276	(0.121)	-0.0351	(0.139)
	Pop. 0-19 × Searches	0.182	(0.311)	0.315	(0.545)	0.376	(0.654)	0.482	(0.733)
	Income × Searches	-0.0496	(0.0620)	-0.0993	(0.120)	-0.116	(0.152)	-0.160	(0.167)
	Homicides × Searches	-0.0126	(0.0111)	0.00539	(0.0192)	-0.00769	(0.0213)	-0.0148	(0.0257)
	FFL Density × Searches	0.0808	(0.0646)	0.0747	(0.0889)	0.131	(0.117)	0.182	(0.126)
Roseburg , OR	Voter Dem. × Searches	0.0907	(0.0806)	0.0987	(0.159)	0.0810	(0.181)	0.104	(0.195)
10/1/2015	White × Searches	0.139*	(0.0683)	0.381*	(0.158)	0.398*	(0.165)	0.474**	(0.177)
	Pop. 0-19 × Searches	0.375	(0.303)	0.718	(0.553)	0.921	(0.614)	1.070	(0.749)
	Income × Searches	-0.108	(0.0693)	-0.113	(0.115)	-0.117	(0.128)	-0.205	(0.143)
	Homicides × Searches	0.0151	(0.0102)	0.0376*	(0.0189)	0.0448*	(0.0200)	0.0506*	(0.0254)
	FFL Density × Searches	-0.0575	(0.0539)	-0.118	(0.103)	-0.139	(0.112)	-0.155	(0.130)
San Bernardino, CA	Voter Dem. × Searches	0.0548	(0.360)	0.0648	(0.713)	-0.143	(0.863)	-0.0843	(1.047)
12/2/2015	White × Searches	0.342	(0.303)	1.294*	(0.631)	1.266	(0.730)	1.434	(0.805)
	Pop. 0-19 × Searches	0.581	(1.158)	0.899	(2.161)	0.990	(2.656)	1.088	(3.105)
	Income × Searches	-0.255	(0.293)	-0.715	(0.547)	-0.736	(0.622)	-0.674	(0.627)
	Homicides × Searches	0.0516	(0.0407)	0.131	(0.0694)	0.169	(0.0868)	0.209*	(0.103)
	FFL Density × Searches	-0.330	(0.228)	-0.499	(0.494)	-0.566	(0.565)	-0.681	(0.599)
Fort Lauderdale, FL	Voter Dem. × Searches	0.348**	(0.123)	0.736***	(0.222)	0.903***	(0.255)	0.775**	(0.300)
1/6/2017	White × Searches	-0.0348	(0.109)	0.125	(0.196)	0.166	(0.222)	0.246	(0.261)
	Pop. 0-19 × Searches	1.405	(0.815)	0.726	(1.044)	0.787	(1.172)	0.973	(1.339)
	Income × Searches	0.0781	(0.120)	-0.198	(0.181)	-0.282	(0.201)	-0.378	(0.224)
	Homicides × Searches	-0.0115	(0.0200)	0.00444	(0.0349)	0.000636	(0.0406)	0.0165	(0.0444)
	FFL Density × Searches	0.0960	(0.0760)	0.106	(0.113)	0.113	(0.129)	0.00997	(0.173)
Sutherland Springs, TX	Voter Dem. × Searches	-0.211	(0.114)	-0.283	(0.176)	-0.432*	(0.190)	-0.635**	(0.228)
11/5/2017	White × Searches	-0.0339	(0.113)	-0.0547	(0.320)	0.0252	(0.314)	0.151	(0.348)
	Pop. 0-19 × Searches	-0.280	(0.233)	-0.237	(0.348)	-0.317	(0.381)	-0.573	(0.484)
	Income × Searches	0.0498	(0.0421)	0.0602	(0.0678)	0.140*	(0.0700)	0.252**	(0.0831)
	Homicides × Searches	0.00357	(0.00704)	0.00716	(0.0124)	0.0119	(0.0147)	0.0126	(0.0171)
	FFL Density × Searches	-0.0861	(0.0592)	-0.111	(0.0911)	-0.176	(0.0972)	-0.200	(0.114)
Parkland, FL	Voter Dem. × Searches	-0.0531	(0.166)	0.0655	(0.267)	0.00973	(0.285)	-0.0219	(0.360)
2/14/2018	White × Searches	0.111	(0.176)	0.202	(0.220)	0.219	(0.285)	-0.0444	(0.292)
