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UNIVERSITY OF CALIFORNIA, IRVINE

Essays on the determinants of state-level policies in the US

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in
Economics

by

Avik Sanyal

Dissertation Committee:
Amihai Glazer, Professor of Economics, Emeritus, Chair
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2023

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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ABSTRACT OF THE DISSERTATION

Essays on the determinants of state-level policies in the US

by

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Doctor of Philosophy in Economics

University of California, Irvine, 2023

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This dissertation delves into the determinants of state government policies pertaining to welfare, mental health, and immigration in the United States. By examining the effects of shock events, residential segregation, and skilled immigration, this study sheds light on the factors shaping policy decisions at the state level. In the first chapter, the impact of mass shootings as shock events on mental health policy is explored. Through the creation of a unique dataset combining mass shooting data, media coverage, and state-level mental health legislation, the research reveals that while mass shootings lead to an increase in introduced legislation, the enacted policies predominantly focus on mental healthcare in schools. The second chapter focuses on the relationship between resident segregation and welfare policies. A novel measure of segregation and interracial exposure at the state level is developed, and analysis across states and time uncovers that decreased segregation and increased interracial exposure generally result in increased welfare generosity. However, certain states in the deep south experience a contrary effect, likely attributed to historical racism and a higher proportion of African Americans. Turning to immigration, the third chapter investigates the connection between skilled immigration and support for welfare generosity among the college-educated. Drawing on various surveys such as the American Community Survey, Current Population Survey, and American National Election Survey, the study explores fiscal burden-sharing and economic anxiety induced by skilled immigrants. However, the results do not provide conclusive evidence of skilled immigration significantly influencing attitudes towards redistribution. Overall, this dissertation emphasizes the endogeneity of state government policies and scrutinizes the impact of shock events, racial stereotypes, and skilled immigration. The findings contribute to a deeper understanding of policy determinants and offer insights that can assist policymakers in assessing the outcomes of their decisions.

Chapter 1

Impact of mass shootings on mental health policy

Abstract

How do shock events that highlight a policy shortcoming impact the policy-making process? With the recent disturbing rise in mass shootings, is it possible that their association with mental illnesses can provide an impetus for better mental health care policies by highlighting the failure of existing mental health policies? This paper examines how mass shootings impact mental health policy-making by analyzing state governments' responses to such events. I construct a novel dataset of mass shootings, media coverage, and mental health legislation to investigate how these events impact the introduction and passage of laws related to mental health care. The findings indicate that mass shootings increase mental health-related legislation introduced and enacted by state governments, with a more pronounced effect on legislation that improves access to mental health care in schools and other educational settings. The study also finds that higher media coverage of mass shootings increases bills but has no effect on whether they are enacted into law. Furthermore, there is no evidence that the political party in power or the shooter's race impacts mental health policy. The findings suggest that mass shootings highlight the dangers of un-diagnosed mental illnesses and create a 'policy window' for enacting policies aimed at improving access to mental health care, with the effect being more noteworthy for school-related mental health policies.

1.1 Introduction

The recent horrifying mass shootings at Michigan State University, Monterrey Park, and Half Moon Bay are the latest in a string of shooting rampages committed by perpetrators who were allegedly mentally ill. Arguably, the most heinous of such mass shootings in recent years occurred on May 24, 2022, when a lone gunman went on a shooting rampage at Robb Elementary School in Uvalde, Texas. The massacre claimed 21 lives, including 19 children between the ages of 9 and 11. Despite not being the first mass shooting of 2022, the massacre generated unimaginable horror as it occurred in an elementary school and claimed the lives of 19 children. Texas Governor Greg Abbott blamed the shooting on mental illness. A month later, in June, the State of Texas introduced a school safety legislation appropriating \$105.5 million for mental health-related initiatives in schools to prevent future shootings (Mizan, 2022). This policy response was similar to how California and Colorado enacted legislation to improve insurance coverage of mental illnesses following the San Jose railyard and Indianapolis FedEx facility shootings in 2021. These examples appear to indicate that mass shootings may make the issue of mental illnesses more salient by highlighting the dangers of when they are not diagnosed, in turn leading to governments enacting policies to make mental healthcare more accessible. However, there are also instances, such as the Oxford High School shooting in Michigan, where legislators introduced legislation to improve insurance coverage of mental illnesses, but it did not get enacted into law. Because mass shootings are often attributed to mental illness, with Folham (2016) claiming that almost 60 % of American mass shooters were mentally ill, how do they shape mental health policy at the state level? What factors determine whether mental health-related bills that are introduced are enacted into law? What are the different kinds of avenues via which state governments try to make mental healthcare more accessible? How does the disproportionate level of media coverage following a mass shooting impact mental health policy? Is mental health policy only affected when the perpetrator is white?

This paper examines whether mass shootings induce policy change in mental health policies of US states and the effect of factors like media coverage, political party, and the racial background of the victims and perpetrators in the same. For this purpose, I begin by assembling an original dataset of mass shootings from various articles, media coverage of mass shootings from media archives such as the Vanderbilt Television News Archive (VTNA), mental health legislation from legal databases like LexisNexis, and various other political, demographic and institutional variables from data sources such as the Census Bureau's County Business Patterns (CP) and FBI's Supplementary Homicide Report (SHR). I then create a state-year panel dataset from 2001 to 2020 where the main dependent variable is a measure of mental health-related legislation and the explanatory variables are measures of mass shootings, media coverage as well as other political, demographic, and institutional covariates. The analyses then employ both count and binary data models on the aforementioned data I collected to analyze the impact of mass shootings on both the probability of introduction of bills and laws and the count of bills and laws enacted at the state level. I also analyze how factors such as the media coverage of mass shootings, the political party in power, and the race of the perpetrator and victims shape the legislative impact.

The analyses yield several key results. First, a mass shooting leads to an increase in legislation aimed at improving access to mental healthcare in schools in terms of both bills and laws enacted with the results being robust under both count and binary specifications. Mass shootings also lead to an increase in the introduction of bills related to restricting firearm access on grounds of mental illness but have no such effect on laws suggesting that the introduction of bills is a largely symbolic response or 'feel good' legislation (Schildkraut, 2014). The possible reason why school-related bills get enacted into law while firearm-related bills do not could be due to the divisive nature of the latter and the organized opposition it faces. Secondly, the media coverage affects the number of bills introduced but has no statistically significant effect on laws enacted implying that the media coverage generates public outrage to which politicians respond by introducing 'feel good' legislation to appease their constituents. Third, there does not appear to be any evidence of a partisan divide between Democrat and Republican states in terms of their legislative response to mass shootings. Finally, the perpetrator's race does not have any heterogenous policy impact despite the media's framing of white shooters as 'mentally ill lone wolves' (Duxbury et al, 2016).

I perform several robustness checks to test whether the results can be interpreted as a causal impact of mass shootings on mental health policymaking. First, I show that the results are robust to alternative definitions of mass shootings by estimating the main regression with the definition of mass shootings used by Luca et al (2020) and The Violence Project (2022). Second, I test for spillover effects onto neighboring states by including indicators to capture mass shootings in neighboring states in the regression. This exercise reveals that mass shootings in neighboring states or in the same census division have no statistically significant impact on mental health policy. Third, by including an additional regressor for the cumulative count of mass shootings, I show that, while repeated mass shootings over the years exert a snowballing effect on mental health-related policy, the said effect is relatively small in substantive terms. Hence, the baseline estimates do not appear to be notably biased as a result of mass shootings in years prior. Finally, I show that the results are not affected by any temporal trend in mental health policy over the years before by including state-specific time trends in the regression.

The paper contributes to several strands of literature. First, the paper furthers the research on how shock events affect the policy-making process by highlighting a policy limitation,. Existing literature has shown that natural disasters (Gagliarducci et all, 2019; Farley et all, 2007; Ashworth et al, 2018), terrorist attacks (Birkland, 2004; Schmidt, 2017; Kim, 2016), and energy shocks (Grossman, 2013; Dunn, 2006) influence policies in the realm of environment, security, and energy respectively. This paper contributes to said literature, by analyzing and providing evidence that shock events like mass shootings do influence certain categories of mental health policies by highlighting the dangers of undiagnozed mental illnesses.

Second, though relatively nascent, there is emerging empirical literature about how mass shootings impact state and local policy in the US where existing research has focused mainly on gun control policy (Luca et al, 2020; Schildkraut et al 2014; Fleming et al, 2016), labor productivity (Brodeur and Yousaf, 2022) and electoral shares (Yousaf, 2021), but very little on mental health policy which is a gap I intend to fill.

Third, the paper also contributes to the literature on the mental health impact of mass shootings, where existing research has focused mainly on how mass shootings affect the mental health of survivors (Lowe and Galea, 2017) or shape perceptions towards mentally ill individuals (McGinty et al, 2013) but little on how they affect state-level mental health policy which is also a gap that the paper intends to fill.

Fourth, there is a growing effort to document and collect data on mass shootings (*Mother Jones*, 2022, *The Violence Project*, 2022), which this paper contributes to with an originally created novel dataset of mass shootings in the US.

Fifth, there is emerging empirical literature on the determinants of state mental health policies such as insurance parity laws (Hernandez and Uggen, 2015). This paper contributes to said literature by studying how shock events like mass shootings, which are often attributed to mental illness, impact state-level mental health policy.

Sixth, the paper contributes to the literature on how media coverage influences policy-making (Eisensee and Stromberg, 2007; Durante and Zhuravskaya, 2018) as mass shootings receive outsized media attention relative to other forms of violent crime (Luca et al, 2020) with the media often touting improved access to mental healthcare as a possible solution to prevent future mass shootings (Jashinsky, et al 2017).

Finally, the paper contributes to the literature on the role of race in shaping US government policy. Previous research in this area has shown that the race of a welfare recipient determines welfare generosity (Gillens, 1996; Schramm et al 2010), and that of criminals shapes the punitiveness of criminal justice policies (Peffley and Hurwitz, 1989). This paper extends the analysis to mental health policy by analyzing whether the race of the perpetrator and victims of a mass shooting plays a role in shaping mental health policy. Additionally, though gun policies are not the main focus, the paper contributes to the literature on how mass shootings and gun policy (Luca et al, 2020) are related by analyzing how gun policies related to mental illnesses (such as mandatory mental health evaluations for purchasing a firearm) are impacted by mass shootings.

The remainder of the paper is structured as follows: section 2 describes the policy window hypotheses and section 3 describes the process of collecting and compiling the data and creating the variables. Section 5 and 6 describes the empirical specification and main results. Sections 7, 8, and 9 explore the role of media coverage, political party, and race of the shooter and victims.

1.2 Conceptual framework

This paper empirically examines the policy window hypothesis, which posits that policy-makers are more likely to enact new policies when an issue emerges as an urgent problem that requires attention, and there is a politically beneficial solution available. The theory, originally formulated by Kingdon (1984), suggests that "focusing events," such as natural disasters or acts of mass violence, can serve as catalysts for policy change by highlighting the shortcomings of existing policies and creating an opportunity (Baumgartner, 2009) for new policy solutions to be considered.

Mass shootings are a particularly notable example of a catastrophe that can serve as a "focusing event" for policy change, as they are widely considered to be acts of extreme violence that frequently elicit public and political debates (Chapel, 2014). These events are likely to be a catalyst for policies aimed at preventing mass shootings. Despite being statistically rare, mass shootings generate a climate of fear (Studdert, 2014) as evidenced by the fact that nearly half of Americans fear being killed in a mass shooting (Brennan, 2019). Though there is no conclusive evidence of mental illness being the primary driver of mass shootings, these events draw significant attention to the issue of undiagnosed mental illnesses and can provide an impetus for policymakers to enact policies aimed at improving access to mental healthcare in order to prevent future occurrences.

Berkland and Schweble (2016) argue that the way the media frames a focusing event plays a crucial role in the policy-making process. As mass shootings receive an out-sized amount of media coverage relative to other forms of violent crime (Luca et al, 2020), media coverage would play a crucial role in determining the policy window and subsequent legislative outcomes.

In the policy window hypothesis of Kingdon (1984), the political landscape or the party in power plays an important role in determining whether a focusing event will lead to the opening of a policy window. This is because the political incentives to enact policy are shaped by the party in power, as is the case with mass shootings and mental healthcare. For example, Republicans often argue that easy access to firearms is not the main cause of mass shootings and gun violence (Parker et al, 2017), but rather mental illness is. As such, they might be more likely to introduce mental health legislation after a mass shooting in order to prevent future occurrences, as opposed to Democrat states which might rely on gun control to do the same. This also applies to other areas of policy such as insurance parity legislation. Republicans tend to be less supportive of insurance parity laws as the opponents of these laws are usually health insurance companies (Hernandez and Uggen, 2016).

While the theory of policy windows suggests that "focusing events" such as natural disasters or acts of mass violence can create opportunities for policy change by highlighting the shortcomings of existing policies, there is research that has shown focusing events to not always lead to concrete policy change (Birkland and Schweble, 2016). This is mainly due to the actions of organized interest groups, such as the National Rifle Association (NRA), which may oppose certain policies. Schildkraut et al (2014) and Birkland and Lawrence (2016) have demonstrated that mass shootings may lead to an increase in gun-control-related bills being introduced, but these bills often do not get enacted into law due to opposition from interest groups like the NRA. These bills can be considered as "feel good" legislation, introduced by politicians in response to public angst generated by the outsized media coverage of mass shootings.

1.3 Data and variables

The dataset used in the paper is a state-year panel dataset from 2001 to 2020. The key explanatory variables are measures of mass shootings, whether the shooter was mentally ill, along with the level of media coverage received by all mass shootings in a given state-year. The main outcome variables are measures of mental health legislation enacted by state governments.

1.3.1 Mental health legislation

I begin by counting the number of bills introduced and laws enacted in a state's legislature in a given year that are aimed at improving access to mental health care. The Bill Tracker provision in the Lexis Nexis database has a list of all bills, joint resolutions, concurrent resolutions along with the date they were introduced, a brief synopsis and a timeline, introduced in each state legislature from 1990 onwards. Upon searching using five keywords: 'mental health', 'behavioral health', 'schizophrenia', 'depression' and 'psychiatrist' etc, I obtain the list of bills introduced in different State Legislatures in different years in the realm of mental health.

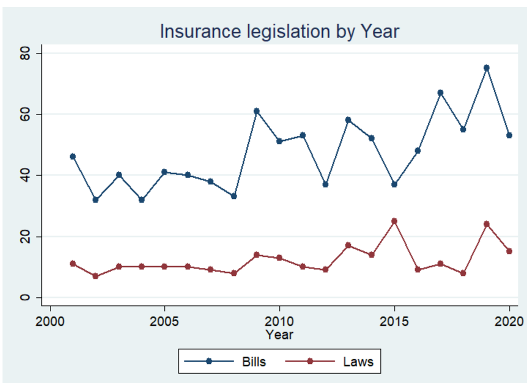
The number of mental health related bills introduced is quite high with about 1000 to 1500 bills introduced each year across different state legislatures and a total of approximately 26,000 bills introduced across state legislatures from 2001 to 2020. Due to such a high volume of bills, I restrict my analysis to four specific categories of mental health legislation that are aimed at: (1) improving insurance coverage of mental illnesses, (2) improving access to mental healthcare in schools and universities, (3) constructing or improving community based mental health clinics and (4) restricting access to firearms for those deemed mentally ill. I use a provision in the LexisNexis database that allows for additional filtering of bills using keywords such as 'school', 'university', 'insurance', 'medicaid', 'community', 'firearm' etc to obtain a list of bills introduced in state legislatures in the different categories and create variables for the count of bills introduced by category in every state-year. I also create a variable for the number of bills that were eventually enacted into law. Table 1.1 displays the list of keywords used to search and filter for the aforementioned legislation categories.

Table 1.1: Legislation and keywords

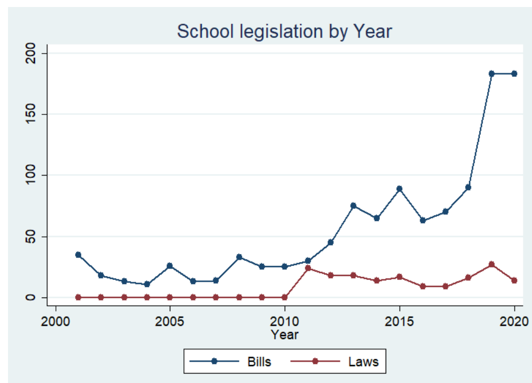
Category	*Keywords in the LexisNexis*
All Mental Health related Legislation	'mental health', 'behavioral health', 'psychiatry' 'schizophrenia', 'depression'
Subcategories	*Additional filter under keywords*
• Insurance	'insurance, 'medicaid', 'coverage', 'parity'
• School	'school', 'education, 'university'
• Community	'community
• Firearm	'firearm', 'evaluation', 'background check'

Figure 1.1: Mental health related bills and laws across time

(a) Insurance bills and laws

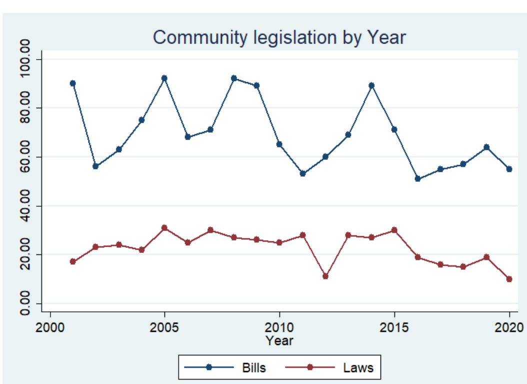


(b) School bills and laws

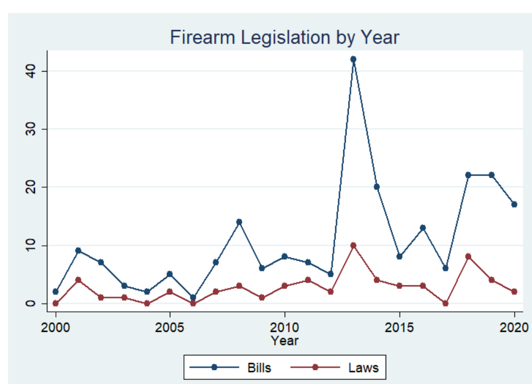


Notes Figure 1.1 displays trends in the total number of bills and laws introduced by category over the years. The blue lines depict trends in bills introduced across years while the red lines depicts trends in laws enacted. The count of laws enacted is quite low relative to the count of bills introduced. We also observe alternating years of high and low bill introductions for most categories which is due to more bills being introduced in the first year of a legislative biennum

(c) Community bills and laws



(d) Firearm bills and laws



The school bills category includes bills recommending educating teachers on mental health issues, incorporating the topic of mental health in the school's education curriculum, hiring mental health professionals as school counselors, etc. The insurance related bills are those requiring private insurance companies to comply with federal parity laws or bills seeking to expand medicaid coverage of certain kinds of mental health treatment. The community bills category denotes bills that seek to improve community based mental healthcare facilities for low-income individuals with chronic mental health conditions. The firearm bills category denotes bills specifically introduced to restrict access to firearms to those deemed mentally ill such as those requiring mental health evaluations to obtain a firearms permit.

