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The Relationship between School Shootings and Gun Acquisition Rates

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Abstract

In this paper, I seek to understand how communities respond to tragic events involving violence, exploring the relationship between school shootings and gun acquisition rates. Using National Instant Criminal Background Check System (NICS) as a proxy for firearm acquisition rates, I estimate an event study framework, finding that gun acquisition rates increase by up to 32% one month after a school shooting compared to firearm acquisition rates one month before a school shooting. Furthermore, I supplement my analysis by using Google Search data on firearms. Additionally, I stratify my analysis by the four census regions and whether a school shooting occurred in a majority-minority county. My results contribute to existing literature, investigating the linkages between Google search data and social phenomena and the impact of mass shootings on the social sphere.

Keywords: K-12 school shootings; gun acquisition rates; Google Trends data

JEL Classification Numbers: I12, I18, K42

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How do school shootings affect gun ownership rates? Since 2009, there have been over 170 school shootings, with over 356 victims (CNN, 2019). In the aftermath of these school shootings, communities and governments have responded in different ways. Politicians have passed stricter gun legislation, making it harder for citizens to acquire deadly firearms to deter future mass shootings (Kwon and Baack, 2005). Altering the American public's psyche, mass shootings and the extensive media coverage it receives has led to an onslaught of unforeseen and foreseen effects, including active shooter drills in K-12 schools, the deterioration of physical and mental health among students, and many causalities (Moore-Petinak et al., 2020). The variety of social responses induced by school shootings provides insight into how communities react to public tragedies involving violence.

Considering the diverse array of community responses to school shootings, I analyze the impact of K-12 school shootings on gun acquisition rates. Estimating an event-study framework, I quantify the effects of school shootings on gun ownership six months after a K-12 school shooting, using data from NICS Firearms Background Check Data as a proxy for gun ownership rates. My results suggest that gun ownership rates remain constant up to one month before a school shooting, increasing by up to 32% relative to the month of the school shooting, after which the effect levels off. Further, I find weak evidence to suggest that majority-white counties purchase more firearms compared to majority people of color (POC) counties in the months following a school shooting.

I add to existing literature, which has documented how communities respond to mass shootings. Liu and Wiebe (2019), using U.S. data on firearm checks as a proxy for gun sales and data on mass shootings between 1998 and 2016, found that in the aftermath of a mass shooting, gun purchases increased by up to 21%, while, in some instances, it decreased gun sales by 18%. Further, Wallace (2014) finds a delayed response to gun ownership increases after a mass shooting, using panel data OLS. Additionally, Studdert et al. (2017), using time series analysis, finds that gun acquisition rates increased after the mass shootings in Newtown, CT, and San Bernardino, CA, in 2012 and 2015, respectively. Moreover, Porfiri et al. (2019) finds that increased media coverage of mass shootings induces increased firearm acquisitions.

On a broader societal scale, some communities react to school shootings by enrolling their children in private schools (Abouk and Adams, 2013). At the state level, in the aftermath of a school shooting, politicians seek to pass stricter gun legislation bills (Luca, Malhotra and Poliquin, 2020). The bills' efficacy, if passed, depends on whether Republicans or Democrats govern the state-legislature (Luca, Malhotra and Poliquin, 2020). At the individual level, research has documented increased levels of mental and physical illness among students who experience a school shooting the students who experience a school shooting (Addington, 2003; Studdert et al., 2017; Suomalainen et al., 2011). Considering the diverse array of responses to school shootings, I seek to understand how a politicized and public tragedy affects gun acquisition rates, revealing a fundamental facet of American society.

My study adds to existing literature while differing in the following ways. First, I expand the definition of a mass shooting. Many studies define a mass shooting as an incident with at least four or more casualties (Studdert et al., 2017; Wallace, 2014). In restricting the definition of a mass shooting, such studies lose out on variation in shootings. Figure 1 illustrates that approximately 97% of school shootings had fewer than five casualties.

Second, I supplement my results by performing a series of robustness checks and extending my primary specification results, using Google search data on 416 common and uncommon gun manufacturers and models and data from the National Instant Criminal Background Check System (NICS). I also stratify my analyses by the 4 Census regions and whether the shooting occurred in a predominantly white or minority neighborhood.

Third, I conduct my analysis on K-12 schools only. Mass shootings occur in many of America's public arenas, from movie theaters to gay bars. By not including such mass shootings in my analysis, I can explore how communities react to tragedies involving only K-12 students. It can be assumed that the public's response to a K-12 school shooting, a population that has not become politicized, will differ from that of a mass shooting in a gay bar, considering the history of homophobia in the United States. Thus, while research has found that mass shootings induce an increase in firearm acquisition rates, stratifying my analysis to a less politicized population will reveal the possible homogeneity or heterogeneity of the public's response to tragic events involving violence towards K-12 students.

My paper is organized in the following order. I first provide a background of K-12 school shootings in the United States and their effects on American society while also exploring the process of acquiring a firearm in the United States. Second, I outline my data sources and summary statistics relevant to my analysis. Third, I specify my Econometric model and its associated assumptions. Fourth, I conduct a series of robustness checks and expand upon my main results. Fifth, I document my results, comparing and contrasting them to work already done in this field. And, lastly, I conclude with future directions this research could take.

I Background

The United States has a unique relationship to firearms. Guaranteed as a fundamental right in the U.S. Constitution's Second Amendment, the right to bear firearms is a hallmark of American culture and, among certain circles, viewed as a fundamental right bestowed to the American people (Woolf, 2017). Intended initially to deter British influence during America's founding, the Second Amendment has become a symbol of individual liberty and freedom, two fundamental tenets that guide American politics (Woolf, 2017). Strong support for the Second Amendment has resulted in the creation of large, powerful gun-rights lobbying groups, including most notably the National Rifle Association (NRA) (Waldman, n.d.).

Despite the mounting pressure for gun control reform in the wake of mass shootings, such lobbying groups have successfully blocked the passage of stricter gun control legislation while also limiting research into firearms (Kramer and Harlan, 2019; Raphelson, 2018). Most notably, the NRA has successfully stifled study and data collection initiatives related to guns through the Dickey Amendment of 1996 (Rostron, 2018). The amendment required that the Centers for Disease Control and Prevention (CDC) cannot use its funds to research that could be used to "advocate or promote gun control" (Rostron, 2018). The NRA has been successful in its other initiatives to preserve the Second Amendment's sanctity despite research that has documented the positive relationship between liberal gun control legislation and mass shootings (Kaste, 2021; Raphelson, 2018; Reeping et al., 2019).