	Pop. 0-19 × Searches	-0.848	(0.557)	-0.822	(0.846)	-1.202	(0.928)	-1.789	(1.194)
	Income × Searches	-0.160	(0.119)	-0.382	(0.205)	-0.263	(0.211)	-0.458	(0.262)
	Homicides × Searches	0.0194	(0.0256)	-0.0134	(0.0452)	0.0316	(0.0432)	0.00957	(0.0581)
	FFL Density × Searches	0.0398	(0.134)	0.116	(0.170)	0.0459	(0.200)	0.168	(0.213)
Santa Fe, TX	Voter Dem. × Searches	0.234*	(0.0987)	0.322	(0.217)	0.347	(0.231)	0.347	(0.276)
5/18/2018	White × Searches	0.163	(0.104)	0.165	(0.177)	0.363	(0.211)	0.301	(0.255)
	Pop. 0-19 × Searches	-0.606*	(0.292)	-1.182	(0.658)	-1.392	(0.775)	-1.580	(0.850)
	Income × Searches	-0.0834	(0.0933)	-0.0878	(0.172)	-0.219	(0.186)	-0.165	(0.240)
	Homicides × Searches	0.00474	(0.0159)	-0.00373	(0.0299)	0.00771	(0.0383)	0.00525	(0.0426)
	FFL Density × Searches	0.0900	(0.0460)	0.130	(0.128)	0.223	(0.136)	0.237	(0.148)
Pittsburgh, PA	Voter Dem. × Searches	0.172	(0.408)	0.0269	(0.226)	-0.522	(0.283)	-0.267	(0.361)
10/27/2018	White × Searches	-0.334	(0.294)	-0.416	(0.297)	-0.909**	(0.326)	-1.423**	(0.440)
	Pop. 0-19 × Searches	-0.199	(0.375)	0.0316	(0.439)	-0.989	(0.520)	-0.836	(0.685)
	Income × Searches	-0.0772	(0.160)	-0.318*	(0.125)	-0.469***	(0.137)	-0.332	(0.198)
	Homicides × Searches	-0.00139	(0.0155)	-0.0216	(0.0261)	-0.0549*	(0.0263)	0.00401	(0.0384)
	FFL Density × Searches	0.0850	(0.241)	0.0993	(0.175)	0.0590	(0.199)	0.0244	(0.262)
Thousand Oaks, CA	Voter Dem. × Searches	0.285	(0.313)	0.597	(0.357)	0.857*	(0.435)	1.052	(0.621)
11/7/2018	White × Searches	0.326	(0.203)	0.460	(0.334)	0.753*	(0.375)	0.518	(0.569)
	Pop. 0-19 × Searches	1.863	(1.113)	2.695	(1.708)	4.079*	(2.013)	6.119*	(2.915)
	Income × Searches	0.0164	(0.164)	-0.317	(0.304)	-0.139	(0.336)	-0.146	(0.486)
	Homicides × Searches	-0.0117	(0.0514)	0.0630	(0.0654)	0.0683	(0.0778)	0.0777	(0.114)
	FFL Density × Searches	0.299	(0.565)	0.229	(0.587)	0.0944	(0.622)	0.0915	(0.823)
Virginia Beach, VA	Voter Dem. × Searches	-0.168	(0.177)	-0.554*	(0.275)	-0.743*	(0.373)	-1.306**	(0.445)
5/31/2019	White × Searches	-0.378*	(0.166)	-1.024***	(0.275)	-1.046**	(0.352)	-1.610***	(0.439)
	Pop. 0-19 × Searches	-0.577	(0.457)	-0.430	(1.058)	-0.401	(1.490)	-0.704	(1.804)
	Income × Searches	0.200	(0.110)	0.286	(0.200)	0.412	(0.242)	0.604	(0.315)
	Homicides × Searches	0.0195	(0.0368)	-0.0133	(0.0508)	0.00644	(0.0621)	-0.0581	(0.0801)
	FFL Density × Searches	-0.0468	(0.0533)	-0.0937	(0.0749)	-0.119	(0.107)	-0.313	(0.223)

Standard errors are in parentheses. * p<0.05 ** p<0.01 *** p<0.001. All covariates are time-varying lagged values and symbol × represents the interaction. All horizontal lines indicate a different cross-sectional regression model for each event.