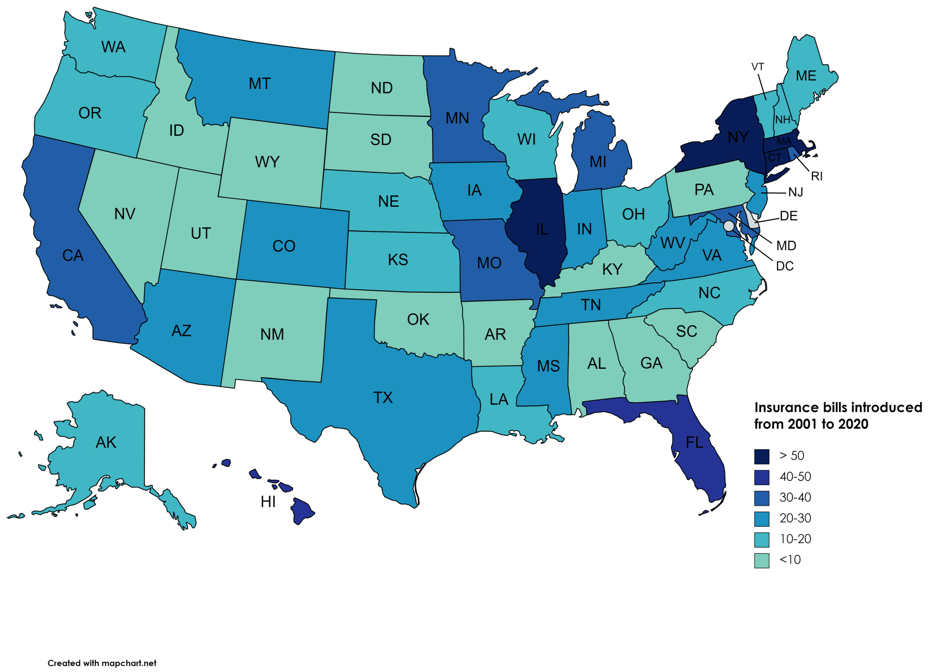
For school related bills, we observe that the period between 2012 and 2015 and the period between 2018 and 2020 witnessed a surge in the introduction of school related bills with the latter being particularly high in magnitude (see upper right panel of figure 1.2). The states of Connecticut, Illinois, Florida, New York, Massachussets and to a lesser extent California (see lower panel of figure 1.1), have introduced the most.

For insurance related bills, the period between 2008 and 2010 and between 2012 and 2014 witnessed a surge in bills introduced (see upper left panel of figure 1.1) and a relatively smaller surge in laws enacted. The former period coincides with the passage of Mental Healthcare and Addiction Parity Equity Act (MHPEA) of 2008 by the Federal Government which mandated insurance carriers to offer coverage for mental healthcare and subsequently led states to introduce their own legislation for insurance coverage. The period from 2012 to 2014 coincides with the passage of the Affordable Care Act (ACA or Obamacare) which mandated insurance carriers to cover certain mental health conditions like schizophrenia under its 'essential benefits' provision. Similar to the MHPEA of 2008, the ACA also led to states passing more legislation to ensure insurance parity. The states of California, Texas, Minnesota, New York, Massachusetts and Virginia have introduced the most insurance related bills (see map on upper panel of figure 1.2).

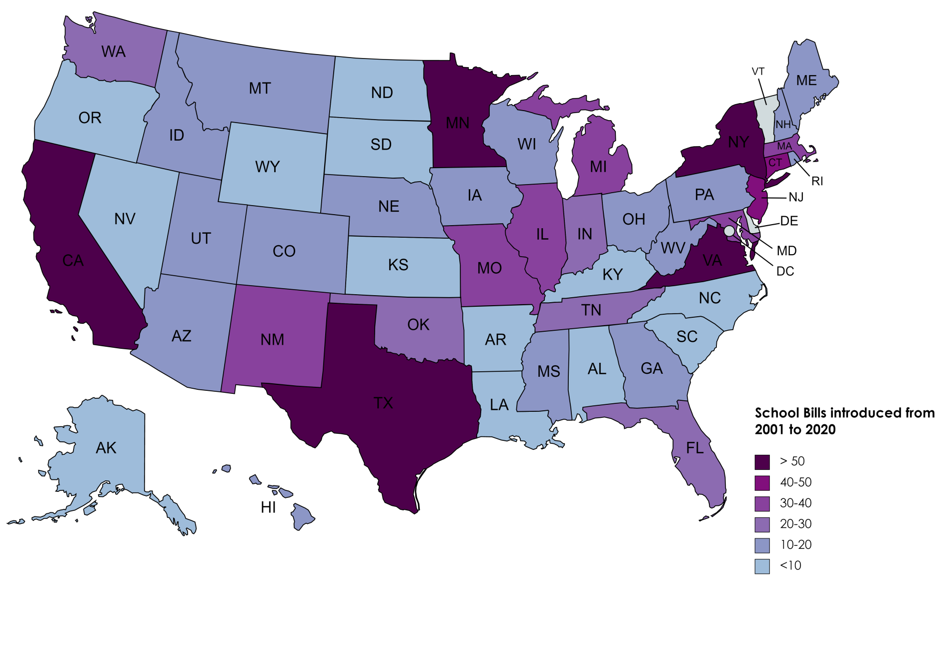
Community bills have no upward trend and thus are different from the other categories in this regard. We observe a noticeable decline from 2008 which was possibly caused due to the financial crises of 2008 (see lower left panel on figure 1.1) leading to federal and state governments reducing the budgets for publicly funded mental health services such as community mental health clinics. This was followed by a noticeable increase in the 2012 to 2015 period. Similar to insurance and school bills, Illinois, New York and California (see map on upper panel of figure 3) are among the states that have introduced the most number of bills in this category.

The count of firearm bills introduced is low but there are three noticeable surges (see lower right panel on figure 1.2). Illinois, Virginia, Connecticut, New York, Florida and Maryland (see map on lower panel of figure 1.3) are the states that introduced the most firearm-restrictive bills related to mental illness.

Figure 1.2: Total insurance and school bills introduced by state

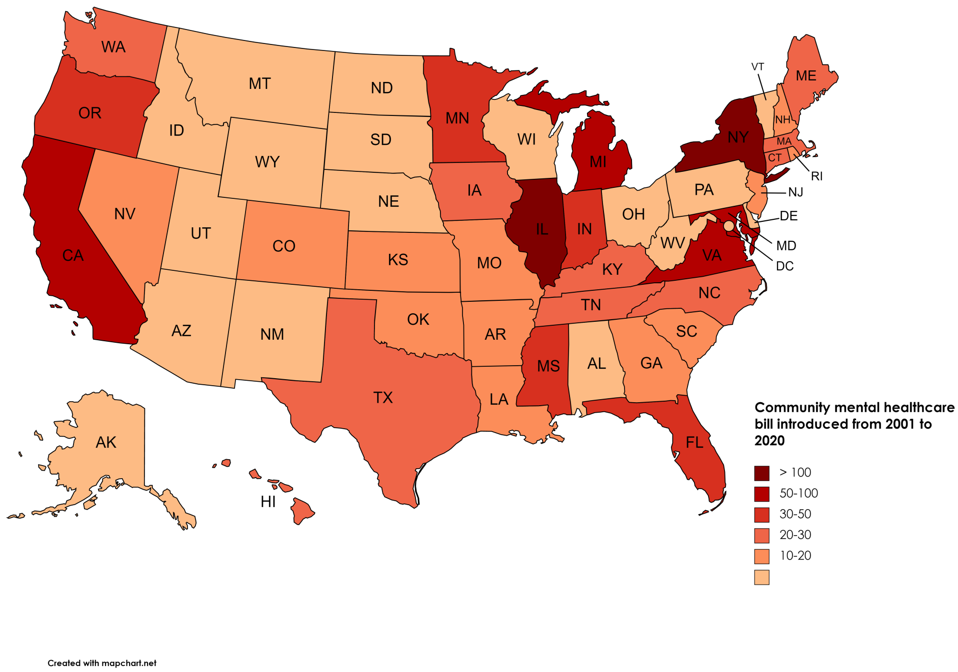


Total insurance bills introduced by state

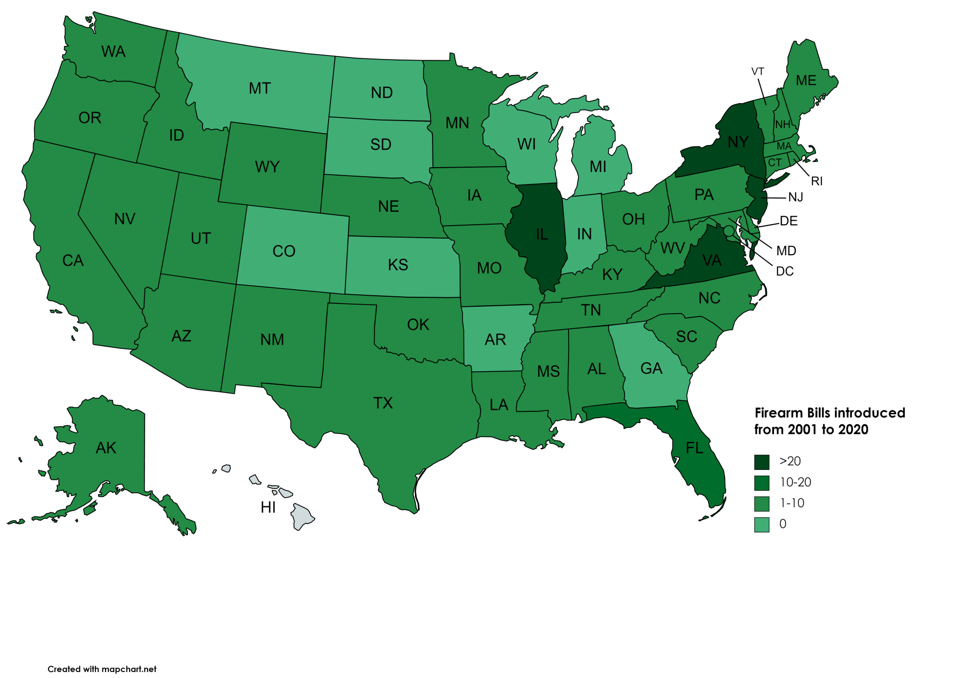


Total school bills introduced by state

Figure 1.3: Total count of community and firearm bills introduced by state



Total community bills introduced by state



Total firearm bills introduced by state

1.3.2 Mass shootings

Mass shootings are generally defined as incidents of gun violence where a lone perpetrator kills and/or wounds multiple victims. The Congressional definition of *mass murder* was originally defined as any incident of homicide that led to the deaths of four or more people but was later expanded in 2014 to also include incidents with three or more fatalities. For the definition of mass shootings, *Mother Jones* magazine, America's longest-running investigative journalism entity, and the book '*Violence Project: How to stop a mass shooting epidemic* by Densley and Peterson(2021) both describe a mass shooting as a single incident where a lone gunman, who has no personal relationship with the victims, indiscriminately kills 4 or more people in a public setting. This categorization excludes family murders or any shooting where the shooter and victims shared any kind of personal relationship. Another definition is given by *Gun Violence Archive*, a non-profit research group that collects data on firearm related homicides, and Stanford University's *Mass Shootings of America* database where a mass shooting is described as any incident of gun violence where at least four people are shot but not necessarily killed and in both public and private venues with no restrictions on the type of relationship between the shooter and victims. This broader definition includes gang and organized crime related shootings as well. Luca, Malhotra, and Poliquin (2020), similar to *Mother Jones* and the *Violence Project*, also uses the definition of four or more people killed and includes shootings in both private and public settings but excludes any shooting where the perpetrator and victims shared any personal relationship (i.e family murders).

For this paper I define a mass shooting as any incident of gun violence where 3 or more individuals are killed (similar to the congressional definition of *mass murder*) but slightly expand the definition to also include incidents where two people are killed and at least two others wounded in both public and private settings which also includes shootings where the victims and the perpetrators shared any kind of relationship. Unlike *Mother Jones*', Luca et al (2020) and the *Violence project*, this paper's categorization does not restrict the shooter's motivation to random and indiscriminate killing and thus includes shootings driven by personal vendetta (such as familicides) since such shootings can also make the issue of mental illness more salient (such as Pike Country, Ohio murders of 2017). My definition also differs from Luca et al (2020) in that I use the updated Congressional definition of mass murder of three or more deaths (slightly expanded to include incidents with 2 fatalities and 2 non-fatal injuries) instead of four or more deaths as the fatality threshold of a mass shooting. The Congressional definition is intended to determine whether the US Department of Justice has the authority to provide investigative assistance to state and local agencies in the event of a mass homicide. As such mass shootings which meet the fatality threshold, are likely to fall under the investigative jurisdiction of Federal authorities and would be more salient to policymakers. Unlike Stanford University and Gun Violence Archive's broader categorization I restrict the definition to shootings with multiple fatalities as higher fatalities are more likely to garner more media attention and induce the Government to take action and exclude gang related shooting due to their non-random nature. My categorization also includes spree killings, which are homicides occurring at multiple locations by the same perpetrator, if there is no significant pause between the different incidents and if they fit the aforementioned criterion of at least 3 people killed or 2 people killed and an additional two wounded.

This paper's definition captures mass shooting incidents that would likely play a role in creating an impetus for policy change in the realm of mental health. The use of the updated Congressional definition implies that the mass shootings recorded in my database fall under the investigative jurisdiction of the federal Government and are thus likely to have received media attention and induce state governments to enact policies. Including familicides and mass shootings driven by personal vendetta whilst excluding gang related shootings ensures that my dataset records mass shootings that are likely to be attributed to mental illness and would have received sufficient media coverage. Table 1.2 compares the paper's definition with that of other databases.

Table 1.2: Comparison of mass shooting databases

	Sanyal(2022)	Luca et al (2020)	Mother Jones	Violence Project	Gun Violence Archive	Stanford' MSA
Casualties	3 or more fatalities or 2 fatalities and 2 injures	4 or more fatalities	4 or more fatalities	4 or more fatalities	4 or more injuries	3 or more injuries
Location	Any	Public	Public	Public	Any	Any
Personal relationship between shooter and victims	✓	×	×	×	✓	✓
Gang violence	×	×	×	×	✓	✓
Spree Killings	✓	✓	×	×	✓	✓

I assemble an original dataset of such mass shootings from 2001 to 2020 for all 50 states primarily from newspaper articles. The main newspapers I use are the *New York Times*, the *Los Angeles Times*, the *Chicago Tribune* and the *Washington Post*. For each newspaper, I use the advanced search feature on their respective websites to filter by year and keywords such as 'mass shooting in Nevada' or 'multiple homicide in Alabama' to obtain a list of shootings by state that meet the aforementioned definition. As an additional source, I use the FBI's Supplementary Homicide Report (SHR) database which is an incident-level database of homicides committed in the US from 1988. The database contains detailed information about each homicide such as the age, race, gender, and weapon used. Using the information about the date and city/county of a mass shooting incident from newspaper articles, I look up every mass shooting incident on the SHR database in order to corroborate them. However, reporting homicides to the FBI is voluntary for police departments and many do not report at all. I find that approximately 10.19 % of mass shootings reported in newspapers do not appear on the FBI-SHR. The FBI-SHR database is thus somewhat limited in this regard as many mass shootings reported in newspaper articles do not show up on the FBI-SHR. For such mass shootings that do not show up in the FBI-SHR but show up in the aforementioned newspapers, I rely on local newspapers in order to corroborate them.

I create an indicator variable at the state-year level if there was any mass shooting, and another variable for the total number of shootings in each state in a given year. Further, I create variables for the total fatality and injury counts from all mass shootings in a given state year and whether any of the shootings occurred in schools, places of worship, were driven by racial or political hatred or labelled a terrorist act.

I also code each mass shooting incident in terms of whether the perpetrator was allegedly mentally ill as per newspaper reports. It is important to note that media reports about a mass shooting perpetrator being mentally ill (which are often based on initial rumors) are subjective in nature and does not necessarily imply that the perpetrator was diagnosed with a mental illness by a qualified professional. However, *perception* of a perpetrator being motivated by mental illness is a key factor in the level of importance that the issue of mental health acquires in the aftermath of a mass shooting and media articles can definitely shape such perceptions. Around 70.1 % of perpetrators have atleast one article dedicated to them being mentally ill in aforementioned news paper articles.