While the NRA and other lobbying groups have sought to preserve the Second Amendment, their policy agenda has dramatically redefined the K-12 American school system (Raphelson, 2018). Instead of making acquiring firearms more onerous, the U.S. government, backed by public interest groups, have turned K-12 schools into what some educators describe as a "war zone" (Davis, 2019; Raphelson, 2018) K-12 students are regularly subject to active shooter drills, where schools will simulate fake shootings to prepare students for such a tragedy. This approach is summarized by the acronym and company ALICE – Alert, Lockdown, Inform, Counter, and Evacuate – who trains schools to implement active shooter drills to prepare students for a school shooting (O'Regan, 2020). Many educators have criticized this approach to deterring school shootings, arguing such exercises traumatize students. Instead, they have advocated for stricter gun control legislation, increased access to mental health resources for students, and the creation of more inclusive school environments (O'Regan, 2020; Vossekuil et al., 2004).

While it is improbable that students will experience a school shooting, the threat of school shootings looms large on the American populace, contributing to the public perception that school shootings are a grave threat (Muschert, 2007). Exemplified by the term the Rashomon effect, where eyewitness accounts of events often mislead the public's understanding of events, the media and fear-mongering culture caused in part by school shootings lead Americans to react to school shootings (Muschert, 2007).

Figure 3 highlights the locations of all U.S. school shootings, with the magnitude of the causalities represented by the size of the circle. However, with much of the nation transitioning to remote learning due to the COVID-19 pandemic, school shootings have become less common, as evidenced by the drop in school shooting counts portrayed in Figure 2. Politically controversial and nuanced, school shootings and their public natures are a manifestation and space where one of America's core ideals, individual liberty, is tested and challenged.

A Background: The Process of Acquiring Firearms

To combat gun violence, the US government passed the Brady Act, creating a federal database of criminal, mental, and drug history for individuals known as NICS. NICS gathers data from the National Crime Information Center, the Interstate Identification Index, and the NICS index (Center, 2020). The National Crime Information Center collects data on missing person reports, criminal records, protection orders, and more (Center, 2020). The Interstate Identification Index has information on individuals who have been arrested or convicted of felonies or serious misdemeanors (Center, 2020). The NICS index gathers data not covered in the two categories mentioned above, including mental health records and citizenship status (Center, 2020). However, it is essential to note that individual states have the discretion on whether they share, with the federal government, a citizens' criminal history, mental health, drug abuse, and domestic violence records, leading to an incomplete database (Center, 2020).

Individuals who wish to purchase a firearm must fill out a Firearms Transaction Record (ATF Form 4473), which records the individual's personal identifying information and present a government-issued photo ID to the firearms dealer (Center, 2020). The dealer will then contact the NICS Operation Center, providing them with the information listed on the ATF Form 4473 (Center, 2020). It is important to note here that the Bureau of Alcohol, Tobacco, Firearms, and Explosives (ATF) are prohibited from collecting data on gun purchases due to pro-gun lobbying efforts (Center, 2020).

After the application has been processed through NICS, the buyer will receive one of three decisions: an instruction to proceed with the firearm sale, instruction to deny the firearm permit, or instruction to delay to gather furthermore information on whether the individual is eligible to purchase a firearm (Center, 2020). If NICS does not contact the dealer within three business days, the sale can continue. Most gun permits are denied on the grounds of a felony or misdemeanor crime conviction (Center, 2020).

There is, however, a lot of variability in whether an individual is granted a firearm permit (Center, 2020). Some states are much more stringent with their background checks; states and local authorities may conduct their background checks, alongside the NICS background check, to determine eligibility to purchase for all types of firearms (Center, 2020). These states include California, Colorado, Connecticut, Florida, Hawaii, Illinois, Nevada, New Jersey, Oregon, Pennsylvania, Tennessee, Utah, Virginia, and Washington. Some states also conduct more than one background check depending on the type of firearm (Center, 2020). For example, Maryland, Nebraska, New Hampshire, Washington, and Wisconsin conduct their background checks for individuals trying to acquire handguns (Center, 2020). There is a great deal of variability in whether an individual is granted a gun license (Center, 2020).

II Data

I construct a novel data set using publicly available data from Google Trends, the Pew Research Center, K-12 School Shooting Database operated by the Center for Homeland Defense and Security, United States Census Bureau, and NICS database, gathering my data at the state, year, and month level. I exclude 2020 from my analysis, given that the number of school shootings decreased due to, in part, education's transition to remote learning (Kumar, 2020).

I manipulate and merge these data sets to estimate my Event Study Frameworks. Table 1 and 2 present my summary statistics of interest. Of interest, the mean number of NICS background checks was 25,522, while the average number of search "hits" was 10.46. The number of causalities for each school shooting ranged from 0 to 35.

A Independent Variable: Proxies for Gun Ownership and American's Interest in Firearms

I use NICS and Google Trends data as proxies for Gun Ownership and American's Interest in Firearms, respectively, merging them with my control variables when necessary for my analysis.

A.1 National Instant Background Check System (NICS)

As there is no comprehensive database containing the number of guns sold, I use the National Instant Criminal Background Check System (NICS) database. While gun control legislation varies by state, an individual who wishes to buy a firearm must undergo a criminal background check through NICS. While people may be denied a permit to buy a gun, NICS still documents the number of background checks conducted for each state and year. The NICS data set may not reflect the actual number of firearms purchased; however, this data set is the best available proxy for gun-ownership rates (Raphelson, 2018). I restrict my analysis periods from January 2000 to 2019 December, in monthly increments, given data availability.

A.2 Google Trends Data

To supplement my main analysis, which uses NICS data, I mine data from Google Trends, gathering data on the relative number of searches for four-hundred and sixteen terms related to gun manufactures and models for all fifty states and D.C. in monthly increments for my analysis periods[1]. I restrict my analysis periods from January 2004 to December 2019, as Google Trends began collecting the most accurate data beginning in 2004. After mining data, I am left with a search "hits" index for each term by month, year, and state, which ranges from 0 to 100, and measures the following:

> "The index does not capture the actual volume or magnitude of individual searches over time. Instead, it provides a measure of search activity relative to the month or week with the highest search volume level within the period examined. For example, an analysis of monthly search activity over a year would express each month's search activity relative to the month with the highest search activity level. The month with the highest level of relative search activity is given a score of 100. An analysis of weekly search activity uses the same approach, but with weeks as the unit of comparison instead of months." (Lam, 2018)

After getting an index for each search term by month, year, and state, I calculate the mean value of "hits" for all 416 terms by date and state. This variable serves as a proxy for American citizens' interest in guns and, more broadly, a measure of interest in firearms.

B Control Variables

B.1 Center for Homeland Defense and Security K-12 School Shooting Database (SSDB), and U.S. Census Bureau Intercensal County Population Data

I use data from the Center for Homeland Defense and Security K-12 School Shooting Database, which documents the date, school, state, number of casualties, a reliability index, firearm type, race of the shooter, victims' race, and more. The database is unique in that it documents "every instance a gun is brandished, is fired, or a bullet hits school property for any reason, regardless of the number of victims, time of day, or day of the week" (Friedman,

[1] I gather the list of terms from a Pew Research Study Center Study (Lam, 2018). The terms can be found in this Google Drive folder linked here Google Trends search terms.