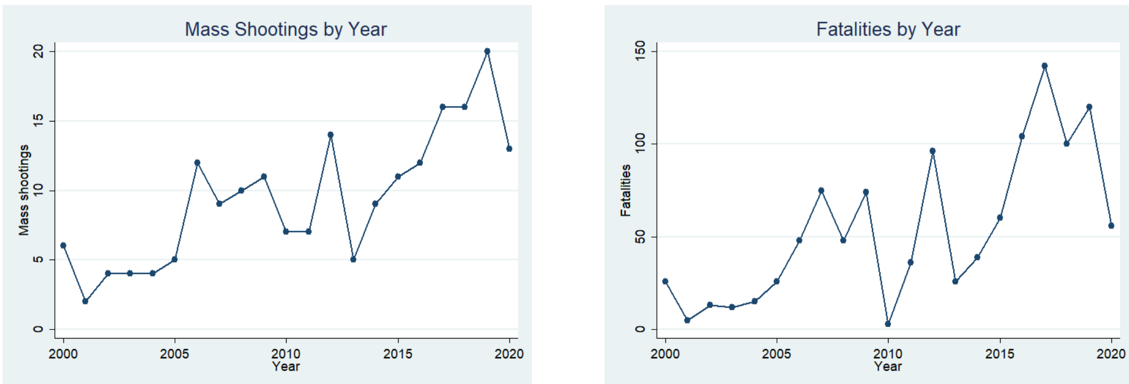
I further create two additional variables to capture the racial aspect of a mass shooting. The first variable is a dichotomous indicator variable which equals 1 if any of the mass shootings in a given state-year was carried out by a white perpetrator. The second variable, which captures the demographic composition of the victims, is the share of victims who are white. The data for both are obtained from the Supplemental Homicide Reports section of the FBI's Uniform Crime Reports (UCR) database. In our sample of 216 mass shootings, approximately 65.9 % of shootings are committed by perpetrators listed as White in the

FBI-SHR (see figure 6) while approximately 39.6 % of victims of mass shootings were listed as white.[1]

Figure 1.4: Mass shootings and fatalities by year

(a) Mass shootings by year

(b) Fatalities by year



As per my criteria, there were 216 mass shootings that occurred between 2001 and 2020. In comparison, *Mother Jones* magazine and *Violence Project*, with their relatively stricter definitions recorded 87 and 94 mass shootings in the sample period respectively. Some examples of prominent mass shootings included in my dataset but not in the two aforementioned ones are the Chardon high school shooting of 2012 (which had less than four fatalities) and the Christopher Dornier manhunt of 2013 (which was a spree-killing), both of which received substantial media coverage (71 and 150 minutes respectively). *Gun Violence Archive* with their broader criterion recorded 2701 mass shootings in the period from 2014 to 2020 (the periods for which their website contains publicly available data) while my dataset records 95 mass shootings in the same time frame. Their dataset includes many mass shootings which mine does not due to the shootings not crossing the required fatality threshold in my criteria. One such example is the Little Rock nightclub shooting in Arkansas where 28 people were shot but none were killed and was attributed to a gang rivalry.

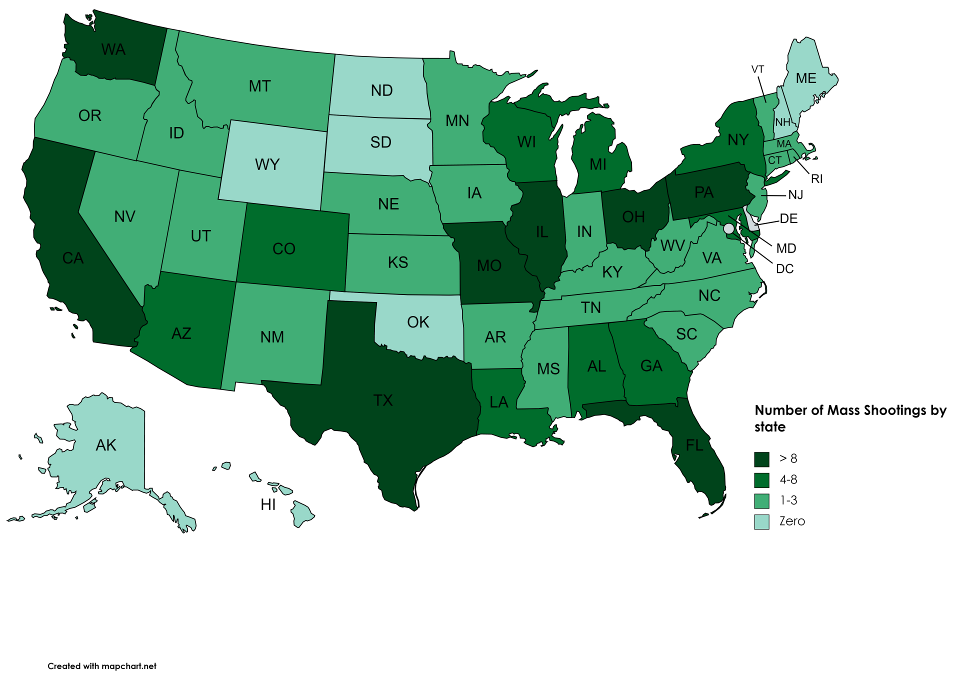
There is a noticeable increase in the number of mass shootings and fatality counts per year after 2010 (see figure 1.4), particularly in the latter half of the decade with 2019 witnessing the highest number of mass shootings in a given year at 20 and 2017 witnessing the highest number of deaths from mass shootings at 134. The period from 2015 to 2020 witnessed an increase in mass shootings and some of the deadliest shootings in the history of the US such

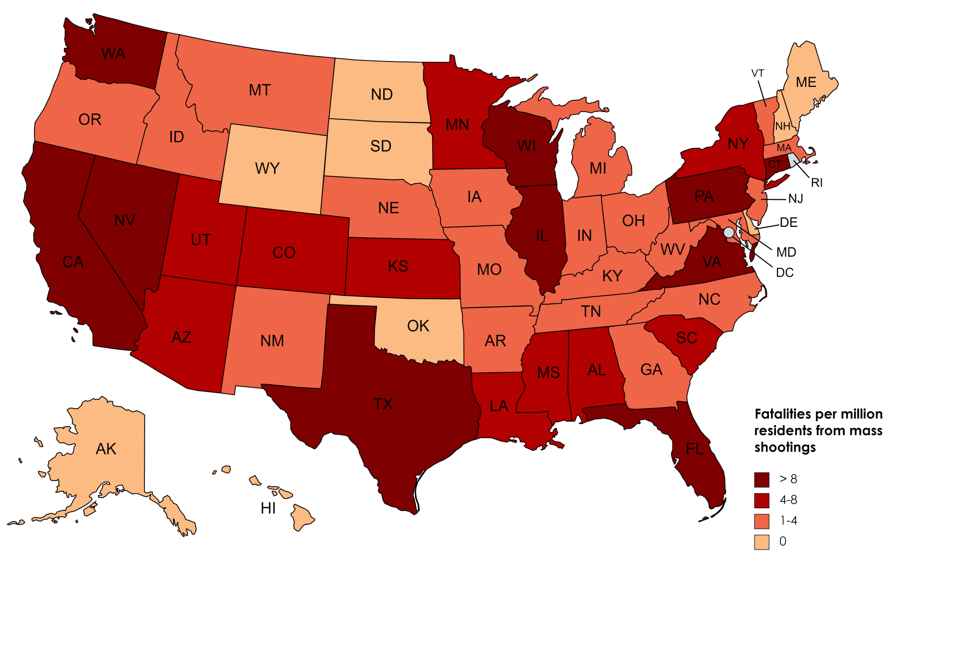
[1]For the handful of shootings that are not recorded on the FBI-SHR, I rely on a combination of media reports and the databases of *Mother Jones* and *Violence Project* to obtain information on the race of the shooter and victims.

as the Las Vegas shooting of 2017, the Orlando shooting of 2016 and the El Paso shooting of 2019 as a result of which, the time series graph shows a surge in both the number of mass shootings and fatalities in the latter half of the 2010s. Of all the mass shootings listed in the dataset, the Las Vegas nightclub shooting in 2017 was the deadliest in terms of number of fatalities with 60 people killed.

More populous states like California, Florida, Texas, Pennsylvania, Illinois and New York have higher number of mass shootings and higher per-capita fatalities. A number of states like Nevada, Virginia, Connecticut, Wisconsin and Alabama witnessed fewer mass shootings but high levels of per capita fatality counts due to a handful of high casualty mass shootings such as the Las Vegas concert shooting in case of Nevada and the Sandyhook shooting in case of Connecticut. Since 2015, there has been a rise in mass shootings, almost half of which can be attributed to the states of California, Florida, Texas, Pennsylvania and Illinois.

Notes The upper map denotes the total number of mass shootings by state and the lower map denotes per capita fatalities by state. States are shaded based on the total number of mass shootings and the total fatalities per capita from 2001 to 2020. Nevada, Virginia and Connecticut are among states with higher fatalities per capita relative to the number of mass shootings they witnessed.





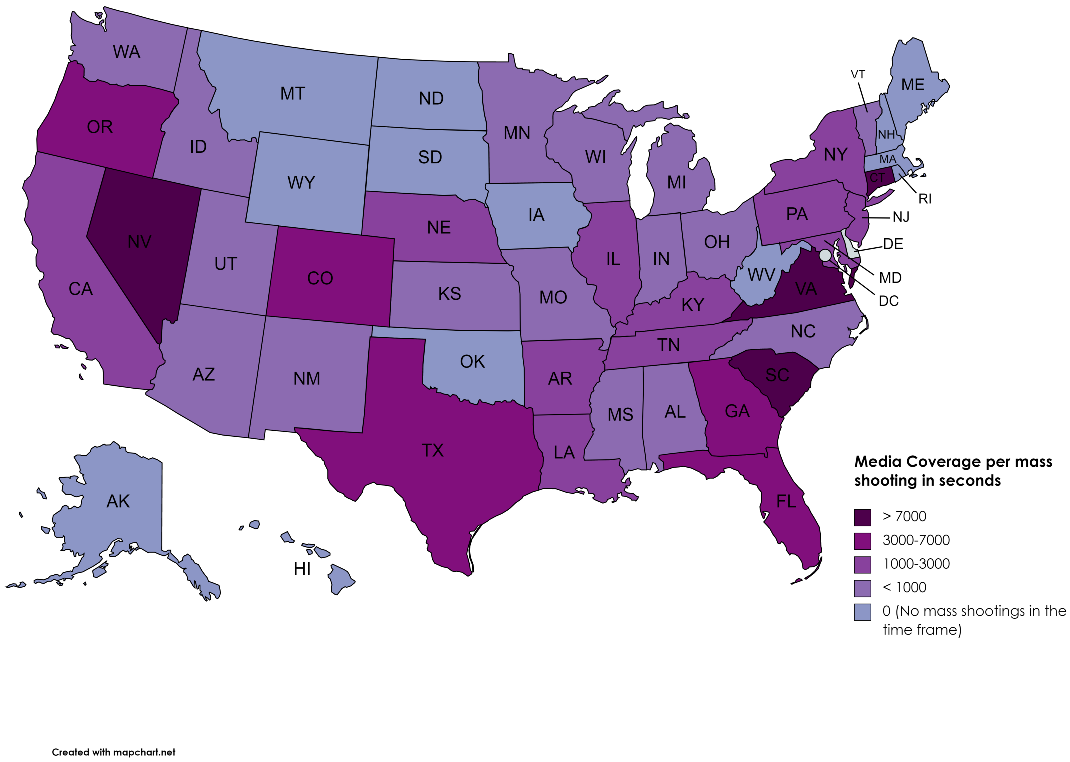
Media coverage

The paper uses an approach similar to Luca, Malhotra, Poliquin (2020) where the authors calculate the total amount of television news coverage for every mass shooting incident from 2001 to 2020 using information from the Vanderbilt Television News Archive (VTNA). The Vanderbilt Television News Archive is a database of news segments from major Television networks such as CBS, ABC, NBC, CNN etc. The use of Television news as a measure of media coverage (as opposed to newspapers) is motivated by the fact that the viewership of prime time news exceeds the readership of major newspapers (such as the New York Times) by a factor of five or more (U.S Securities and Exchange Commission, 2017).

To calculate media coverage of a mass shooting incident, I take all news segments dedicated to the mass shooting in question in the ten days following the mass shooting and sum the duration of all these news segments in seconds to obtain a measure of media coverage of a mass shooting. The Vanderbilt Television News Archive however, does not have news clips from FOX news which I obtain from their website by using their advanced search feature to look up each mass shooting incident and then adding the time in seconds for all the clips that appear in the ten days following a mass shooting. The data on FOX's website is only available from 2010 till the present.

The mass shooting incidents that received the most coverage were the Sandyhook Elementary School shooting in Connecticut (1166 minutes and 38 seconds), the Orlando nightclub shooting in 2016 (552 minutes), the Virginatech shooting (556 minutes), the Las Vegas Nightclub Shooting in 2017 (555 minutes and 19 seconds) and the Fort Hood shooting of 2009 (407 minutes and 20 seconds). Mass shootings that were hate-crimes or were politically motivated received an average of 105 minutes of media coverage, shootings in schools or educational institutions received an average of 176 minutes and 46 seconds of media coverage while those labelled as terrorist attacks on average received 223 minutes and 23 seconds of coverage. Mass shootings at military installations also received a relatively higher amount of media coverage at an average of 177 minutes and 46 seconds. Mass shootings which occurred after 2010 received on average 46 minutes and 30 seconds of coverage while those that occurred before 2010 received on average 30 minutes of coverage. Shootings at private residences received comparatively less amount of coverage with the Pike county murders of 2016 having received the most at 29 minutes and 40 seconds of coverage. A number of shootings in the sample, particularly those that occurred in private residences, did not receive any media coverage at all in the major news networks. This is especially true for shootings that happened in 2020 which could be due to the Covid-19 pandemic and the Black Lives Matter movement taking up most of the media spotlight.

Figure 1.6: Media coverage per mass shooting



Notes: The above map represents the average media coverage per mass shooting which is obtained by taking cumulative media coverage for all mass shootings in a state and dividing it by the total number of mass shootings that occurred in a state from 2001 to 2020. The media coverage here is measured in seconds and the data is obtained from news clips in the Vanderbilt Television News Archive(VTNA). Nevada, Virginia, South Carolina and Connecticut report higher levels of media coverage despite having fewer mass shootings overall. California, Pennsylvania and Washington have moderate levels of coverage per shooting despite having an overall higher count of mass shootings.

The map of figure 1.6 is a map of media coverage per shooting by state. Comparing it to the map of mass shootings by state in page 5, we see that mass shootings in the states of Nevada, Connecticut, South Carolina and Virginia received the most amount of media coverage per shooting despite having relatively fewer shootings overall. This is mainly due to a handful of mass shootings in the aforementioned states that received a disproportionately high amount of media coverage such as the Sandyhook shooting in Connecticut, the Las Vegas concert shooting in Nevada, the Charleston Church shooting in South Carolina and the Virginia-tech shooting in Virgnia. On the other hand, mass shootings in the states of Washington, Pennsylvania and California received relatively lower amounts of media coverage per shooting despite the states witnessing higher numbers of mass shootings.

1.3.3 Control variables

The control variables can be divided into four main categories: political, demographic, institutional and mental healthcare related. The political controls include a set of dummy variables indicating whether a state's legislature is Democrat controlled, Republican controlled or split(defined as a state legislature where both parties each control one chamber of the state legislature) and whether the the Governor of the state is a Democrat or Republican. The data is obtained from the National Conference of State Legislatures.

The demographic controls include a state's population, the share of a state's population who are women, older than 65 and younger than 25 and the share of female legislators in a state. The data is obtained from the Kaiser Family Foundation and the US Census Bureau's American Community Survey's 1 year estimates. I also use the state's unemployment rate as a control variable as higher unemployment can influence public support for mental health policies (Hernandez and Uggen, 2016).

The institutional controls include dummy variables for whether the state legislature is in session in a given year and the year of the legislative biennum. The first dummy variable captures whether a state legislature is in session in a given year (many states have biennial legislatures that meet every two years). The second dummy variable, denotes the first year of a legislative biennum (a two year period of law-making) which varies by whether states hold elections in odd or even years.

For the mental healthcare-related controls I begin with the share of a state's workforce employed in Mental healthcare establishments. The data is drawn for the US Census Bureau's County Business Patterns (CBP) data where an establishment is 'A single physical location where business is conducted or where services or industrial operations are performed.' The CBP contains the near universe of establishments in the US from 1998 to 2019. Using the North American Industrial Classification system (NAICS) codes for different industries, I extract data on the number of firms and level of employment in different mental health-related establishments (see Deza et al (2020) and Swensen (2015)). By adding the total number of employees in all mental health related establishments, I obtain the share of labor force employed in mental healthcare establishments in a state in a given year.

Finally, I obtain data on suicide incidents (measured in terms of number of deaths from suicide per 100000 people) from the Centre for Disease Control's (CDC) Web Based Injury Statistics and Query System (WISQARS) which contains data on deaths from fatal injury.

1.3.4 Summary Statistics

Table 1.3: Summary statistics

Variable	Observation	Mean	Standard Deviation	Min	Max
Mass shooting indicator	1050	0.1514	0.498	0	1
Cumulative count of mass shootings	1050	1.608	2.783	0	31
Fatalities	1000	1.04	4.102	0	61
Mentally ill shooter indicator	1050	0.1161	0.3206	0	1
Media coverage (in minutes)	1050	7.5562	53.4116	0	1166.63
Insurance-related bills	1000	0.948	1.424	0	9
Insurance-related laws	1000	0.232	0.517	0	5
School-related bills	1000	1.105	2.54292	0	31
School-related laws	1000	0.158	0.539	0	8
Community mental healthcare related bills	1000	1.385	2.6758	0	31
Community mental healthcare related laws	1000	0.417	0.861	0	10
Firearm-related bills	1000	0.22477	0.7003	0	10
Firearm-related laws	1000	0.0542	0.2468	0	2
Democrat control dummy	1050	0.3657	0.4818	0	1
Republican control dummy	1050	0.478	0.499	0	1
Population (in thousands)	1000	6127	6789	492	3951
Regular session	1050	0.9285	0.2576	0	1
First year of biennum	1050	0.4484	0.5001	0	1
Share of elderly(65+)	1000	0.133	0.0338	0.0134	0.213
Share of women	1000	0.507	0.0076	0.4799	0.522
Unemployment rate	1000	5.948	1.988	2.2	13.7
Share of female legislators	1000	0.23898	7.281	7.9	0.522
Share of labor force employed in mental health care	1000	0.0125	0.0115	0.00104	0.182
Suicide rate	1000	14.103	4.182	4.6	29.67

Table 3 describes the summary statistics of the main variables used in the analyses. The mass shooting related variables all have a relatively low mean due to the fact that most sample observations are zero. The fatality and media coverage variable have a high variance relative to the mean owing to some state-years witnessing a high fatality count from mass shootings and subsequently high levels of media coverage (such as Nevada in 2017). An important feature of the data is the relatively low mean and variance for the counts of different categories of bills. This is due to the sample observations containing a large number of zeros as many states did not introduce any bills for certain years. According to the data, the percentage of zero sample observations are 52 % for community bills, 52.38 % for insurance bills, 58.5 % for school bills and 85.91 % for firearm bills(see histogram in the data appendix). Even when states did introduce any bills, the count is usually low with most states introducing between 1 to 5 bills. Owing to such a high number of zeros and a relatively low count for the non-zero values, the subsequent regressions will utilize both binary and count data models.

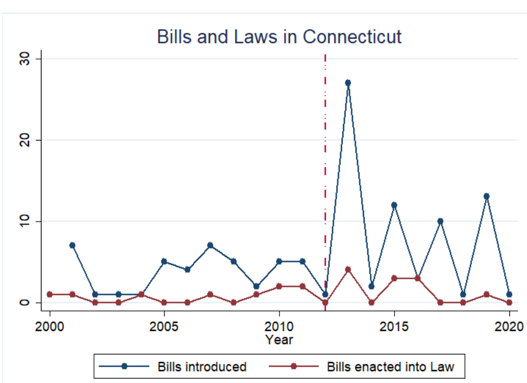
1.4 Preliminary overview of the data

Before describing the empirical methodology, this section provides a brief glimpse into the data.

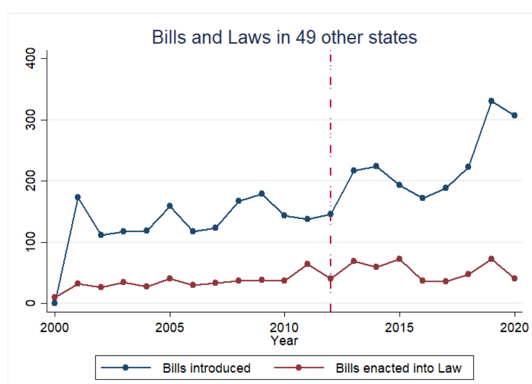
I begin by exploring the impact of three of the deadliest shootings: the Sandyhook elementary school shooting of 2012 in Connecticut (the shooting with the most coverage), the Las Vegas music concert shooting of 2017 in Nevada (the deadliest shooting in terms of the number of fatalities) and the Virginia tech massacre of 2008 in Virginia (the deadliest school shooting in the sample period). Then, for each of the three shootings I graphically compare the trends in the total number of bills and laws in the state where the shooting occurred and the remaining 49 states.

Figure 1.7: Mental health bills and laws in Connecticut versus other states

(a) Connecticut



(b) Other 49 states



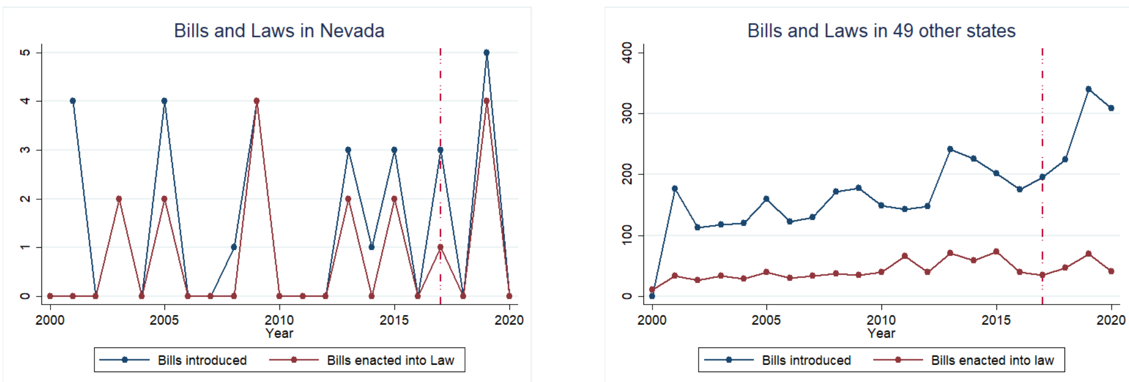
Notes

The above figures graph the trends across years in the total count of bills and laws in Connecticut and the remaining 49 states. The dashed line denotes the year 2012 when the Sandyhook shooting occurred.

Figure 1.7 compares the trends in the total number of bills and laws across the years between Connecticut and the 49 remaining states. The dotted line denotes the year 2012 when the Sandyhook shooting occurred. From the figure we observe that Connecticut witnessed a much steeper increase in bills and laws compared to the 49 other states. Connecticut alone introduced 27 additional mental health-related bills, with four enacted into law. In comparison, the other 49 states introduced 71 additional bills with 29 enacted into law. It appears that the Sandyhook shooting disproportionately impacted Connecticut compared to the other states.

Figure 1.8: Mental health bills and laws in Nevada versus other states

(a) Nevada (b) Other 49 states



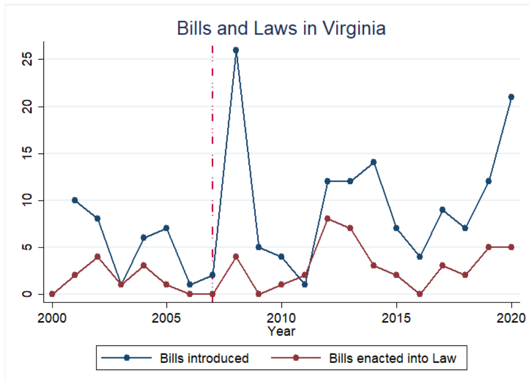
Notes The above figures graph the trends across years in the total count of bills and laws in each category in Nevada and the remaining 49 states. The dotted line indicates the year 2017 when the Las Vegas concert shooting occurred.

The graph in Figure 1.8 compares trends in bills and laws between Nevada and the 49 other states, and shows that Nevada, which has a bi-annual legislature that meets every odd-numbered year when bills are introduced and enacted into law, exhibits a saw-edge pattern of zero bills introduced every alternate year. Following the Las Vegas shooting of 2017, Nevada introduced 5 additional bills with 4 enacted into law. However, it's hard to say whether the effect was disproportionate as the nation as a whole experienced more mass shootings in the years that followed.

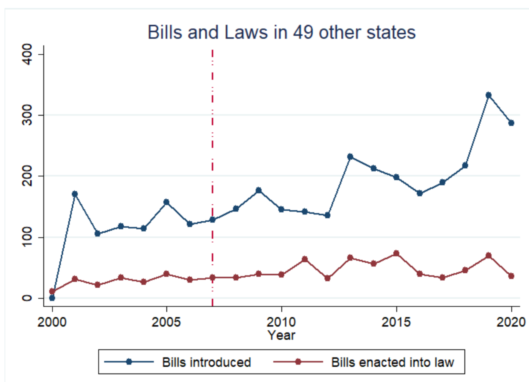
From Figure 1.9, it is clear that the Virginia Tech shooting, which occurred in 2007, had a significant impact on state legislation in Virginia. Specifically, the state introduced 24 additional bills the following year, with 4 of them being enacted into law. This is compared to the remaining 49 other states, which introduced 16 additional bills of which three were enacted into law. This indicates that the Virginia Tech shooting disproportionately impacted state legislation in Virginia relative to other states, similar to the observed pattern following the Sandy Hook shooting in Connecticut.

Figure 1.9: Mental health bills and laws in Virginia versus other states

(a) Virginia



(b) Other 49 states



**Notes* The above figures graph the trends across years in the total count of bills and laws in each category in Virginia. The dashed line indicates the year 2007 when the Virginia tech shooting occurred.

Overall, the graphs in this section show a noticeable correlation between mass shootings and the introduction of bills and laws by states in the year after. The subsequent sections empirically analyze how mass shootings impact mental health legislation by category.

1.5 Empirical specification

The main purpose of this paper is to analyze how mass shootings act as a focusing event which creates a policy window that induces state legislatures to introduce and enact legislation that can improve access to mental health care. The baseline empirical specification is given by:

$$y_{st} = \beta_0 + \beta_1 * Sh_{st-1} + \beta_2 * X_{st} + \alpha_s + \gamma_t + \epsilon_{st} \tag{1.1}$$

y_{st} is a measure of mental health-related legislative activity which could be either a count of bills introduced or laws enacted by the state 's' in year 't' or a dummy variable indicating whether any bill or law was introduced by state s in year t by category. Sh_{st-1} is an indicator for whether mass shootings occurred in state s in year 't-1'. Some specifications will have an additional regressor for the cumulative count of mass shootings witnessed by state 's' up to year 't-1' [2] The vector X_{st} is a vector of political, demographic, and institutional control variables. α_s and γ_t are state and year fixed effects respectively. The inclusion of state-fixed effects reduces omitted variable bias as mental health-related legislation could plausibly be influenced by unobservable state-specific institutional, social and cultural factors (such as the level of stigma towards mental health). Similarly, certain years also witnessed a surge in the introduction of mental health-related bills such as 2008 (due to the financial crises) or 2020 (due to the Covid-19 pandemic) which implies year-fixed effects reduce further omitted variable bias. [3]

In my baseline model, equation 1 is estimated using a fixed effects Poisson model similar to Luca, Malhotra, and Poliquin (2020), where y_{st} denotes the count of bills introduced across all categories in state s in year t. I then estimate the same for the count of bills introduced for each category. In the latter case, owing to the high number of zeros in the data for bills and laws(see Histogram in Data appendix), I also estimate the aforementioned equation at the extensive margin or probability of introducing any bill or law. Here, I estimate equation 1 using binary data models where the dependent variable y_{st} is a dichotomous indicator for whether a state s introduced any bills or laws in any of the four categories. I estimate both a conditional fixed effects Logit model and a Linear Probability Model. The conditional fixed effects Logit model drops observations with all zeros in the dependent variable leading to a slightly reduced final sample size (Beck, 2018). This is especially the case for firearm-related bills as many states did not introduce any such bills in the sample period (see map on figure

[2]The baseline model assumes that mass shootings do not influence legislation in neighboring states. To account for such spillovers I run a robustness check with a variable for a mass shooting in a neighboring state in Appendix A1. The results remain the same.

[3]It is possible that legislation enacted in a state is influenced by legislation enacted in prior years. To account for these I estimate equation 1 with state-specific time trends as a robustness check in Appendix A1. The results show that the magnitude and direction of the estimates remain roughly the same.

3) and also for the specifications involving bills enacted into laws.

Due to the erratic nature of mass shootings, it is plausible to assume that they are exogenous and uncorrelated with the error term in equation 1. Nonetheless, there could be some potential endogeneity concerns that I have attempted to deal with. First, assuming that mental illness is a major underlying cause of mass shootings, there could be a potential reverse causality at play between mental health legislation and occurrences of mass shootings. This is mitigated by taking the lagged values of the mass shooting and coverage variables in equation 1. Second, certain states may have institutional and cultural factors that may lead to more (or less) mass shootings such as ease of access to firearms which will hopefully be mitigated by the inclusion of state fixed effects. Third, certain years may witness more mass shootings due to a 'copycat effect' where media coverage of a mass shooting incident inspires subsequent mass shootings (Pew, 2021) which will hopefully be mitigated by the inclusion of year fixed effects.

1.6 Results

1.6.1 Impact of mass shootings on the total number of mental health-related bills and laws

Table 1.4 displays the estimates from estimating equation 1 for the total count of bills using a linear and Poisson specification. After all control variables are included in the regression, the estimate reveals that the occurrence of a mass shooting leads to a 72.05% increase in the linear model and an 82.09 % increase in the Poisson model. For the average state, this is a 2.717 and 3.007 increase in the number of bills introduced the year following a mass shooting. Once state and year-specific unobservables are controlled for with fixed effects, the effect is still statistically significant but lower in magnitude with an additional 1.479 and 1.271 bills introduced by the average state under the linear and Poisson specifications respectively. Overall, there is a sizeable increase in the total, aggregated number of bills introduced by a state in the year following a mass shooting.

Table 1.4: Impact of mass shootings on the total number of bills introduced

Dependant Variable: Total Count of bills introduced across categories						
	(1)		(2)		(3)	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
Mass shooting	2.717*** (0.466)	0.606*** (0.038)	2.64*** (0.447)	0.599*** (0.0392)	1.479*** (0.371)	0.298*** (0.0438)
Marginal Effect	74.1%↑	83.3 %↑	72.05%↑	82.09 %↑	40.3%↑	34.7%↑
Mean	3.664		3.664			3.664
Controls	No		Yes		Yes	
Fixed Effects	No		No		State, Year	
No of Observations	1000		1000		1000	

Table 1.5 displays the results for estimating equation 1 for the total number of laws enacted by a state. The estimates are similar to those obtained in table 1 in terms of magnitude, direction, and statistical significance. After the inclusion of fixed effects and control variables, a mass shooting leads to a 52.1 % and 45.6% increase in the number of laws enacted under the OLS and Poisson specification. For the average state, this implies an additional 0.449 and 0.448 new laws enacted by the average state under the OLS and Poisson specification respectively. Similar to bills introduced, mass shootings also lead to more laws enacted by states the year after.

Table 1.5: Impact of mass shootings on the total number of bills enacted into law

Dependent Variable: Total Count of bills enacted into law across categories						
	(1)		(2)		(3)	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
Mass shooting	0.758*** (0.126)	0.678*** (0.0767)	0.504*** (0.135)	0.599*** (0.078)	0.449*** (0.1204)	0.3764*** (0.088)
Marginal Effect	88.03% ↑	96.9% ↑	58.5% ↑	82.09 %↑	52.1%↑	45.6%↑
Mean	0.861		0.861			0.861
Controls	No		Yes		Yes	
Fixed Effects	No		No		State, Year	
No of Observations	1000		1000		1000	

Based on the estimates of tables 1.4 and 1.5, it is evident that a mass shooting increases legislative activity (both bills introduced and enacted into law) in the realm of mental healthcare. It is plausible that the horrifying nature of mass shootings highlights the dangers of untreated mental illness and creates an urgent need for mental healthcare policy reform. Mass shootings can thus be said to open a 'policy window' for state governments to enact policies related to mental healthcare.

The specification thus far has assumed that mass shootings can only impact mental health policy the year after and that the cumulative total number of mass shootings witnessed by a state does not have any snowballing impact. To account for this I introduce an additional regressor for the cumulative count of mass shootings in a state over all the years in the sample period. Tables 1.6 and 1.7, display the results from an alternate specification. From the estimates, it is apparent that the cumulative count does have a statistically significant positive impact on the total count of bills and laws. For bills, the cumulative count does have a notable impact in the OLS models under most specifications, but the magnitude of said impact is lower under the Poisson specification. Overall, the 'stock effect' of the cumulative count of mass shootings is relatively small in substantive terms compared to the 'flow account' of the mass shooting indicator, especially when the count nature of the bills variable is taken into consideration. The estimate with the largest magnitude is the OLS specification without fixed effects, which is an increase of 0.53 additional bills for the average state. The substantive effect is even smaller for the total count of laws enacted with the highest magnitude being 0.0998 additional laws enacted. Overall the 'stock effect' of mass shootings in terms of cumulative totals in a state is relatively small in substantive terms compared to the 'flow effect' of impacting mental health policy the year after.

Table 1.6: Effect of mass shootings and their cumulative counts on bills introduced

Dependent Variable: Total Count of bills introduced across categories						
	(1)		(2)		(3)	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
Mass shooting	0.9518** (0.5117)	0.304*** (0.0448)	0.938* (0.4875)	0.3327*** (0.045)	0.813* (0.3775)	0.217*** (0.046)
Marginal Effect	25.7%↑	35.5 %↑	25.6%↑	39.47%↑	22.18%↑	24.2%↑
Cumulative count	0.532*** (0.0709)	0.0718*** (0.004)	0.536*** (0.069)	0.0602*** (0.0453)	0.473*** (0.073)	0.0504*** (0.007)
Marginal Effect	14.5%↑	19.5%↑	14.6%↑	6.18%↑	12.9%↑	5.16%↑
Mean	3.664		3.664		3.664	
Controls	No		Yes		Yes	
Fixed Effects	No		No		State, Year	
No of Observations	1000		1000		1000	

Notes: The table displays regression output for estimating an OLS and Poisson model on the total count of mental health-related bills introduced by a state in a year. The specifications successively add control variables, fixed effects, and state-specific time trends. Stars following coefficients represent p-values less than .10 (*), .05 (**), and .01 (***). The main explanatory variables are an indicator for whether any mass shooting occurred the year before and the cumulative count of mass shootings in a state up to the year before. Standard errors are robust and clustered at the state level. The marginal effects are calculated as a percentage increase from the mean.

Table 1.7: Effect of mass shootings and their cumulative counts on bills enacted into law

Dependent Variable: Total Count of bills enacted into law across categories	(1)		(2)		(3)	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
Mass shooting	0.425** (0.141)	0.445*** (0.088)	0.38** (0.1394)	0.392*** (0.089)	0.343** (0.124)	0.314*** (0.092)
Marginal Effect	49.3%↑	56.01% ↑	44.1% ↑	47.9 % ↑	39.8%↑	36.8%↑
Cumulative count	0.1005*** (0.0195)	0.058*** (0.0089)	0.0966*** (0.0197)	0.0521*** (0.009)	0.074*** (0.024)	0.0373* (0.015)
Marginal Effect	11.6%↑	5.97%↑	10.08%↑	5.34%↑	8.67%↑	3.8%↑
Mean	0.861		0.861			0.861
Controls	No		Yes		Yes	
Fixed Effects	No		No		State, Year	
No of Observations	1000		1000		1000	

Notes: The table displays regression output for estimating an OLS Poisson model on the total count of mental health-related laws enacted by a state in a year. The specifications successively add control variables, fixed effects, and state-specific time trends. Stars following coefficients represent p-values less than .10 (*), .05 (**), and .01 (***). The main explanatory variables are an indicator for whether any mass shooting occurred the year before and the cumulative count of mass shootings in a state up to the year before. Standard errors are robust and clustered at the state level. The marginal effects are calculated as percentage increase from the mean.