Jernegan and O'Neill, 2020). Given that there were instances where there were more than 1 school shooting in a month, I sum the total number of causalities from school shootings for every given year-month in my data set. I then create a dummy variable C that takes on a value of 1 if a school had more than 1 casualty and takes on a value of 0 if otherwise.

Further, I utilize the Census' Intercensal County Population Data by Age, Sex, Race, and Hispanic Origin, which contains data on each county's demographic makeup from 1999 to 2020. Using this data set, I calculate the percentage of minority groups in each county. Specifically, I sum the total number of African-Americans in a given county and year, then divide that number by the respective state's total population, multiplying this figure by 100. Studies have used different percentage thresholds to determine whether a community is a majority POC neighborhood, ranging from 20% to 30% (Candipan, 2019). I use a less conservative threshold than that of previous studies. I create a dummy variable, taking on a value of 1 if more than 20% of a county's population identify as Black, and 0 if otherwise for each school shooting in my month-year time period, coding this variable as POC. In instances where more than 1 school shooting occurred in a majority Black county, I code it as 1. I merge this data set with my SSDB by time and county where the school was located in.

I am left with a data set with monthly time increments from January 2000 to 2019 December and its associated dummy variables, C and POC. I merge this data set with my independent variable databases, NICS and Google Trends Data.

III Empirical Strategy

To estimate the effect of school shootings on gun ownership rates, I estimate the following event-study state-year-month fixed effects framework:

$$ln(Permit_{it}) = \sum_{k=1}^{6} \beta_k ln(Permit_{it+k}) * C_{it} + \sum_{k=-6}^{-1} \gamma_k ln(Permit_{it+k}) * C_{it} + \delta_i + \sigma_t + \varepsilon_{it} \quad (1)$$

where $\ln(Permit_{it})$ is the proxy for the number of gun ownership rates in state i and month-year t, as measured by the number of firearm background checks. The 50 U.S. states and D.C. are indexed by i, while t spans periods in monthly increments from November 1998 to December 2019, inclusive. k indexes the number of firearm background checks k months before and after a school shooting. I exclude the month of the school shooting to avoid perfect multicollinearity. I seek to capture whether school shootings with one more causalities induced an increase in firearm acquisition rates, interacting $Permits$ with C.

I include state and time fixed effects, represented by δ_i and σ_t, respectively, capturing time trends and societal factors that influence gun ownership rates.

My variables of interest are the lead interacted coefficients in the months following a school shooting. I expect to find statistically positive or negative coefficients on the variables mentioned above. On the one hand, in response to school shootings, communities may respond with more vigilance, as evidenced by the widespread implementation of ALICE protocols in schools, increasing gun acquisition rates. On the other hand, communities may respond by purchasing fewer firearms, diverting resources to fund mental health initiatives, and rehabilitative resources.

For causal identification, I assume that school shootings are exogenous. Depending on the school shooting scale, school shootings become the headlines of major news outlets and often shock a community social order, albeit many Americans, given the frequency of school shootings, have become desensitized to such news (Person, 2019). Given the shock school shootings induce upon communities, it can be assumed there is an element of surprise in such events. Therefore, I assume that my event study will capture an exogenous shock to the social order and capture the actual change in gun purchases in the aftermath of a school shooting. Further, I assume that a school shooting's effects will solely be captured by changes in gun-ownership rates conditional on the control variables, considering that my control variables will capture any confounding events that influence gun ownership rates.

There are, however, several threats to the identification. First, with its considerable lobbying influence in D.C., the NRA has limited data collection and gun-related research (Raphelson, 2018). Thus, NICS data is not the best proxy for gun ownership rates, resulting in measurement error of my dependant and independent variables. As NICS records all gun permit applications they receive, without regard to whether an individual is issued a license or not, the NICS data does not reflect the actual number of gun purchases in the United States. For example, guns can and are obtained through illegal means (Raphelson, 2020).

Furthermore, individuals who purchase firearms from a person's home, internet, or gun show are not subject to a background check Raphelson (2020). Such sales are thus not included in the NICS dataset (Raphelson, 2020). Second, some states, including California, make it harder for individuals to acquire firearms, including enacting stricter firearm legislation, mandatory firearm use training, and enhanced background checks (Raphelson, 2020). The factors mentioned above will lead to measurement errors in my dependant and independent variables.

A Extensions and Robustness Checks to Main Results

A.1 Robustness Check: Google Trends Data

To supplement my main results, which uses NICS data as a proxy for gun ownership rates, I estimate a level-log event-study state-year-month fixed-effects framework, using Google search data as my dependant variable:

$$Search_{it} = \sum_{k=1}^{6} \beta_k ln(Search_{it+k}) * C_{it} + \sum_{k=-6}^{-1} \gamma_k ln(Search_{it+k}) * C_{it} + \delta_i + \sigma_t + \varepsilon_{it} \qquad (2)$$

The indexes subscripts and variables are the same as equation 1 besides the coefficient $Search$ and its indexing variable k. The variable $Search$ is the log of the mean value of "hits" for all term searches for a given state, month, and year, calculating the average number of "hits" for all search terms for guns for a given state and all periods that Google Trends has data on. k indexes the average number of search "hits" for gun manufacturers and models six months before and after a school shooting, excluding the school shooting month and year of the school shooting to avoid perfect multi-collinearity. As Google Trends began calculating its data most accurate data starting in 2004, I restrict my analysis periods from January 2004 to December 2019 in monthly increments indexed by i.

For this event-study analysis, I do not seek to find a causal linkage between gun ownership rates in the aftermath of school shootings. I strive to explore the relationship between Google searches for terms before and after a school shooting, supplementing my main results, given the issues with Google Trends data.

There are several issues with the Google Search index, which will bias my results. First, approximately fifteen percent of the U.S. population do not have access to the internet, implying that Google searches cannot truly represent the actual number of interest in guns and firearm acquisitions (Lam, 2018). Second, searching for a term does not mean that an individual seeks to buy a firearm without knowing the motivations for such searches, the best conclusion that can be made from Google Trends data is American peoples' interest in firearms. Thus, I use Google Trends as a proxy for Americans' interest in firearms.

A.2 Extension to Main Results: Census Regions

Complementing my primary analysis of Event Study Framework 1, I estimate the heterogeneous effects of background checks for firearms by the four census regions (Agnich, 2014).[2]

[2]The Census divides up the United States into four different areas. The Northeast region consists of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, &

I estimate regression 1 but estimating four separate regressions based on the Census region.

A.3 Extensions to Main Results: County Demographics

Complementing my analyses, I seek to explore whether county demographics of where a school shooting occurred impacts the number of firearm acquisition rates. I estimate two event study analyses similar to that of framework 1, stratifying my sample into schools located in majority-white and Black counties.

A.4 Extensions to Main Results: The Predictive Ability of Google Trends

Similar to that of framework 1, I seek to explore the relationship between permit applications and Google searches with Event Study Framework 3 with the following equation:

$$ln(Search_{it}) = \sum_{k=1}^{6} \beta_k ln(Permit_{it+k}) * C_{it} + \sum_{k=-6}^{-1} \gamma_k ln(Permit_{it+k}) * C_{it} + \delta_i + \sigma_t + \varepsilon_{it} \quad (3)$$

The model variables and assumptions are the same as the analyses above.

IV Results

A Main Results

Figure 3 and Table 4 highlight the results of Event Study Framework 1. Consistent with prior literature, I find that in the month following a school shooting, firearm acquisition rates increases by up to 32% *($p<0.05$)* one month after a school shooting relative to the month of the shooting. My results suggest this effect subsides after one month, as evidenced by statistically insignificant coefficients in the months following a school shooting.

A.1 Google Trends Data

Complementing my aforementioned results, Table 4 and Figure 5 show the results of Event Study Framework 2. Using Google Trends data, I find that Americans' interest in

Pennsylvania. The Midwest region consists of the states: Indiana, Illinois, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, & South Dakota. The South region consists of the District of Columbia and the following states: Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma & Texas. The West region consists of Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming, Alaska, California, Hawaii, Oregon, & Washington.

guns as measured by Google search data shows that firearms' interest increases by 0.0123 index points *($p<0.05$)* a month before a school shooting relative to the month of the school shooting. In the subsequent months, there are no statistically significant coefficients.

Comparing the results of Event Study Framework 1 and 2, both results complement each other. An increase in searches for firearms the month before could indicate a future school shooting, while increases in permit applications in the month following a school shooting reveal that communities respond to school shootings with more vigilance.

There are several caveats associated with my interpretation of results. Given that Google calculates their search index relative to the period with the highest search activity levels, the index does not capture the "real" number of searches, resulting in measurement error in variables, inconsistent, and less precise estimates.

A.2 Census Regions

After stratifying my sample my the four Census regions, I find that the rate of firearm acquisition in the month following a school shooting differs. My results are presented Table 5 and Figure 6.

My results suggest there is no significant difference between gun permit applications based on the Census regions, considering the statistically insignificant coefficients.

Many factors could be attributed to the null results in NICS permit applications in the Midwest, South, and West regions, including the severity of gun legislation in each respective area, culture of gun ownership, and more. However, due to my model's nature, I cannot tease out the under-guiding variables that affect the magnitudes' coefficients mentioned above.

A.3 County Demographics

Table 6 and Figure 7 portray the results of my county demographics regression. I find weak evidence to suggest that schools located within majority-white counties experienced a higher rate of gun acquisition rates than schools located in majority Black counties in the aftermath of a school shooting. Specifically, schools located within majority Black and white counties experienced approximately a 56% *($p<0.01$)* and 65% *($p<0.001$)* increase in NICS application rates compared to the month of the school shooting, albeit both these point estimates, are within the range of each other.

Such results should, however, be interpreted with caution. First, counties cover broad areas and, with school and neighborhood segregation, the at-large country demographics may not mirror that of the school's demographics. For example, Cook County, IL, spans the City of Chicago and some suburbs, missing out on the demographic variation within a county.

Second, schools located in a majority POC neighborhoods may experience higher crime rates and, thus, more exposure to firearms (Hipp, 2007). To counter this issue, gathering data on the demographics of each school and running my analyses with such data could yield more economically meaningful results.

A.4 Predictive Ability of Google Trends

Estimating the relationship between permit applications and Google searches, I find there is little relationship between Google Searches for firearms and gun acquisitions, as evidenced by 7. While there is a statistically coefficient in the month before a school shooting, implying that a one-unit increase in one permit applications, increases Google Searches for firearms by approximately 8%, when analyzing the coefficients in the months following a school shootings, my statistically insignificant coefficients do not reveal a relationship between Google Searches and gun permit applications.

V Conclusion

My study seeks to understand how communities respond to tragic events involving violence, analyzing school shootings' impact on gun acquisition rates. Using data from NICS and school shootings, I construct a novel data set, estimating an event-study analysis. In line with existing literature, I find that in the month following a school shooting, NICS background checks increases by 32% compared to the month of the school shooting. Despite its data issues, my results reveal that Americans react similarly to school shootings, as they do with mass shootings, responding with more vigilance and purchasing more firearms.

Extending my analyses to heterogeneity across the four Census regions, I find little evidence to suggest that region affects gun acquisition rates following a school shooting. However, I find weak evidence to suggest that schools located within majority-white counties have higher levels of gun acquisition rates after a school shooting compared to majority-Black counties.

My study adds to existing research that touches on the relationship between firearm acquisition rates and mass shootings, Google Trends data, and its predictive ability to forecast future social events, including but not limited to unemployment rates (D'Amuri and Marcucci, 2017; Lam, 2018; Nagao, Takeda and Tanaka, 2019).

My results contribute to the existing literature on mass shootings and how society responds to them while also revealing new research questions. Given that firearm acquisition rates increase in the months following a school shooting, it would be interesting to investigate the cascading effects of increased firearm acquisitions, researching whether such increases in firearms cause more or less social turbulence. Furthermore, other avenues of research could stratify my analysis at the county-state level, accounting for the additional variation of firearm purchases at the county level.

When viewed in conjunction with existing literature that has documented the positive relationship between firearms and gun violence, my results suggest that lawmakers should enact stringent gun control legislation, closing the loopholes that allow individuals to purchase firearms (Raphelson, 2018; Reeping et al., 2019).