1.6.2 Effect of mass shootings on the number of mental health-related bills introduced and laws enacted by category

In this section, I analyze how mass shootings affect the number of mental health-related bills introduced and laws enacted by estimating equation 1 using a fixed effects Poisson model for each category of legislation. The dependent variable, in this case, is a count of mental health-related bills introduced and laws enacted in each category.[4] [5]

Introduction of bills

Table 1.8: Effect of mass shootings on the number of mental health-related bills introduced.

Dependent Variable: Count of bills introduced in different categories					
	Insurance Bills	School Bills	Community Bills	Firearm Bills	Total
	(1)	(2)	(3)	(4)	(5)
Mass shooting	0.2698** (0.0890)	0.527*** (0.0785)	0.0392 (0.0751)	0.798* (0.167)	0.298*** (0.043)
Marginal Effect	30.9%↑	69.3%↑	3.99%↑	122.1%↑	34.7%↑
Sample mean	0.951	1.109	1.448	0.281	3.664
No of Observations	996	996	956	796	1000

Notes: The table denotes regression output for estimating a fixed effects Poisson model on the count of mental health related bills introduced. The specification includes Political, Demographic, Institutional and Mental Health related controls Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***) The main explanatory variables are an indicator for mass shootings at the state-year level. Standard errors are robust and clustered at the state level

[4] I also estimate the same equation at the extensive margin using a fixed effects logit and linear probability model. The results, which are in Appendix A2, are similar to those obtained under the count specification with some estimates being slightly less precise.

[5] The same equation with the cumulative count of shootings as an additional regressor is estimated in Table 22 in Appendix A3. The effect of the cumulative count is low in substantive terms for almost all four sub-categories and does not appear to be a more likely causal channel once the bills are disaggregated.

Table 1.8 shows the estimated coefficients of the impact of mass shootings on the number of mental health-related bills introduced. Mass shootings have a positive and statistically significant impact on the number of bills with the exception of community bills. The estimates presented in this study demonstrate a strong relationship between the occurrence of a mass shooting and subsequent legislative actions. Specifically, our findings reveal that a mass shooting event leads to a significant increase in the introduction of firearm-related bills, with a substantial rise of 122.1% (100*(exp(0.798)-1)). Furthermore, we observe a notable 69.3% (100*(exp(0.527)-1)) increase in the number of school-related bills introduced in the following year. Additionally, insurance-related bills experience a statistically significant effect, with a 33.2% increase in the number of bills introduced. These results lend support to the hypothesis that a shock event like a mass shooting brings attention to deficiencies in existing state policies concerning access to firearms for individuals with mental illness, insurance coverage for mental health, and availability of mental healthcare services in schools. As a consequence, policymakers respond by proposing bills aimed at enacting policy changes in these three categories.

Enactment of laws

Table 1.9: Effect of mass shootings on number of mental health laws

Dependent variable: Count of laws enacted in each category					
	Insurance Laws	School Laws	Community Laws	Firearm Laws	Total
	(1)	(2)	(3)	(4)	(5)
Mass shooting	0.357*	0.391*	0.3413*	0.608	0.3764**
	(0.1732)	(0.206)	(0.129)	(0.335)	(0.088)
	,				
Marginal effect	42.9%↑	47.84%↑	40.6%↑	83.6% ↑	45.7% ↑
Sample mean	0.232	0.198	0.465	0.096	0.8619
No of Observations	956	956	896	796	1000

Notes: The table denotes regression output for estimating a fixed effects Poisson model on the count of mental health-related bills enacted into laws. The specification includes Political, Demographic, Institutional and Mental Health related controls. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). The main explanatory variables are an indicator for mass shootings at the state year level Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations without any within cluster variation.

[6] [7] Table 1.9 presents the estimated coefficients capturing the influence of mass shootings on the enactment of bills across different categories. The specifications encompass comprehensive controls, state and year-fixed effects, and clustered standard errors by state. Our findings reveal a positive and statistically significant impact of mass shootings on the number of laws enacted in all categories, except firearm laws.

Notably, the effect is most pronounced in school-related laws, where a mass shooting leads to a substantial increase of 47.84% (100*(exp(0.391)-1)) in the number of school-related bills eventually enacted into law. Insurance and community-related laws also experience a statistically significant increase, with corresponding figures of 42.9% (100*(exp(0.357)-1)) and 40.6% (100*(exp(0.3413)-1)), respectively.

Comparing these results with those from Table 1.6, we observe that while mass shootings have an impact on the introduction of firearm-related bills, this effect does not extend to firearm-related laws. Conversely, community-related legislation exhibits no impact on the number of bills introduced, but it does affect the number of laws enacted.

Interestingly, the estimates indicate that mass shootings do not influence laws pertaining to firearm restriction based on mental health criteria, despite a positive effect on the introduction of bills. In contrast, community-related bills show no impact on politicians introducing bills (as seen in Table 1.6), but they do lead to an increase in the number of bills that successfully transition into laws. A plausible explanation is that issues related to firearm restriction tend to garner significant media coverage and become highly contentious topics following mass shootings, leading politicians to introduce more bills in response to constituents' concerns. However, the politically divisive nature of firearm restriction prevents these bills from being enacted into law. On the other hand, the establishment of community mental health clinics, being less newsworthy, does not elicit symbolic responses in terms of bill introductions by politicians. Yet, any bills introduced in this context are more likely to be enacted into laws, possibly due to the less divisive nature of the issue.

Furthermore, compared to the estimates derived from fixed effects logit and linear probability models for enacted laws (see Appendix A2), our results demonstrate that mass shootings do

[6] The same equation with the cumulative count of shootings as an additional regressor is estimated in Table 22 under Appendix A3. Here again, the effect of the cumulative count is low in substantive terms for almost all four sub-categories and does not appear to be a more likely causal channel once the bills are disaggregated.

[7] I also estimate the same specification with the sample restricted to mass shootings that received non-zero seconds of media coverage. The results in table 23 of Appendix A4 show that the legislative impact is slightly higher for shootings with positive magnitude though not very high in substantive terms.

have a statistically significant impact on the number of insurance and community-related laws enacted. This implies that mass shootings do not affect the extensive margin of laws enacted in these categories but rather influence the count of such laws (as shown in Table 6). Consequently, in certain states, mass shootings have resulted in the introduction of multiple laws pertaining to insurance coverage and community mental health clinics.

In our analysis, the impact of mass shootings on legislative outcomes is consistently observed across different specifications. Notably, school-related legislation, encompassing both bills and laws, emerges as the category most influenced by mass shootings, with robust results observed under both binary and count specifications.

This heightened impact on school-related legislation can be attributed to several factors. Firstly, school shootings often receive extensive media coverage and evoke a strong public outcry due to the vulnerability of the victims, who are often minors, and the perception of schools as safe environments free from gun violence. The resultant "moral panic" (Schildkraut et al., 2014) experienced by the public, wherein perceived threats to societal values are amplified (Springhall, 2019), leads to community mobilization and a heightened demand for legislative reforms across various domains.

Furthermore, mental illness is frequently associated with school shootings (Lemieux, 2014; Schildkraut et al, 2016; Rees et al, 2019), with perpetrators of high-profile incidents such as Sandy Hook, Virginia Tech, and Parkland confirmed to have had mental health conditions. Consequently, the general public may expect their governments to enhance access to mental healthcare in schools as a preventive measure against future mass shootings. This aligns with recommendations from studies such as Paolini (2015) and Katsianis et al (2018) emphasizing the importance of improved school-based mental healthcare.

An additional factor contributing to the relative prominence of school-related legislation is the absence of organized opposition compared to other categories. While firearm restriction faces opposition from organizations like the National Rifle Association (NRA) and insurance coverage legislation encounters resistance from health insurance corporations, school-related mental healthcare lacks such organized opposition.

Collectively, these factors highlight the unique dynamics surrounding school-related legislation in response to mass shootings. The convergence of media attention, public concern, the attribution of mental illness, and the absence of strong opposing forces contribute to the increased demand for legislative reforms in this particular domain.

Previous studies by Kleck (2009) and McGinty et al. (2019) highlight that mass shootings involving mentally ill perpetrators tend to generate increased support for firearm restrictive policies among the general population. However, in contrast to the estimates for firearm legislation, our findings indicate that mass shootings lead to an increase in bills proposed for firearm restrictive legislation but have no effect on the enactment of such laws. This discrepancy may be attributed to the highly divisive nature of gun control issues. In cases where legislators might resist passing firearm restrictive laws, they may still support the introduction of school-based mental healthcare laws as a means to signal their responsiveness to constituents' concerns regarding mass shootings. Furthermore, mass shootings demonstrate an impact on insurance-related legislation, as evidenced by the increase in both the count of bills introduced and the number of laws enacted, as indicated by the fixed effects Poisson specification. This suggests that mass shootings strengthen arguments for insurance parity, leading states to propose a greater number of bills and enact more laws in this domain. Conversely, for firearm restrictive legislation, we observe an increase solely in the number of bills introduced under both specifications, with no corresponding effect on the enactment of laws. This implies that the proposed bills may serve as symbolic measures ("feel good" legislation, as noted by Schildkraut et al, 2014) aimed at appeasing public sentiment, but face organized opposition to gun control, preventing their transition into laws.

The results confirm that mass shootings act as "focusing events," bringing attention to undiagnosed mental illness and emphasizing the importance of implementing mental healthcare policies. This creates a policy window for legislatures to address these issues. Notably, the policy window leads to enduring policy change specifically in the realm of school-based mental healthcare. On the other hand, legislation targeting firearm access restrictions is more likely to be introduced but not enacted, suggesting that they may serve as symbolic measures rather than substantive policy changes aimed at satisfying constituents.

1.7 Media coverage and mass shootings

As mentioned before, the media's coverage of a focusing event like a mass shooting likely plays a role in how subsequent policy responses are formulated. In order to capture the role of the media in the determining the legislative impact of a mass shooting, I use an approach similar to Luca et al (2020), where they interact the mass shooting indicator in equation 1 with the total amount of media coverage received by all mass shootings in the respective state-year. As the media coverage is only calculated when a mass shooting occurs, this specification would address how amount of media coverage changes the effect of a mass shooting occurring. Recall that the data for FOX News is only available from 2011 to 2020 so different sample periods will be analyzed for coverage. There is a potential endogeneity issue as the media coverage of mass shootings can be biased towards certain states (mass shootings in some states may receive more news coverage than others) and also towards certain years (mass shootings may become more salient in certain years to the general public leading to more media coverage). My assumption is that the inclusion of state and year fixed effects can mitigate these as well.

Table 1.10: Effect of media coverage of mass shootings on mental health bills using a Poisson model

Dependent Variable: Count of bills introduced in different categories										healthcare-related school-based
feel-good	Insurance Bills		School Bills		Community Bills		Firearm Bills		Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mass shooting Indicator	0.1959* (0.0947)	0.1277 (0.1231)	0.3793*** (0.0847)	0.234* (0.098)	0.0259 (0.07914)	0.1338 (0.1137)	0.5012* (0.1856)	0.5759** (0.2088)	0.20047*** (0.047)	0.127* (0.058)
Mass shooting times Media coverage (excluding FOX)	0.000923** (0.000335)		0.00166*** (0.000275)		0.000253 (0.00052)		0.0034*** (0.00073)		0.001302*** (0.00017)	
Mass shooting times Media coverage (including FOX)		-0.00065 (0.0005382)		0.0014*** (0.0013)		-0.0016 (0.00128)		0.00084 (0.00083)		-0.0007 (0.0019)
No of Observations	996	430	996	400	956	410	796	260	1000	550

Notes: The table displays regression output for estimating a fixed effects Poisson model on the count of mental health-related bills introduced when the variables for media coverage are introduced in the regression. The specification includes Political, Demographic, Institutional, and Mental Health related controls. The first media coverage variable excludes FOX news and includes CNN, ABC, NBC, and CBS. The second variable includes FOX news but is restricted to the years 2010 to 2020 due to data limitations. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations which have all zeros in the dependent variable.

Table 1.10 denotes the results for bills introduced when the media coverage variable is interacted with the mass shooting indicator. The odd-numbered columns include media coverage for networks like CNN, ABC, NBC and CBS but not FOX news while the even-numbered columns include media coverage by FOX news as well but are restricted to 2011 to 2020 due to data availability.

The amount of media coverage significantly increases the effect of mass shootings on all categories except community-related mental healthcare bills. The effect is the highest for firearm-related bills. To illustrate, I compare two hypothetical mass shootings with zero and thirty minutes of coverage respectively. The mass shooting with 30 minutes of coverage is associated with a 100*[exp(0.5012+0.0034*30)-1) or an 82.7 % increase in the number of firearm bills introduced while the one with zero minutes of coverage leads to a 100*[exp(0.5012)-1)] or 65 % increase in the same. The added effect of media coverage is a 17.7% increase in the introduction of bills. For school-related bills the media coverage has a sizeable change on the impact of mass shootings as every additional 30 minutes of media coverage is associated with a 100*[exp(0.3793 + 0.00166*30)-1- exp(0.3793)-1] or 7.1 % increase in the impact of mass shootings number of bills introduced that aim to improve access to mental health care in schools. The results indicate that restriction of firearms on grounds of mental health is the most likely political response induced by mass shootings and their subsequent media coverage and suggests that politicians propose bills restricting access to firearms to those deemed mentally ill as a primary policy measure to prevent future mass shootings. For school-related bills, the high and statistically significant estimates could be attributed to the fact that many school shootings, which received disproportionate amounts of media coverage, were committed by mentally ill perpetrators (Virginiatech, Sandyhook, Parkland, etc) and therefore politicians may feel the need to propose bills improve access to mental healthcare in schools so as to prevent future occurrences.

Insurance-related bills also witness a statistically significant increase in the effect of mass shootings with higher media coverage though the magnitude is smaller suggesting that media coverage of mass shootings also induces legislative action in the realm of improving insurance coverage of mental illness.

The even-numbered columns are a specification where the media coverage variable includes coverage by FOX news as well as with the sample being restricted to 2011 to 2020. Though the sample size is smaller the results are still meaningful as around two-thirds of mass shootings occurred in this sample period. Compared to the first specification only estimates for the total count and school-related bills for both the mass shooting and media coverage variable retain their statistical significance. The main difference now is that the magnitude of firearm bills is smaller and no longer statistically significant. A possible explanation is that FOX news generally has an anti-gun control stance and may have covered the mass shooting incidents in a way that discouraged any form of firearm restriction as a potential solution. When combined with the fact that FOX news has a much larger viewer base than the other networks in the data (and as a result may have a larger impact on public perceptions), it is plausible that the inclusion of FOX's coverage may lead to no such effect on firearm bills compared to the specification without FOX (where the other networks would probably not be against firearm restriction as much as FOX). [8]

Table 1.11: Effect of mass shootings and their media coverage on number of mental health laws using a Poisson model

Dependent Variable: Count of bills enacted into laws in each category										
	Insurance Laws		School Laws		Community Laws		Firearm Laws		Total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mass shooting indicator	0.4674* (0.177)	0.337 (0.251)	0.2115 (0.223)	0.2296 (0.224)	0.5216** (0.1982)	0.531** (0.199)	1.021* (0.46)	1.04 (0.451)	0.392** (0.121)	0.407** (0.121)
Mass shooting times Media coverage (excluding FOX)	-0.00246 (0.0019)		0.00064 (0.00083)		0.00066 (0.00084)		-0.0065 (0.0076)		0.00013 (0.00055)	
Mass shooting times Media coverage (including FOX)		-0.0019 (0.0018)		0.0004 (0.0008)		0.0004 (0.0008)		-0.0058 (0.0063)		-0.00008 (0.0005)
No of Observations	996	430	996	400	956	410	796	260	996	539

Notes: The table denotes regression output for estimating a fixed effects Poisson model on the count of mental health-related bills enacted into law when the variables for media coverage are introduced in the regression.The specification includes Political, Demographic, Institutional and Mental Health related controls. The first media coverage variable excludes FOX news and includes CNN, ABC, NBC, and CBS. The second variable includes FOX news but is restricted to the years 2001 to 2020 due to data limitations. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations which have all zeros in the dependent variable.

Table 1.11 denotes the results for laws enacted when the media coverage interacted with the mass shooting indicator. The media coverage interaction variables (with or without FOX news) have no impact on the number of laws enacted, unlike the case with bills introduced where the impact was positive (see Table 1.10). This indicates that the effect of mass shootings on bills introduced with higher media coverage is more of an attempt by politicians to appear to address their constituents' concerns due to the outcry caused by higher media coverage of mass shootings. Higher media coverage could also galvanize opponents of such legislation (such as the National Rifle Association, or Health insurance companies) who may use their lobbying power to prevent bills from being enacted into law.

Overall the effect of mass shootings when there is higher media coverage is largely symbolic in that it generates enough public angst to induce politicians to introduce bills. But the bills rarely end up being enacted into law suggesting that they are 'feel good legislation' aimed

[8] I also estimate the specification at the extensive margin using a fixed effects Logit and Linear probability model in Appendix A3. The results are mostly similar in terms of magnitude and direction.

to appease the general public. The role of the media in creating a policy window when there is a mass shooting is restricted to advancing an agenda through bill introduction.