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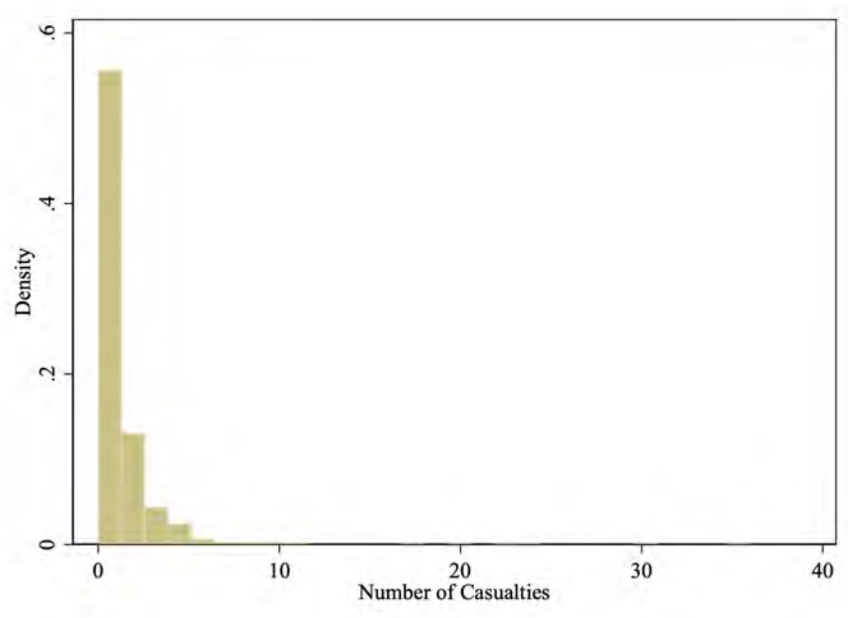
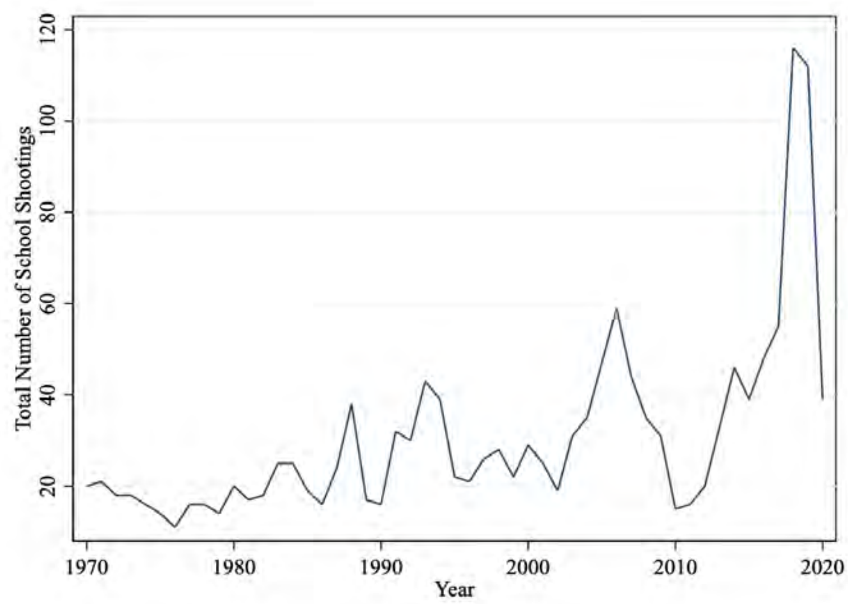
Figures

Figure 1: Total Casualties from School Shootings between November 1998 - May 2020



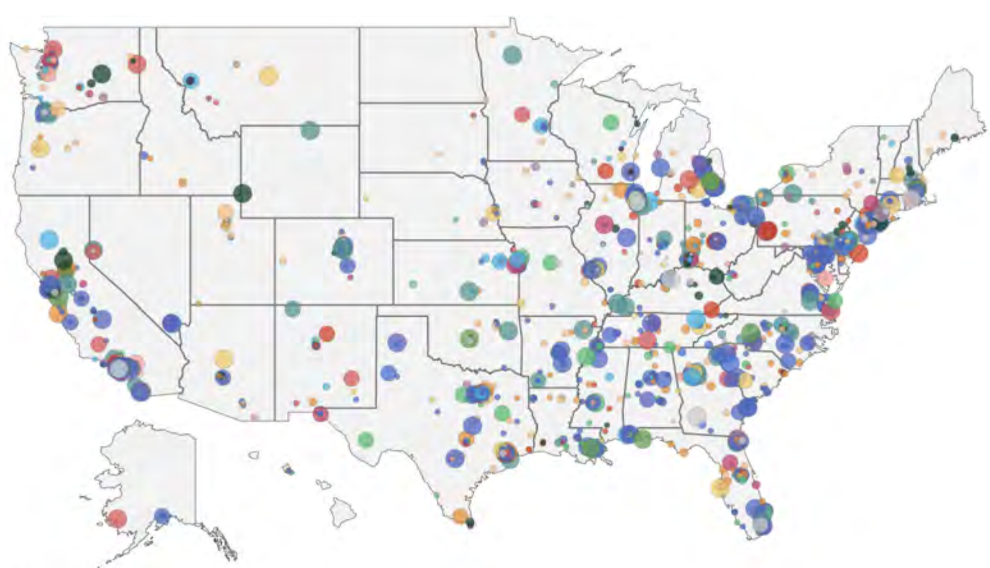
Source: SSDB.

Figure 2: School Shooting Count by Year in the United States



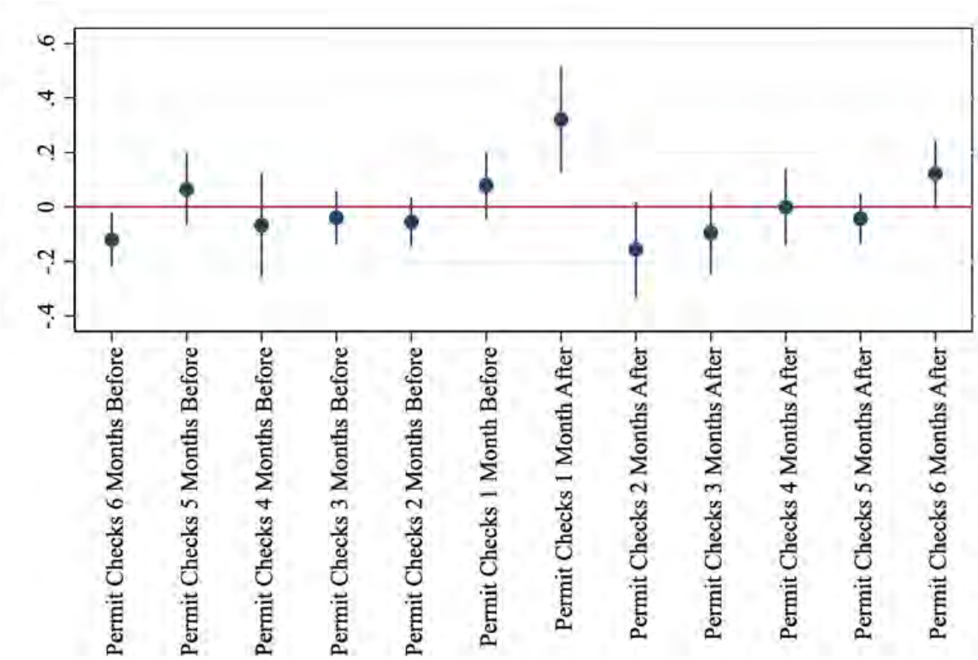
Source: SSDB.

Figure 3: School Shooting Map



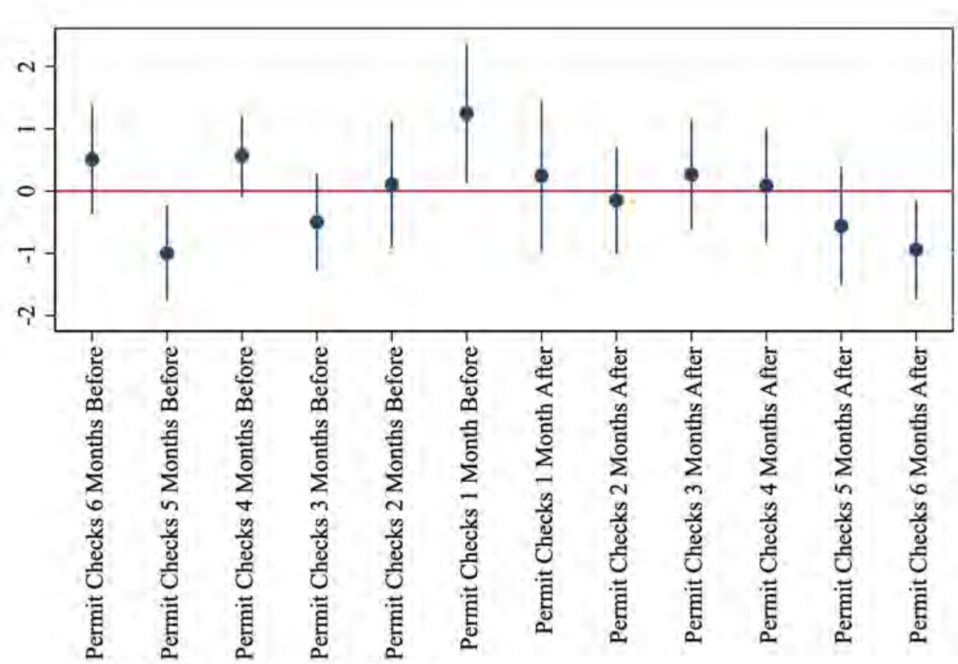
Source: SSDB. Each circle represents a school shooting, while the size of the circle denotes the magnitude of the school shooting. The data spans from January, 1970 to May, 2020

Figure 4: Event Study Framework (1)



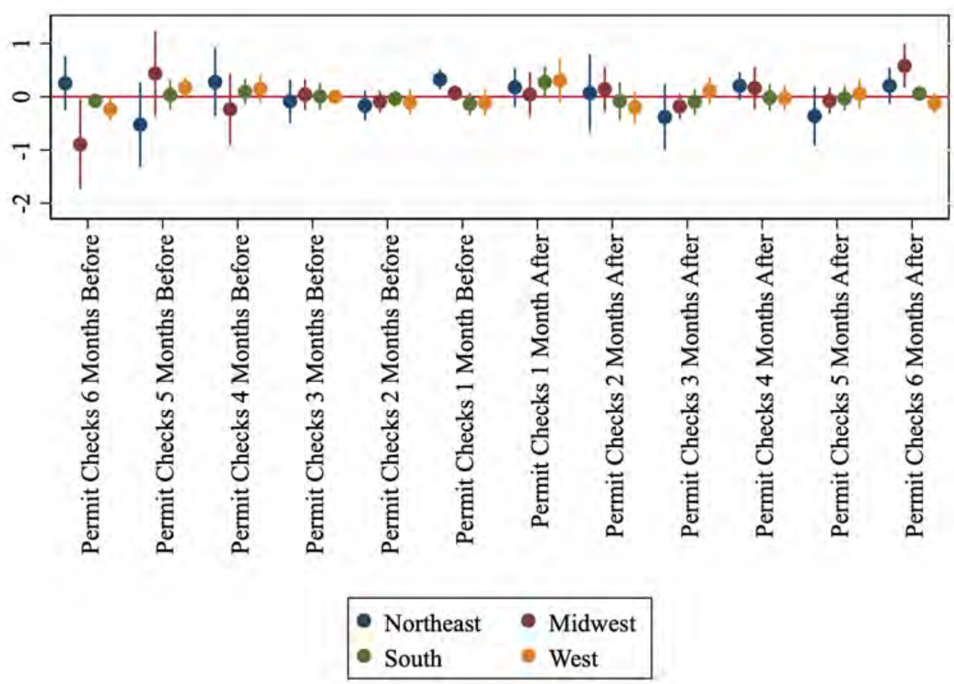
Source: SSDB Database. Event Study Analysis (1) conducted using NICS data as a proxy for gun acquisition rates.

Figure 5: Event Study Analysis using Google Trends Data (2)



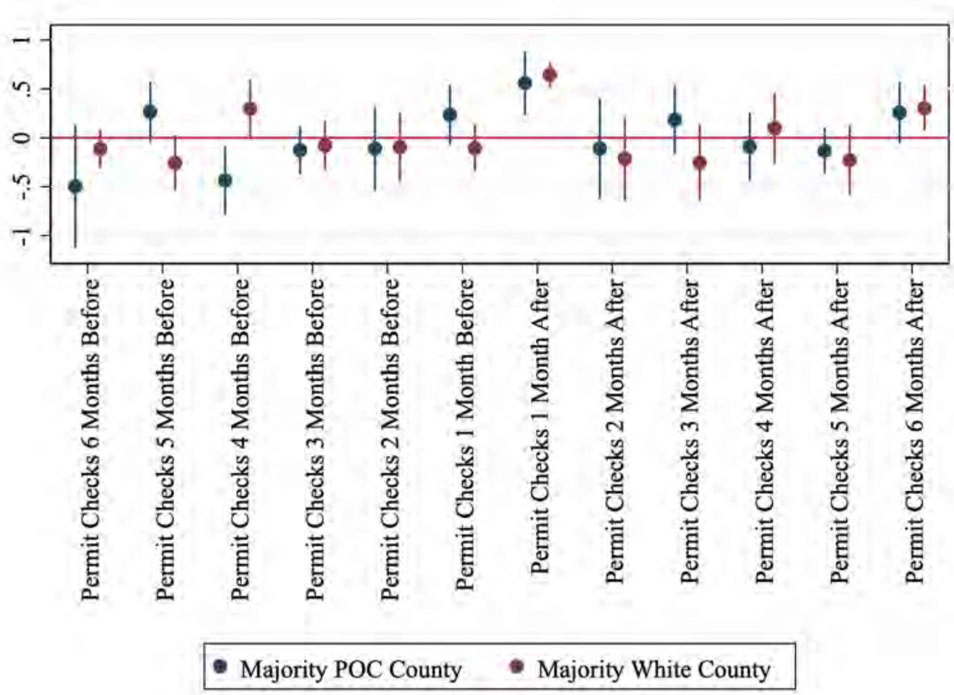
Event Study Analysis conducted using Google Trends data as a proxy for Americans' gun-ownership rates and/or gun interest.