1.8 Heterogeneity by political party

This section explores whether legislative outcomes in the realm of mental health in the wake of a mass shooting have a partisan response. Luca, Malhotra and Poliquin (2020) demonstrated, that there is significant heterogeneity when it comes to responses to mass shootings in terms of Gun policy. The authors show that Democrat-controlled state legislatures are more likely to enact laws that aim to tighten access to guns while Republican-controlled State legislatures were more likely to introduce bills aimed to loosen restrictions on firearms. The results are in line with both parties' official stances on gun control with Democrats supporting increased restrictions on firearms and Republicans supporting fewer restrictions. While mental health policy is not as polarizing as gun control policy, there are likely avenues of partisanship. As Republicans often favor the notion that easy access to firearms is not the main cause of mass shootings and gun violence (Parker et al, 2017) but mental illness is, they might view mental health policies as more of an effective response to prevent future mass shootings than Democrats who might rely on gun control policies to do the same. Other avenues of partisanship could be when it comes to insurance parity bills, Republicans are less in favor as opponents of insurance parity laws are usually health insurance companies (Hernandez and Uggen, 2016).

In order to analyze the role of political parties in determining the legislative outcomes to mass shootings, I first restrict the analyses to mental health-related bills enacted into laws. Introduction of bills may not be a good measure of partisanship, particularly when measured at the extensive margin, as the data and estimates will include bills introduced by Democratic politicians in a Republican controlled legislature which will not be indicative of partisanship. However, enacted laws will be a better measure of partisanship as they require approval of a majority of legislators. I then interact the mass shooting indicator in equation 1 with dummies denoting whether a state legislature is Democrat controlled (Democrats control both chambers) and split (both parties control one of the chambers each). Legislatures which are Republican controlled are the omitted group.

Table 1.12: Heterogeneity by political party

Dependent Variable: Count of bills enacted into laws by category					
	Insurance Laws	School Laws	Community Laws	Firearm Laws	Total
	(1)	(2)	(3)	(4)	(5)
Mass Shooting	0.0788	0.503	0.0917	0.217	0.2008
	(0.287)	(0.3202)	(0.222)	(0.501)	(0.143)
Dem Leg * Shooting	0.30514	-0.2332	0.241	0.128	0.037
	(0.4058)	(0.343)	(0.31)	(0.749)	(0.2)
Split Leg * Shooting	0.801*	0.435	0.026	0.538	0.254
	(0.478)	(0.5713)	(0.452)	(0.5)	(0.26)
Democratic Legislature	0.1377	-0.2332	-0.122	-0.583	-0.138
	(0.2664)	(0.3439)	(0.194)	(0.574)	(0.134)
Split Legislature	-0.7688*	0.0571	-0.445*	-0.342	-0.477
	(0.3212)	(0.35)	(0.204)	(0.6171)	(0.146)
No of Observations	956	797	896	560	996

Notes: The above table denotes regression output for estimating a fixed effects Poisson model on the count of mental health related laws enacted when the mass shooting variable is interacted with dummies for democrat and split control of state legislatures.The specification includes Political, Demographic, Institutional and Mental Health related controls. The omitted group is Republican legislatures. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). Standard errors are robust and clustered at the state level.

Table 1.12 shows the results for partisanship. In years where there is no mass shooting, Democrat-controlled legislatures enact 14.2 % more laws related to insurance coverage of mental health compared to legislatures where Democrats are not in power. This is in line with Barry et al (2014) who show that Democrats are more supportive of insurance parity laws and Hernandez and Uggen(2016) who show that Democrat-controlled legislatures are more likely to enact the same. [9]

When a mass shooting does occur, there does not seem to be any difference between Democrat and Republican-controlled legislatures in terms of the number of laws enacted based on the interaction term of mass shootings times Democrat. However, split legislatures enact more laws related to insurance coverage and fewer laws related to community mental healthcare

[9] I also estimate the above model at the extensive margin using logit and linear probability models. The results are mostly similar with most statistically significant estimates driven by a single state.

in the aftermath of a mass shooting with the estimates revealing a 122.7 % increase in the number of insurance-related laws enacted. However, both these results are largely driven by the state of Washington which enacted 3 additional laws related to insurance coverage and 1 fewer law related to community mental health clinics in 2016 the year preceding which it witnessed a mass shooting (the Marysville Pillchuk high school shooting). When the state of Washington is dropped from the analyses, mass shootings no longer have a statistical effect on the number of insurance and community mental health laws enacted by split legislatures.

Overall, the estimates reveal no conclusive evidence of partisanship in the legislative response to mass shootings in the realm of mental health.

1.9 Race and mass shootings

In this section I explore how the race of the perpetrator of a mass shooting influences the subsequent legislative outcome. As Duxbury, Frizzel and Lindsey (2018) show, by analyzing news articles of mass shootings, white shooters are more likely to be framed as mentally ill compared to Black and Latino shooters and also more likely to be portrayed as sympathetic characters. Mass shootings with non-white perpetrators are more likely to receive media coverage (Schildkraut, 2018) as are crimes with white victims (Sorensen, Manz and Berk, 1998).

To explore the role of race in the legislative outcomes of mass shootings, I begin by creating two variables: a dummy variable for whether any of the perpetrators in a given state year are white and the share of victims who are white. I then estimate a fixed effects Poisson model where the dependant variables are the count of bills enacted into law and the main explanatory variables are interaction terms where the mass shooting indicator is interacted with the dummy for any shooting being white and the percentage of white victims.

Table 1.13: Race and mass shootings

Dependent Variable: Count of bills enacted into law in each category					
	Insurance Laws	School Laws	Community Laws	Firearm Laws	Total
	(1)	(2)	(3)	(4)	(5)
Mass shooting Indicator	-0.073 (0.316)	0.084 (0.362)	0.125 (0.225)	0.557 (0.55)	0.0831 (0.155)
Mass shooting * Atleast 1 white shooter	0046 (0.306)	-0.074 (0.334)	-0.069 (0.225)	0.149 (0.59)	-0.07 (0.15)
Mass shooting * Percentage of victims who are white	0.617 (0.396)	0.458 (0.404)	0.3977 (0.294)	-0.122 (0.666)	0.384 (0.192)
No of Observations	889	738	851	513	996

Notes: The table denotes the regression output for estimating a fixed effects Poisson model with the count of bills enacted into law in each category as the dependent variable. The specification includes Political, Demographic, Institutional and Mental Health related controls. The main explanatory variables are an indicator for whether a mass shooting occurred interacted with a dummy variable for whether any of the shooters were white and the percentage of victims who are white. The sample is restricted to state-years where a mass shooting occurred. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). Standard errors are robust and clustered at the state level

Table 1.13 denotes the results for the model when the race of the perpetrators and victims are taken into account. Based on the estimates of the interaction terms, shootings committed by white perpetrators or with a higher share of white victims are not more likely to result in more laws being enacted.

Overall, neither the race of the perpetrator nor the victims seem to have any impact on the enactment of laws. While white shooters are more likely to be portrayed as 'mentally ill lone wolves', this does not translate into state legislatures enacting more laws related to mental healthcare.

1.10 Conclusion

Based on the results, mass shootings do serve as focusing events that create a 'policy window' where state governments are more likely to introduce policies aimed at improving access to mental healthcare. The effect appears to be the strongest for legislation aimed at improving access to mental healthcare in schools where the results are robust under both count and binary specifications. This seems to indicate that school shootings, where the victims are likely to be minors, are the most effective as focusing events that create a policy window for legislation related to mental healthcare. Legislation seeking to improve insurance coverage of mental illness and establishing community mental health clinics also witness an increase following a mass shooting under some specification, suggesting they are viewed as a policy response to prevent future mass shootings. Mass shootings also lead legislatures introducing more bills related to firearm restriction on grounds of mental illness but the bills rarely get enacted into law which could be attributed to their divisive nature and the organized opposition they face.

Another key finding is how the level of media coverage leads to an increase in the introduction of bills but has no such effect on laws. This suggests that politicians largely introduce 'feel good' legislation which do not get enacted into law as a result of the media's coverage of a mass shooting incident and the subsequent public angst it generates. The role of the media coverage in creating a policy window is largely symbolic as it serves to appease the general public but not create any tangible reform.

An interesting takeaway is how the political party in power has no impact on policy window despite Republicans being more likely to attribute mental illness as the primary cause for mass shooting. Similarly the race of the perpetrator also does not shape the policy window despite white perpetrators being more likely to be labelled as mentally ill lone wolves.

Overall, the results show that shock events, even when they are rare and infrequent, can play a crucial role in policy consideration and change by highlighting the failures of the existing system and drawing attention to issues that need addressing. As to whether the enacted policies fulfill their stated purpose of preventing future occurrences is still an open question.

Chapter 2

Impact of residential segregation on welfare generosity

Abstract

This study investigates the relationship between residential segregation, public attitudes toward welfare policies, and the level of welfare generosity in the United States. Despite increasing diversity, residential segregation persists, which can perpetuate racial biases and stereotypes. The study introduces a novel measure of racial segregation at the state level, capturing interracial exposure between white and African American populations. The analysis examines the impact of variations in interracial exposure on welfare generosity, measured by cash benefit limits and Medicaid's coverage of mental healthcare services. The findings indicate that a decrease in segregation and increased inter-racial exposure contribute to higher levels of welfare generosity, potentially driven by greater empathy for economically disadvantaged African Americans. However, for states in the deep south, higher exposure leads to less generous welfare policies, possibly due to African Americans being perceived as a threat, given their larger population in those states. These results highlight the detrimental effects of residential segregation on inter-group interaction and policy attitudes, emphasizing the importance of policy interventions to reduce segregation, promote social integration, and foster equitable policies.

2.1 Introduction

Residential segregation remains a persistent feature in contemporary American society, shaping the spatial distribution of different racial and ethnic groups. As scholars continue to explore the multifaceted consequences of segregation, several critical questions emerge in the realm of racial attitudes, inter-group dynamics, social cohesion, and policy discourse. In this study, we delve into the intricate relationship between familiarity with other races/ethnicities, empathy levels, inter-group conflict, social cohesion, and the racialized discourse surrounding welfare policies in the United States. Specifically, we aim to address the following key questions within the context of multi-ethnic societies: Does a lack of familiarity with other races/ethnicities lead to decreased empathy? Can reduced inter-group conflict result from limited exposure to other races/ethnicities, leading to a diminished perception of threat? How does the presence of diversity, coupled with high levels of segregation and dissimilarity, impact social cohesion? Moreover, we explore the influence of neighbors' racial identity on race relations, particularly in the context of historically enforced racial residential segregation and its contemporary manifestations. By shedding light on these important issues, our study contributes to a deeper understanding of the complex dynamics linking residential segregation, racial attitudes, and welfare policy discourse, offering valuable insights for policymakers, researchers, and society at large.

While the United States has become more diverse than in the past, residential segregation continues to persist even decades after the passage of the Fair Housing Act of 1965. As of 2010, the country as a whole had a Dissimilarity Index (share of the white and black population who would have to move to a different census tract to achieve full integration) of 70 percent, which though less than in prior decades, was still substantially high. Milwaukee, New York, Chicago, and Philadelphia are some of America's most segregated cities, with all of them having a Dissimilarity Index above 80 percent as of 2010. African Americans remain the most segregated group with respect to white Americans, while Asians and Hispanics experience moderate segregation. Causes of such segregation could range from perceived class differentials of different racial groups to ethnocentric preferences within a group to out-group hostility (Bobo and Zubrinsky,1996), but their consequences are mostly negative, particularly for poor African Americans.

Massey and Denton (1993) first brought attention to the issue of post-Jim Crow residential segregation, attributing it to institutional barriers to upward mobility for poor African Americans in inner cities. Segregation has been associated with interracial disparities in income and education (Cutler and Glaeser, 1997), health disparities (Robert and Ruel, 2006), and even with an interracial survival gap (Popescu, Duffy, Mendelson, Escarce, 2018). [1].

One unexplored avenue of inquiry is whether residential segregation can impact issues such as welfare, which has a strong racial component to its discourse, particularly in support of the enactment of more generous welfare policies. Race has historically influenced the development of the welfare state in the US (Lieberman, 1998), and racial attitudes have shaped public opinion of welfare spending (Gillens, 1999). It is possible that residential segregation and subsequent lack of contact could influence inter-racial perception in a way that affects the discourse surrounding welfare policies through the perpetuation of racial stereotypes, such as the 'welfare queen.'

This study investigates the impact of residential segregation on welfare policies and posits that it can go in two directions. On the one hand, segregation can foster negative racial stereotypes, leading to less support for welfare policies. On the other hand, it can prevent negative inter-racial interactions, resulting in less prejudiced attitudes and greater support for welfare policies. To analyze this, the study develops a new measure of segregation at the state level that captures the level of exposure between white and African Americans in a state and explores how variations in segregation and the subsequent exposure across states and years affect the level of welfare generosity, measured both in terms of cash benefits under the Temporary Assistance to Needy Families (TANF), Unemployment Insurance Replacement and also Medicaid spending on inpatient, outpatient and mental healthcare facilities. To account for endogeneity and further identify the causal effect of changes in residential segregation, I use and Instrumental Variables (IV) approach where I instrument for segregation by using the number of local governments per capita. The results suggest that desegregation and interracial contact lead to more generous welfare policies in states with a lower proportion of African Americans but less generous policies in states with a higher proportion, indicating that racial residential segregation contributes to racial biases in the welfare system. Although the estimates are not highly precise, our results reveal that residential segregation contributes to racial biases in the welfare system and affects the generosity of welfare policies, with the direction of the effect depending on whether the proportion of African Americans in a state is significant enough to be perceived as a threat.

This paper contributes to multiple strands of literature in economics. Firstly, it adds to

[1] Other relevant literature on residential segregation includes Darden and Camel (1999), who analyzed the link between segregation and socio-economic disparities in Detroit, and Squires, Friedman, and Saidat (2002), who did the same in Washington DC

the existing body of research on the impact of race and racial biases on welfare policies in the United States (Gillens, 1996; Schramm et al., 2008) by investigating a distinct channel through which race may affect welfare. Secondly, it enhances the empirical literature on the determinants of state welfare generosity in the US, such as the influence of social capital (Hawes and McCrea, 2008) and levels of immigration (Hero and Preuhs, 2007). Thirdly, the paper contributes to the literature on how racial biases impact access to mental healthcare (Mensa et al., 2021; Alvarez et al., 2022). Finally, this paper also contributes to the literature on the economic and political consequences of racial segregation. In this area, current research has focused on labor market outcomes (Cutler and Glaeser, 1997), educational outcomes (Elder et al, 2021), and health disparities (Yang, Park, and Matthews, 2020; Grady et al., 2012), but has paid little attention to welfare policies.

In section 2, I discuss the literature about the relationship between race and welfare. In section 3, I formalize the causal mechanisms that I hypothesize. Sections 4, 5, and 6 involve the regression design, results, and interpretation, respectively.

2.2 Racial residential segregation in the US

Racial residential segregation represents one of the most visible and persistent forms of structural anti-black racism (Schwartz et al., 2022). Notably, as of 2018, the average white American resided in a neighborhood that was 71% white and 7% black, while the average African American lived in a neighborhood that was 45% black and 31% white (Loh et al., 2020). Despite the enactment of the Fair Housing Act in 1968, which aimed to eliminate discriminatory practices, racial segregation continues to endure in modern times.

This enduring phenomenon can be traced back to historical discriminatory housing policies, such as redlining and zoning ordinances, that perpetuated unequal access to housing opportunities (Menendian et al., 2021). Additionally, structural racism and urban renewal policies further reinforced neighborhood preferences that restricted African Americans from realizing the American dream.

Although the Fair Housing Act of 1968 was expected to be a pivotal step toward dismantling barriers for African Americans, its impact on integration within existing communities was limited (Massey and Denton, 1993). Unlike efforts to desegregate schools, insufficient measures were taken to foster neighborhood integration, resulting in continued segregation. This, coupled with de-industrialization and the out-migration of the middle-class African

American population, led to the emergence of predominantly black post-civil rights ghettos that faced resource and job network constraints (Massey and Denton, 1993). This segregation also spilled over onto suburban neighborhoods, it perpetuates disparities in these areas as well. Racist in-group preferences, rooted in structural racism, drive segregation in minority-dominated suburbs, resulting in lower affluence and inadequate public infrastructure (Williams and Collins, 2001; Alexander, 2012).

The consequences of residential segregation extend beyond socioeconomic realms. Research by Cutler and Glaeser (1998) demonstrates how segregation adversely affects labor market outcomes for African Americans, exacerbating the income gap and hindering access to the American dream. Furthermore, residential segregation has been associated with over-policing (Gordon, 2020; Logan and Oakley, 2017) and housing financing discrimination (Armstrong et al., 2009), perpetuating systemic biases and inequities.

Segregation also has profound implications for public health. Studies have found correlations between residential segregation and various health disparities, including colorectal cancer, Covid-19 fatality rates, and epithelial ovarian cancer (Poulson et al., 2021; Yu et al., 2020; Brown et al., 2021; Westrick et al., 2020). These findings underscore the need to address the impact of segregation on public health outcomes and promote equitable access to healthcare resources.

In addition to its economic and public health concerns, segregation hampers interracial contact and relationships, resulting in social ramifications. Mouw and Entwisle (2006) highlight how racial segregation in schools contributes to 'friendship segregation', with white Americans having fewer non-white friends. Bonilla-Silva and Embrick (2007) further demonstrate how social isolation from African Americans, stemming from segregation, perpetuates a 'white habitus' characterized by racialized perceptions, feelings, and views on racial matters. This habitus, persisting into adulthood, leads many to rationalize isolation from minorities as the norm. Consequently, these racial perceptions likely influence attitudes towards government policies, particularly in racialized discourses such as welfare and criminal justice.

2.3 Race and welfare

The impact of racial biases on policy preferences has been widely acknowledged, particularly in areas such as criminal justice (Peffley and Hurwitz, 1989) and welfare (Gillens, 1996). Studies have shown that the demographic composition of a nation is a significant factor in determining the strength of its welfare state (Wright, 1976). However, Gillens (2006) argues that the portrayal of poverty in the media has increasingly been linked to racial biases, with poverty being increasingly portrayed as exclusively a "Black" problem since 1967. Peffley, Hurwitz, and Sniderman (1997) show how white opposition to welfare has been found to be rooted in racial attitudes, providing an avenue for expressing prejudice towards Blacks without being explicitly racist.

Schramm, Soss, and Fording's (2008) Racial Classification Model (RCM) argue that when minorities become more represented in the welfare discourse, race, and racial classifications often attain salience to policymakers in their policy implementation. Through a survey experiment, the authors show that White respondents who believe in the "blacks are lazy" stereotype are more likely to oppose welfare than those who believe that poor people are lazy, indicating that racial biases have a greater effect on attitudes toward welfare than individualism. Furthermore, the authors demonstrate that the perception of poor black welfare mothers has a greater effect on opposition to welfare than the perception of poor white welfare mothers, indicating that attitudes towards welfare are strongly shaped by racial biases, even more so than general attitudes towards poverty.

In 1996 the United States enacted the Temporary Assistance to Needy Families (TANF), a block grant program, replacing the Aid to Families with Dependant Children (AFDC) program, where impoverished families were given cash benefits. Under the new TANF program, the Federal Government allocated block grants to states and allowed states to design their own welfare programs. This devolution of welfare policies, along with stringent criminal justice policies, have led to poor African Americans being subjected to some of the most punitive forms of social control (Schramm et al., 2008). Aside from attitudes and stereotypes, the implementation of welfare can have racial biases as well, particularly when it comes to sanctions such as reductions in cash benefits for failing to meet hours of work requirements. Monnat(2010) found that black and Latina women are more likely to be sanctioned than white women. Also, while black women may be less likely to be sanctioned in counties with more poor blacks, the reverse is true for Latina women, who are even more likely to be sanctioned in areas with more poor Latinas. Using an experiment where case managers were randomly assigned clients of different races, Schramm, Soss, Fording, and Houser(2009) found that black clients were more likely to be sanctioned than white clients. This racial disparity in sanctions is further exacerbated by the fact that black mothers on welfare find it more difficult to find jobs than white mothers on welfare, thus making them even more vulnerable to being sanctioned [Schramm, Soss, Fording, Houser(2009)]. Kaiser, Mueser, and Choi(2004) show how the level of sanctions often increases with the percentage of the non-white population. The impact of immigration on welfare policies was explored by Hawes and McCrea (2017), who showed how immigration levels impact the 'Social Capital' of the community, which in turn affects its welfare generosity.

While it is undeniable that race and racial attitudes are salient when it comes to the discourse surrounding welfare, it also plays a role in the shaping of state welfare policy (Anderson,2003), even in post-civil rights United States (Brown, 2011). The mechanisms of the race-welfare policy relationship have evolved from institutionalized policies under the New Deal, which limited black welfare participation (Quadagno,1996), to less overt racial biases due to racial attitudes and public opinion. Eger (2010) showed how when racial minorities make up a higher proportion of the population, the generosity of welfare benefits declines, and the terms and conditions for welfare participation become more stringent. The phenomenon appears to hold true whether it is at the state level (Fellowes and Rowe, 2004 Avery and Peffley, 2005) or at the nation-state (Alesina and Glaeser 2004). Shcramm eta al (2009), in their Racial Classification Model (RCM), posits that when racial minorities become more prevalent in the welfare discourse, the salience of race in the context of policy increases. Hurwitz and Pefley (1997) show how when African Americans are perceived as the policy targets, the impact of racial stereotypes enhances, and it leads to African American welfare recipients being seen as less deserving (Fording 2003).

The role of residential segregation in shaping public opinion and welfare policy within the context of race and racial prejudices is a subject of significant interest. Existing literature on inter-racial contact offers insights into this relationship. On one hand, inter-racial interaction has been shown to combat stereotypes and prejudices (Kinder and Mendelberg, 1995). Studies by Forbes (1997) and Voss (1996) indicate that white voters in racially diverse constituencies are more likely to support Black mayoral candidates. On the other hand, proponents of the "Group threat hypotheses" argue that when the minority population is large, increased inter-racial interaction may lead the majority to perceive the minority as a threat. Anderson (2012) found that inter-racial interaction contributed to higher levels of tolerance and that racial attitudes resulting from such interactions explained significant variations in welfare policies across states. Residential segregation, by limiting inter-racial interaction, can potentially heighten or reduce feelings of antagonism, which in turn may shape policy formulations (Herwitz and Peffley, 2007).

Thus, it is reasonable to suggest that exposure to other racial groups influences the role racial biases play in attitudes and the implementation of welfare and criminal justice policies. However, the specific impact of segregation levels and limited familiarity among different racial groups on welfare discourse and perceptions of welfare recipients remains to be explored. Even if segregation and the subsequent lack of exposure do impact public opinion regarding welfare, the question arises whether they also influence state welfare policies. Cutler and Glaeser (1997) have already demonstrated how residential segregation contributes to inter-racial disparities in individual outcomes. But could its impact extend to the macro level, shaping the formulation of welfare policies? It is conceivable that white voters residing in more diverse neighborhoods, having greater interaction with minorities, may exhibit less opposition to minorities receiving welfare and may support less punitive criminal laws. Similarly, white case managers who grew up in or lived in more diverse neighborhoods may demonstrate less severity in sanctioning minority clients. Therefore, the level of segregation and the resulting lack of inter-racial contact in a given region may serve as a critical determinant of the influence of race on attitudes towards welfare policies, as it can either perpetuate stereotypes or prevent minorities from being perceived as a threat by the majority. In the subsequent sections, I delve into an exploration of whether states that have experienced a decrease (or in some cases an increase) in segregation over the past few decades have enacted more generous welfare policies as a result of the corresponding changes in exposure levels.

2.4 Potential hypotheses

According to the inter-group contact theory, greater isolation from minority groups tends to amplify racial prejudices among the majority, while increased interracial interaction can mitigate negative racial stereotypes such as the 'Welfare Queen' (Allport, 1954). Consequently, higher levels of residential segregation, which limit inter-racial contact, are likely to perpetuate racial stereotypes and diminish support for generous welfare policies, particularly concerning African Americans, due to underlying prejudice against them.

Hypothesis 1: *Higher levels of residential segregation will lead to less contact between members of different races, which will cause welfare-related stereotypes about African Americans to perpetuate. This, in turn, will lead to lower support for welfare spending and, consequently, less generous welfare policies. I call this the 'empathy hypothesis'.*

In contrast to the inter-group contact theory, proponents of the group threat theory argue that heightened inter-racial contact, particularly when the minority population size is substantial, can raise the likelihood of negative interactions and contribute to racial conflict that extends into policy domains (Oliver and Mendelberg, 2000; Schramm et al., 2011;

Brown, 2013). As a result, reducing segregation and promoting greater inter-racial contact may exacerbate racial antagonism among the majority, leading to reduced support for and implementation of welfare policies. These findings emphasize the intricate interplay between segregation, inter-group contact, and attitudes toward welfare policies, underscoring the significance of considering multiple theoretical perspectives to comprehend the relationship among these factors.

Hypothesis 2: *Lower levels of segregation will lead to more interracial contact, which will increase the likelihood of conflict (in terms of negative interactions) among different racial groups. This, in turn, would lead to more antagonism towards African Americans, which might lead to less support for generous welfare policies. I call this the 'threat hypothesis'.*

2.5 Data and variables

2.5.1 Index of residential segregation

The analyses in this study uses the degree of racial residential segregation in a state as the main explanatory variable. Massey and Denton (1998) identified five dimensions of residential segregation, including Evenness, Exposure, Concentration, Clustering, and Centralization. However, most segregation studies rely on either the Dissimilarity Index (which measures evenness) or the Exposure index (which measures exposure) as the segregation measure. Since the causal mechanisms under investigation are centered around inter-racial contact (or lack thereof), the Exposure Index is a more suitable explanatory variable.

The Exposure Index is defined as the "probability that a member of one racial group interacts with a member of another racial group" or the likelihood that a member of one racial group shares a neighborhood (or census tract) with a member of another racial group. To calculate the index, two components are used: the portion of a city's total population of a given racial group living in a specific neighborhood and the racial makeup of that neighborhood concerning another racial group. The Exposure Index is then determined by taking the weighted average of a neighborhood's racial makeup with the weights being the share of the population of a racial group living in that neighborhood (or census tract). This index is typically defined for two racial groups and calculated at the census tract level. For example, the Exposure Index between white and black people in a given city is

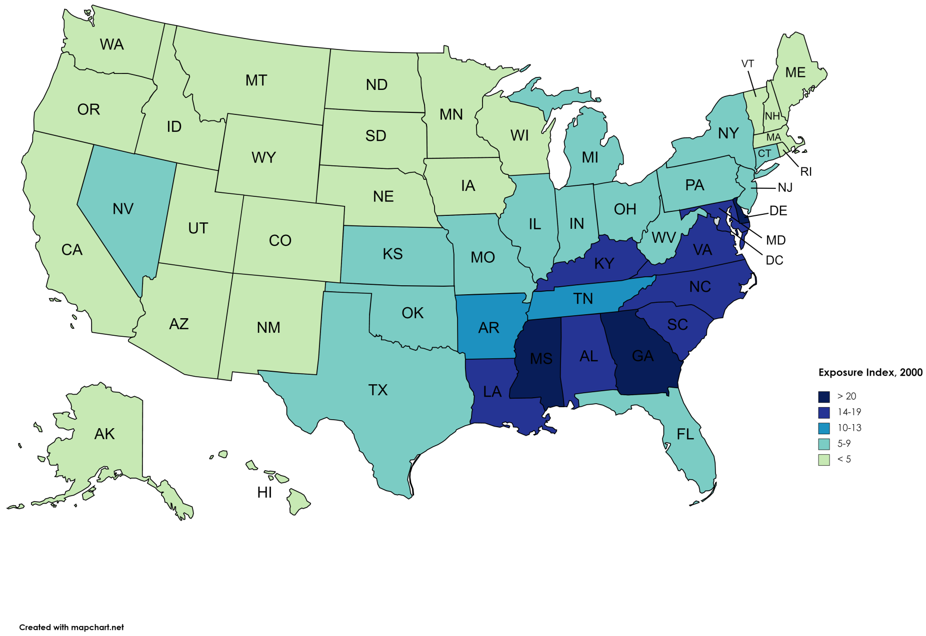
The numerator on the first and second terms represents the population of White and African Americans in a census tract. The denominators of the first and second terms represent the total African American population in the city and the total population of the census tract, respectively. The first term is the proportion of the city's African Americans who live in that census tract and is used as the weight while taking the weighted average of the second term, which is the racial makeup of whites in the census tract.

As an example, let's say there's a city with a population of 70 Caucasians and 30 African Americans, divided into two census tracts. The first tract has 50 Caucasians and 10 African Americans, while the second has 20 Caucasians and 40 African Americans. This means that the first tract has a 33.3% African American population and the second has a 66.6% African American population. The first tract is also 83.3% Caucasian and the second is 33.3% Caucasian. To calculate the exposure index, we take the weighted average of the racial makeup of each tract. So, (0.33 * 0.83) + (0.66 * 0.33) = 0.4719. This means that the probability of a Caucasian person having exposure to an African American person is 0.4719, or that 47.19% of Caucasians are exposed to African Americans living in their neighborhoods.

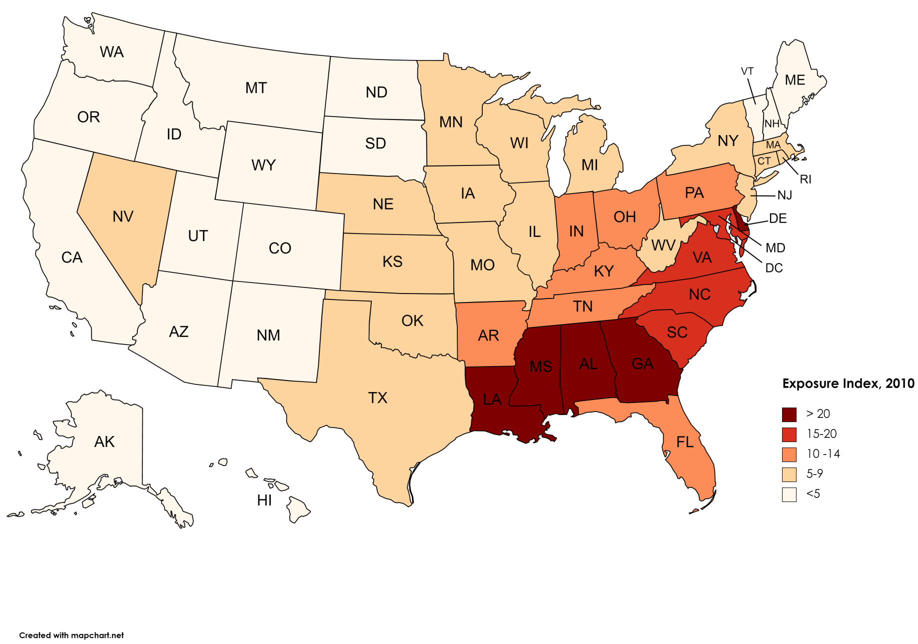
As mentioned before, Gillens (1996) showed using a random survey-based experiment that welfare and opposition to it are most often rooted in prejudice towards impoverished African Americans(White respondents who believed in the 'Blacks are lazy' stereotype were 47% more likely to oppose higher welfare spending). I thus use the White-Black Exposure Index for the regressions. While White-Latino segregation would influence the welfare discourse as well, its effect is restricted to just a few states in the South-West. Running a simple panel fixed effects regression on variables regarding public opinion on welfare and public racial attitudes towards African Americans (data for both obtained from the GSS) reveals a statistically significant relationship with a coefficient of 37%(p-value = 0.00) between opposition to welfare and antagonistic attitudes towards African Americans. Racial attitudes toward African Americans correlate strongly with attitudes toward welfare. The data for the Exposure Index is obtained from The American Communities Project by Brown University. The data is based on the Census of 1980, 1990, 2000, and 2010 and is available at the city level for cities with a population greater than 10000.

While the impact of segregation will be felt mainly at the local level, the policies regarding welfare are set at the state level. My main intention here is to assess the impact of residential segregation on welfare policies with the mechanism operating through racial stereotypes that may be exacerbated due to segregation. Johnson (2003) showed how a state's racial attitudes in addition to its mass ideology and partisanship, is often a determinant of the generosity of its welfare policies. Schramm et al. (2009), in their Racial Classification Model, argue that when African Americans are viewed as policy targets, racial stereotypes, and reputations become a determinant for welfare policy at the state level. Avery and Peffley (2005) and Soss (2001) showed that when African Americans are over-represented among welfare caseloads, policymakers may implement less generous welfare policies due to African Americans being perceived as less deserving. As I am positing that residential segregation causes the perpetuation of racial stereotypes(that Black people are lazy or they are dangerous), it may lead states to adopt less (or more) generous welfare policies due to public opinion regarding welfare recipients (who are perceived to be minorities). In order to assess how the effect of segregation would play out at the state level, I calculate the Exposure Index of a state by taking the weighted average of the Exposure index of the cities, with the weights being in terms of the adult voting age white population of the cities. The goal here is to create an approximate measure of the general level of exposure White Americans have towards African Americans in a given state, thus giving us an approximate measure of the level of inter-racial contact in a state. This enables us to see whether the degree of inter-racial contact in a state has any effect on its welfare policies through public opinion regarding racial stereotypes.

Figure 2.1: Exposure Index by state



Exposure Index by state in 2000



Exposure Index by state in 2010

Notes The maps depict the aggregated Exposure Index by state in 2000 and 2010.

The exclusion of cities with a population of less than 10000, does not affect the index much since we weigh in terms of population. Based on this new aggregate measure, the nation as a whole had an average exposure index of 8.6. Mississippi recorded the highest Exposure index of 29.04 in 2010, while Montana recorded the lowest exposure index of 0.4 in 2000. The Southern States recorded the highest Exposure Indices due to their high proportion of African Americans(see figure 1), while the states in New England and the West recorded the lowest exposure scores possibly due to a lower fraction of African American residents. The Great Lakes region(Ohio, Michigan, Wisconsin, Pennsylvania) has some of the most segregated cities in the country, and as a result, their exposure indices are lower relative to their African American population.

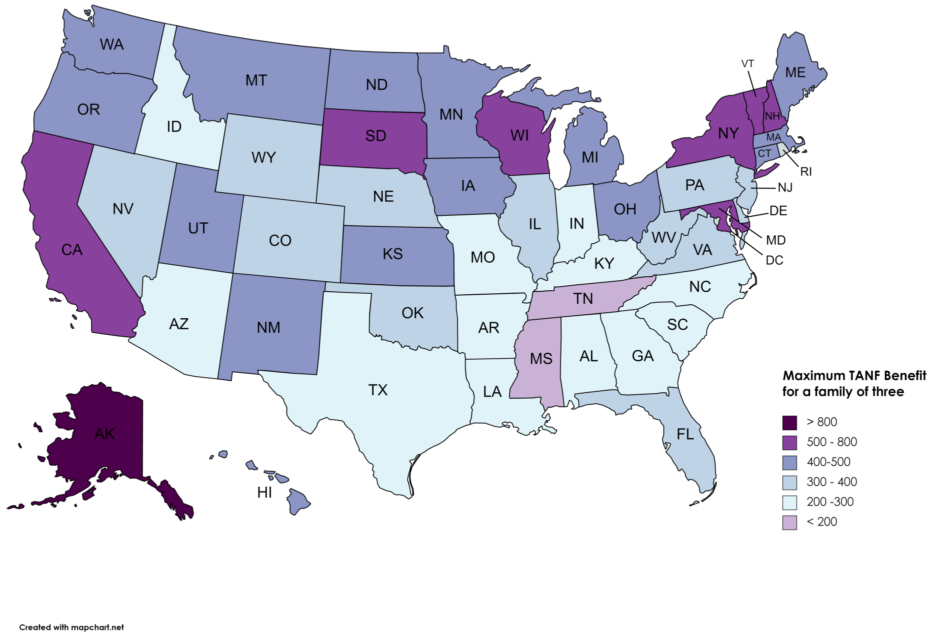
2.5.2 Welfare generosity

This economics paper utilizes various measures to assess welfare generosity at the state level and its relationship with public opinion. The data for welfare-related variables are obtained from the Correlates of State Policies dataset. The primary variable of interest is welfare generosity, which is measured as the ratio of the Maximum TANF Benefit for a family of three (adjusted for 2007 dollars) and the median household income of a state. This measure is chosen due to the state government's almost exclusive control over benefit levels and their no-strings-attached nature, making them a target for critics of generous welfare policy. The data covers the period from 1996, (when TANF was enacted) to 2010. The upper map on figure 2 displays the Maximum TANF benefit by state. There appears to be somewhat of a trend along political lines with liberal states like California, New York and New Hampshire having relatively higher cash benefits while conservative states like Louisiana, Kentucky and Arkansas having among the lowest. South Dakota and Alaska appear to be exceptions in this regard with Alaska having the highest cash benefit levels across all states. The states in the Great Lakes region, which have high levels of segregation, have welfare policies more generous than the Southern states, which have relatively lower levels of segregation but high Exposure Index due to their high proportion of African Americans. However, their welfare policies are less generous than states like Alaska and North Dakota (both of which have some of the highest benefit levels under TANF), which have lower levels of segregation and a lower proportion of African Americans.