Figure 6: Event Study Analysis by Census Region (3)



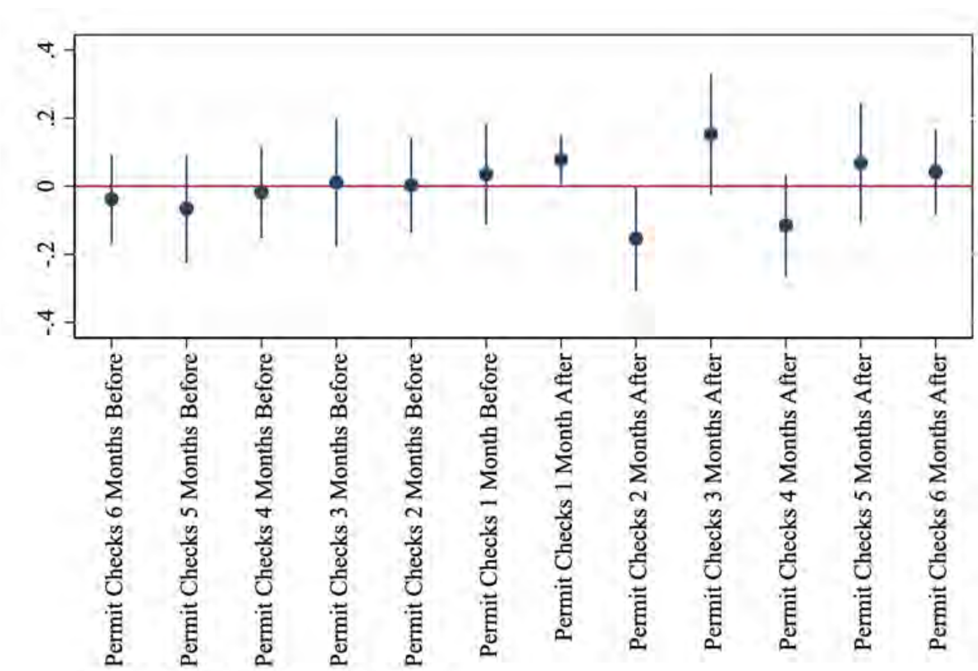
Event Study Analysis by the four Census regions using NICS data.

Figure 7: Event Study Analysis by County Demographics (4)



Event Study Analysis by County Demographics.

Figure 8: Predictive Ability of Google Trends



Event Study Analysis: Predictive Ability of Google Trends.

Tables

Table 1: Summary Statistics I

Variable	Mean	Std. Dev.	Min.	Max.	N
Number of Background Checks	25522.57	38256.97	1	541978	12232
Permit Checks Total (log)	9.47	1.29	0	13.2	12232
Permit Checks 6 Months Before (log)	9.43	1.33	0	13.2	12232
Permit Checks 5 Months Before (log)	9.45	1.3	0	13.2	12232
Permit Checks 4 Months Before (log)	9.46	1.3	0	13.2	12232
Permit Checks 3 Months Before (log)	9.46	1.29	0	13.2	12232
Permit Checks 2 Months Before (log)	9.47	1.29	0	13.2	12232
Permit Checks 1 Month Before (log)	9.47	1.29	0	13.2	12232
Permit Checks 1 Month After (log)	9.48	1.29	0.69	13.2	12232
Permit Checks 2 Months After (log)	9.48	1.29	0.69	13.2	12232
Permit Checks 3 Months After (log)	9.49	1.29	0.69	13.2	12232
Permit Checks 4 Months After (log)	9.49	1.29	0	13.2	12232
Permit Checks 5 Months After (log)	9.49	1.29	0	13.2	12232
Permit Checks 6 Months After (log)	9.5	1.29	0	13.21	12232
Total # of Casualties	1.5	2.67	0	35	722
Casualty Dummy	0.05	0.21	0	1	12232
Permit Checks 6 Months Before (Interaction)	0.48	2.19	0	13.2	12232
Permit Checks 5 Months Before (Interaction)	0.48	2.19	0	12.93	12232
Permit Checks 4 Months Before (Interaction)	0.48	2.19	0	12.93	12232
Permit Checks 3 Months Before (Interaction)	0.48	2.2	0	12.94	12232
Permit Checks 2 Months Before (Interaction)	0.48	2.2	0	12.93	12232
Permit Checks 1 Month Before (Interaction)	0.49	2.2	0	12.95	12232
Permit Checks 1 Month After (Interaction)	0.49	2.2	0	13.2	12232
Permit Checks 2 Months After (Interaction)	0.49	2.2	0	13.11	12232
Permit Checks 3 Months After (Interaction)	0.48	2.2	0	13.11	12232
Permit Checks 4 Months After (Interaction)	0.48	2.2	0	13.11	12232
Permit Checks 5 Months After (Interaction)	0.48	2.2	0	13.09	12232
Permit Checks 6 Months After (Interaction)	0.48	2.2	0	13.21	12232
People of Color (=1 if Majority Black)	1	0	1	1	250
People of Color (=0 if Majority White)	0	0	0	0	306

Source: NICS, U.S. Census Bureau Intercensal County Population Data, & SSDB Database. Analysis time period ranges from January 2000 to December 2019.

Table 2: Summary Statistics II

Variable	Mean	Std. Dev.	Min.	Max.	N
Mean Hits	10.46	5.19	0	39.92	8536
Mean Hits 6 Months Before (log)	2.16	0.63	-0.84	3.69	8536
Mean Hits 5 Months Before (log)	2.17	0.63	-0.84	3.69	8536
Mean Hits 4 Months Before (log)	2.18	0.62	-0.84	3.69	8536
Mean Hits 3 Months Before (log)	2.18	0.61	-0.84	3.69	8536
Mean Hits 2 Months Before (log)	2.19	0.6	-0.84	3.69	8536
Mean Hits 1 Month After (log)	2.21	0.57	-0.84	3.69	8536
Mean Hits 2 Months After (log)	2.22	0.57	-0.84	3.69	8536
Mean Hits 3 Months After (log)	2.22	0.56	-0.84	3.69	8536
Mean Hits 4 Months After (log)	2.23	0.56	-0.84	3.69	8536
Mean Hits 5 Months After (log)	2.23	0.55	-0.84	3.69	8536
Mean Hits 6 Months After (log)	2.24	0.54	-0.73	3.69	8536
Casualty Dummy	0.05	0.23	0	1	8536
Total # of Casualties	1.53	2.78	0	35	591
Permit Checks 6 Months Before (Interaction)	0.12	0.53	0	3.47	8536
Permit Checks 5 Months Before (Interaction)	0.12	0.53	-0.69	3.51	8536
Permit Checks 4 Months Before (Interaction)	0.12	0.53	-0.71	3.62	8536
Permit Checks 3 Months Before (Interaction)	0.13	0.54	0	3.69	8536
Permit Checks 2 Months Before (Interaction)	0.13	0.54	0	3.62	8536
Permit Checks 1 Month Before (Interaction)	0.13	0.54	0	3.68	8536
Permit Checks 1 Month After (Interaction)	0.13	0.54	0	3.48	8536
Permit Checks 2 Months After (Interaction)	0.13	0.54	0	3.55	8536
Permit Checks 3 Months After (Interaction)	0.13	0.54	0	3.6	8536
Permit Checks 4 Months After (Interaction)	0.13	0.54	0	3.58	8536
Permit Checks 5 Months After (Interaction)	0.13	0.53	-0.34	3.62	8536
Permit Checks 6 Months After (Interaction)	0.13	0.53	0	3.47	8536

Source: Google Trends, U.S. Census Bureau Intercensal County Population Data, & SSDB Database. Analysis time period ranges from January 2004 to December 2019.

Table 3: Event Study (1)

	(1) Permit Checks
Permit Checks 6 Months Before	-0.121*
	(0.0494)
Permit Checks 5 Months Before	0.0633
	(0.0670)
Permit Checks 4 Months Before	-0.0672
	(0.0955)
Permit Checks 3 Months Before	-0.0411
	(0.0487)
Permit Checks 2 Months Before	-0.0556
	(0.0453)
Permit Checks 1 Month Before	0.0781
	(0.0614)
Permit Checks 1 Month After	0.320**
	(0.0959)
Permit Checks 2 Months After	-0.157
	(0.0884)
Permit Checks 3 Months After	-0.0958
	(0.0759)
Permit Checks 4 Months After	-0.00113
	(0.0712)
Permit Checks 5 Months After	-0.0441
	(0.0463)
Permit Checks 6 Months After	0.122
	(0.0618)
Constant	9.472***
	(0.000836)
Observations	12232
Adjusted R^2	0.956

Standard errors in parentheses and are cluster-robust at the state level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Event Study Framework using Google Trends Data (2)

	(1) (mean) Hits
Permit Checks 6 Months Before	0.510 (0.440)
Permit Checks 5 Months Before	-1.002* (0.383)
Permit Checks 4 Months Before	0.563 (0.325)
Permit Checks 3 Months Before	-0.502 (0.389)
Permit Checks 2 Months Before	0.106 (0.507)
Permit Checks 1 Month Before	1.245* (0.560)
Permit Checks 1 Month After	0.245 (0.606)
Permit Checks 2 Months After	-0.148 (0.432)
Permit Checks 3 Months After	0.266 (0.441)
Permit Checks 4 Months After	0.0847 (0.458)
Permit Checks 5 Months After	-0.561 (0.476)
Permit Checks 6 Months After	-0.941* (0.394)
Constant	10.48*** (0.00572)
Observations	8536
Adjusted R^2	0.822

Standard errors in parentheses and are cluster-robust at the state level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Extension to Main Results: Census Regions (3)

	(1) Northeast	(2) Midwest	(3) South	(4) West
Permit Checks 6 Months Before	0.255	-0.891*	-0.0765	-0.237*
	(0.223)	(0.386)	(0.0471)	(0.0937)
Permit Checks 5 Months Before	-0.524	0.435	0.0319	0.173
	(0.346)	(0.367)	(0.129)	(0.0812)
Permit Checks 4 Months Before	0.276	-0.235	0.0936	0.153
	(0.280)	(0.306)	(0.109)	(0.114)
Permit Checks 3 Months Before	-0.0841	0.0407	0.00748	0.000920
	(0.177)	(0.131)	(0.117)	(0.0510)
Permit Checks 2 Months Before	-0.164	-0.0930	-0.0349	-0.104
	(0.121)	(0.0904)	(0.0713)	(0.108)
Permit Checks 1 Month Before	0.326**	0.0698	-0.135	-0.112
	(0.0787)	(0.0651)	(0.0985)	(0.113)
Permit Checks 1 Month After	0.176	0.0418	0.276	0.302
	(0.160)	(0.190)	(0.141)	(0.188)
Permit Checks 2 Months After	0.0701	0.142	-0.0814	-0.194
	(0.318)	(0.194)	(0.170)	(0.135)
Permit Checks 3 Months After	-0.382	-0.180	-0.0956	0.113
	(0.268)	(0.107)	(0.113)	(0.118)
Permit Checks 4 Months After	0.205	0.164	-0.0175	-0.0267
	(0.111)	(0.183)	(0.119)	(0.107)
Permit Checks 5 Months After	-0.361	-0.0742	-0.0281	0.0542
	(0.241)	(0.112)	(0.109)	(0.127)
Permit Checks 6 Months After	0.207	0.578**	0.0594	-0.125
	(0.147)	(0.186)	(0.0665)	(0.0854)
Observations	2178	2904	4004	3146
Adjusted R^2	0.975	0.950	0.948	0.960

Standard errors in parentheses and are cluster-robust at the state level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Extension to Main Results: County Demographics (4)

	(1) Majority POC	(2) Majority White
Permit Checks 6 Months Before	-0.497	-0.112
	(0.305)	(0.0966)
Permit Checks 5 Months Before	0.267	-0.258
	(0.151)	(0.140)
Permit Checks 4 Months Before	-0.435*	0.299*
	(0.170)	(0.147)
Permit Checks 3 Months Before	-0.126	-0.0778
	(0.119)	(0.125)
Permit Checks 2 Months Before	-0.110	-0.0954
	(0.209)	(0.176)
Permit Checks 1 Month Before	0.236	-0.106
	(0.148)	(0.120)
Permit Checks 1 Month After	0.561**	0.646***
	(0.160)	(0.0633)
Permit Checks 2 Months After	-0.109	-0.213
	(0.249)	(0.212)
Permit Checks 3 Months After	0.184	-0.255
	(0.169)	(0.193)
Permit Checks 4 Months After	-0.0913	0.0988
	(0.171)	(0.180)
Permit Checks 5 Months After	-0.132	-0.228
	(0.113)	(0.174)
Permit Checks 6 Months After	0.259	0.304*
	(0.154)	(0.117)
Constant	10.35***	10.32***
	(0.0264)	(0.0307)
Observations	250	306
Adjusted R^2	0.950	0.955

Standard errors in parentheses and are cluster-robust at the state level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Extension to Main Results: Predictive Ability of Google Trends (5)

	(1)
	ln(Search)
Permit Checks 6 Months Before	-0.0380
	(0.0650)
Permit Checks 5 Months Before	-0.0661
	(0.0793)
Permit Checks 4 Months Before	-0.0188
	(0.0669)
Permit Checks 3 Months Before	0.0112
	(0.0947)
Permit Checks 2 Months Before	0.00264
	(0.0703)
Permit Checks 1 Month Before	0.0349
	(0.0731)
Permit Checks 1 Month After	0.0777*
	(0.0357)
Permit Checks 2 Months After	-0.154
	(0.0768)
Permit Checks 3 Months After	0.153
	(0.0885)
Permit Checks 4 Months After	-0.115
	(0.0749)
Permit Checks 5 Months After	0.0677
	(0.0877)
Permit Checks 6 Months After	0.0419
	(0.0624)
Constant	2.144***
	(0.000582)
Observations	8955
Adjusted R^2	0.772

Standard errors in parentheses and are cluster-robust at the state level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$