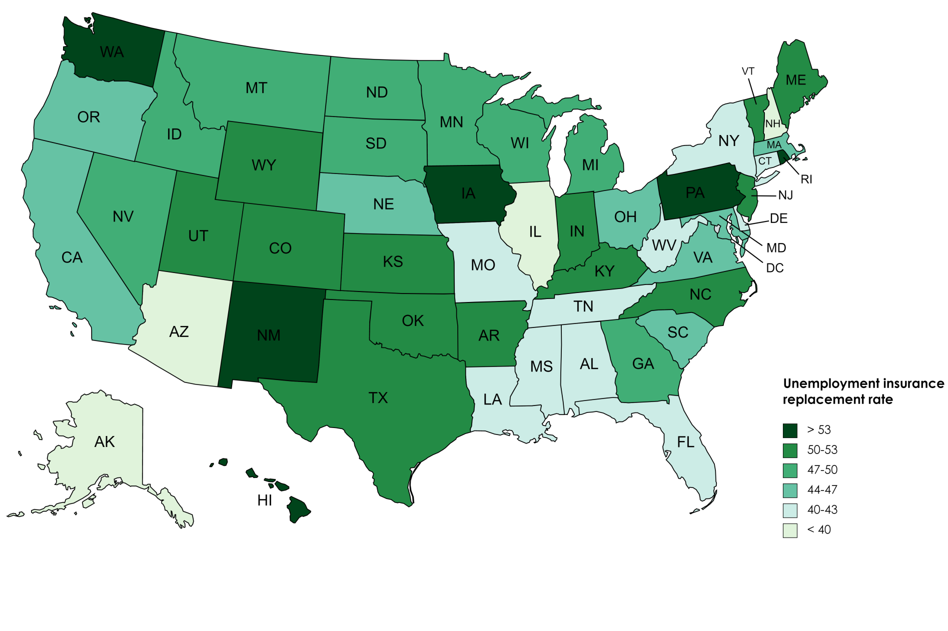
The study also employs the AFDC/TANF coverage rate, obtained by dividing the average number of AFDC/TANF caseloads by the total number of residents whose incomes fall below the federal poverty line. This measure, although somewhat noisy, provides insight into the level of welfare coverage provided by a state.

The paper also employs the unemployment insurance replacement rate as an indicator for welfare generosity similar to Scruggs and Hayes (2017). The unemployment insurance replacement rate is the ratio between the dollar amount of unemployment insurance in a state to the average wage of the state expressed in percentage. As per Scruggs and Hayes (2017), the advantage of using the benefit replacement ratio as opposed to spending is that it can capture variations in income and cost of living while not being sensitive to macroeconomic shocks. In 2010, Hawaii had the highest unemployment insurance replacement rate at 54.85% while Alaska had the lowest at 33.75%

Figure 2.2: Welfare generosity by state



Maximum TANF cash benefit by state



Unemployment Insurance Replacement rates by state

Notes: The maps display variations in welfare generosity by state. The upper map displays the Maximum cash benefit under TANF for a family of 3. The lower map displays the unemployment insurance replacement rate by state. The map on the upper panel displays variations in the maximum TANF benefit by state.

This study also employs various dimensions of Medicaid spending as indicators of welfare generosity. Medicaid serves as one of the primary mechanisms for redistributing resources in the United States, providing health insurance for individuals with low incomes, with African Americans being disproportionately enrolled compared to other demographic groups. However, the historical implementation of Medicaid has been marred by racial biases targeting African Americans, which originated during its establishment in the 1960s. Southern states, where African Americans constitute a higher proportion of the population, actively opposed federal oversight and control of implementation and eligibility criteria, leading to the embedding of racial biases in Medicaid's implementation through the funding practices of these states (Albert et al., 2021). Notably, when the US Supreme Court decided to expand Medicaid in 2012, all 14 states that refused expansion were located in the South, where African Americans are overrepresented. Snowden and Graff (2019) argue that this opposition was largely driven by perceptions of African Americans as part of the "undeserving poor," as the expansion aimed to extend coverage to all adults with incomes up to 138% of the poverty line, a population in which African Americans are disproportionately represented. Considering the adverse economic and public health outcomes associated with residential segregation for African Americans living in segregated neighborhoods, higher Medicaid spending may be required, potentially provoking opposition from white populations. Therefore, one additional component of welfare generosity examined in this study is the proportion of Medicaid spending dedicated to inpatient and outpatient medical services.

Residential segregation also has implications for the mental health outcomes of African Americans (Dinwiddie et al., 2013). The provision of mental healthcare under state Medicaid programs reveals a racialized pattern, with studies such as Samnaliev et al (2009) finding that African Americans are less likely than Whites to receive mental healthcare treatment in community-based settings sponsored by Medicaid. Given that Medicaid is the largest payer for mental healthcare services, racial prejudices regarding the perceived "deservingness" of African Americans can significantly impact the extent and effectiveness of Medicaid's support for mental healthcare. Hence, the proportion of Medicaid spending allocated to inpatient and outpatient hospital services is considered as a potential indicator of welfare generosity in this context.

Finally, the paper employs the "Share of the population of a state that believes that we are spending too much on welfare" as a measure of public opinion. The data is based on the Generalized Sample Survey (GSS), and the study observes fluctuations in the share of the population opposed to welfare spending in the 1980s, followed by an increase from the late 1980s to the mid-1990s. Opposition to welfare has declined since 2000, except for certain states that witnessed a sudden increase in the latter part of the decade.

2.5.3 Control variables

Dye (1984) argues that socio-economic variables are very important determinants of state welfare policy, while Plotnick and Winters(1996) argue that political variables interact with socio-economic variables in a complex way to determine welfare policy. In my analyses, I use both socio-economic and political variables as controls. The socio-economic variables include

i) Share of the African American population: The proportion of African Americans or minorities, in general, is often a predictor of welfare generosity (Fellows and Rowe, 2004)

ii) Poverty rate: States with higher poverty rates will need to adopt more generous welfare policies.

iii) Unemployment Rate: Higher unemployment will necessitate more welfare caseloads and more generous welfare policies.

iv) Share of Urban population: A more urbanized electorate will support more generous welfare policies.

v) Total TANF Caseloads: Higher caseloads might not allow a state to adopt generous welfare benefits.

Hahn et al. (2017) show that states with a higher proportion of African Americans have less generous welfare benefits, especially if African Americans are over-represented in the caseloads. We can thus expect the share of the African American population of a state to be a major determinant when it comes welfare related racial stereotypes which can be exacerbated due to segregation. Moreover, in regions with a higher proportion of African Americans, less segregation may lead to more of a threat perception than empathy. In order to capture this effect, I add an interaction term to the main regression equations consisting of the Exposure Index and the percentage of African Americans in a certain state.

As Schramm et al (2008) and Herwitz and Peffley (1997) show that when poverty is seen as a black problem and black people are viewed as policy targets, black recipients are seen as less deserving, and the opposition to welfare translates into less generous welfare policies at the state level. Hence I include a number of political variables in the latter regressions when I attempt to link public opposition to welfare to policy. The two main political variables in my regression are the degree of electoral competition and partisanship. This is based on Hill and Winton-Anderson (1995), where the authors talk about how the link between public opinion and policy depends on, among other factors, partisanship and electoral competition. A higher degree of partisanship would result in the legislators enacting more partisan policies. Given the very partisan nature of welfare spending, this is likely to play a key role when it comes to whether a state enacts more or less generous welfare policies. In order to account for this in my design I use a measure of state government ideology called ADA / COPE Measure of State Government Ideology based on Ringuist et al (1998). Similarly, higher electoral competition would mean legislators are more likely to cave into public demands regarding policy. As there is widespread opposition to welfare in many states (upto 70 percent in certain states) a more competitive electoral scenario would mean that the legislators would be more likely to enact less generous welfare policies in such states due to public pressure. The measure of Electoral competition I use is the Holbrook and Van Dunk competitiveness measure based on Holbrook and Van Dunk (1995). This is calculated by first taking the averages of the percent of votes the winning candidate Received, Winning Margin, percentages of Uncontested Seats, and percentage of Safe Seats and subtracting it from 100 over 4 yr. Moving Average. As both partisanship and electoral competition seemingly influence one another, I interact with the two and use it as an additional control in my regression equation.

Table 2.1: Summary statistics

	Mean	Standard Deviation	Minimum	Maximum
Exposure Index	7.43	6.08	0.25	29.08
TANF Benefit to income ratio	0.0094	0.003088	0.00444	0.021
AFDC/TANF Coverage rate	0.085	0.0533	0.006	0.006
Unemployment Insurance Replacement rate	0.472	0.047	0.306	0.566
Share of Medicaid spending on mental health facilities	0.011	0.0114	0	0.0519
Share of Medicaid spending on inpatient hospital facilities	0.1172	0.0576	0.0049	0.325
Share of Medicaid spending on outpatient hospital facilities	0.043	0.0261	0.0004	0.1444
Local Governments per 100000 people	23.22	42.76	0	271.3659
Share of African American Population	10.54	10.95	0.22	43.43
Poverty Rate	13.04	3.94	2.9	27.2
Unemployment Rate	5.89	2.15	1.688	18
Share of Urban Population	70.4	15.11	32.2	100
Electoral Competition	40.01	11.6	5.69	66.2
State Ideology	51	25.1	0	97.916
AFDC/TANF Caseloads	56718	91337	327	652070

2.6 Identification and empirical methodology

The aim of the analyses is to identify and estimate how changes in interracial exposure between white and African Americans across states and years, captured by the exposure index, impact the generosity of welfare policies measured in terms of TANF cash benefits and Medicaid's spending on mental healthcare. The baseline equation is given by:

$$W_{st} = \beta_0 + \beta_1 * Exp_{st} + \beta_2 * Exp_{st} * pctAAm_{st} + \beta_3 * X_{st} + \alpha_s + \gamma_t + \epsilon_{st} \tag{2.2}$$

W_{st} is a measure of welfare generosity at the state level which could be either measured in terms of the TANF cash benefit-to-income ratio, Medicaid's spending on mental healthcare and the share of poor people that received benefits under TANF/AFDC. Exp_{st} is the aforementioned exposure index which captures the level of interracial contact between white and Black residents in state 's' and year 't'. At the same time, $pctAAm_{st}$ denotes the share of African American residents in a state. X_{st} is a vector of control variables. α_s and γ_t are state and year fixed effects, respectively which capture state and year-specific factors that may influence state welfare generosity in a given year.

2.6.1 Endogeneity and instrumental variable

Residential segregation within a state is influenced by endogenous factors, such as the presence of racial biases and anti-welfare sentiment, which lead individuals to self-segregate and reside among people of similar backgrounds. To address this endogeneity and identify the causal impact of changes in residential segregation on welfare generosity, I employ an instrumental variables approach inspired by Cutler and Glaeser (1997). Specifically, I utilize the number of local governments in a Metropolitan Statistical Area (MSA) as an instrument for measuring segregation. The rationale behind this instrument is that a greater number of local governments within a MSA reflects policy differentials across regions, which, in turn, encourages further sorting. Given that my analysis operates at the state level, I employ the count of both municipal and township governments within a state, scaled by population size, as a potential instrument.

Although population size may not be inherently exogenous in this context, I conducted several panel fixed-effect regressions of welfare-related variables against population size. The findings indicate no significant correlation between a state's population and its level of welfare generosity, as evidenced by p-values ranging from 0.56 to 0.89. Thus, the population of a state can be reasonably assumed to be exogenous within this context. In the first stage regression, the coefficient is -0.007 and statistically significant, with an F-value of 7.52. This result demonstrates a significant correlation between the instrument and our Exposure Index. Additionally, it can be argued that the instrument satisfies the exclusion criteria, given that the number of counties and local governments in a state was historically determined by settlement patterns (Census Bureau, 1994) and is thus unlikely to influence present-day welfare policies.

Accordingly, my approach entails an instrumental variable panel data analysis with year-fixed effects in the subsequent sections. Considering that the primary explanatory variable is involved in an interaction term with the share of the African American population, I introduce an additional variable: the product of the instrument (number of local governments per 100,000 people) and the share of the African American population. This supplementary variable serves as an additional instrument for capturing the interaction effect between the Exposure Index and the share of the African American population. In the next section, I begin by regressing the public opinion variable on the Exposure Index (using both OLS and instrumental variables) and then move on to whether it translates into enactment or implementation of generous welfare policies.

2.7 Results

2.7.1 Fixed effects model

Table 2.2: Main results for model with fixed effects

	Anti-welfare Opinion	TANF Benefit to income	AFDC/TANF Coverage	UI Replacement Rate	Medicaid Inpatient	Medicaid Outpatient	Medicaid Mental Health
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure Index	-0.021*	-0.00002	-0.003	0.00083	-0.0072	0.0028	-0.0004
	(0.008)	(0.0003)	(0.003)	(0.005)	(0.0066)	(0.0046)	(0.0017)
Exposure Index times Share of Black Population	0.0009*	0.000094	0.0004	0.00006	0.0014	-0.00015	-0.000034
	(0.0003)	(0.000097)	(0.00013)	(0.0002)	(0.0002)	(0.007)	(0.00017)
Share of Black population	0.0124	-0.0004	-0.008	-0.0064	-0.0108	-0.0108	-0.000066
	(0.0128)	(0.003)	(0.004)	(0.0076)	(0.0002)	(0.007)	(0.007)
Constant	1.679	585	799.5	0.617	0.542	0.143	0.0548
	(0.409)	(34.5)	(5.37)	(0.24)	(0.322)	(0.222)	(0.0824)
Political Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistic	5.15	3.76	11.69	0.51	0.0479	0.91	0.74
Adjusted R-Squared	0.0266	0.2819	0.1115	0.0799	1.38	0.0004	0.0178
No of Observations	200	100	100	100	100	100	100

Notes: The above table displays the results for a fixed effects regression where the dependent variables are measures of state welfare generosity. The first stage displays the results when the explanatory variable is regressed on the instrumental variable of number of local governments per 100000 residents. Column 1 displays the results when the dependent variable of interest is the share of a state's population who oppose to higher welfare spending. Column 2 displays the estimates when welfare generosity is measured in terms of the ratio between the maximum TANF cash benefit and median income. Column 3 and display the estimates when welfare generosity is measured in terms of the share of poor residents in a state covered under AFDC/TANF and the Unemployment Replacement Rate. Columns 5, 6 and 7 display the estimates when the dependent variable is the share of medicaid spending dedicated to inpatient hospitalization, outpatient hospitalization and mental healthcare. Standard Errors are clustered at the state level. Stars following coefficients represent p-values less than .10 (*), .05 (**), and .01 (***).

Table 2.2 presents the results of the fixed-effects regressions, focusing on the main variables. In the first column, where the dependent variable is the proportion of a state's population opposing increased welfare spending, the findings indicate that a one-unit increase in the Exposure Index results in a (-0.021 + 0.0009*Percentage of African Americans) increase in the percentage of residents opposing higher welfare spending. For the average state, this translates to a decline of 0.0115% for every one-unit increase in the Exposure Index. However, the net effect is positive for states where the share of African Americans exceeds 23.3%. This group includes deep south states such as Mississippi, Alabama, Louisiana, South Carolina, and Georgia, which exhibit a higher level of opposition to welfare spending. The deep south's historical context of institutional racism and the larger percentage of African Americans residing there likely contribute to this effect. [2]

Similar patterns emerge when examining the regressions for the TANF benefit-to-income ratio and the TANF/AFDC coverage rate (columns 3 and 4). For the average state, a one-unit increase in the Exposure Index leads to a 0.073% and 0.1136% increase in the TANF benefit and coverage rate, respectively. Here again, the empathy hypothesis holds true for most states, with increased exposure associated with more generous welfare policies. However, the effect is reversed for deep south states with a higher proportion of African Americans, although the estimates lack precision and statistical significance.

In terms of the Unemployment Insurance (UI) replacement rate, the effect of increased exposure resulting from desegregation is positive for all states, including those in the deep south. On average, states experience a 0.14% increase in the Unemployment Insurance-to-average wage ratio. The TANF benefit's racialized history in the deep south may explain why its ratio declines while the UI replacement rate remains unaffected by racial dynamics (Monnat, 2010).

Regarding Medicaid and its coverage, noteworthy coefficients emerge for Medicaid's coverage of mental healthcare. Increased exposure through desegregation is associated with a decline in the percentage of Medicaid spending on mental healthcare. On average, a one-unit increase in the Exposure Index leads to a 0.18% decrease in Medicaid spending on mental healthcare. This pattern holds regardless of the share of African Americans. These findings suggest that the threat hypothesis is at play, as higher exposure to African Americans correlates with reduced support for Medicaid covering mental healthcare. This result contrasts with the estimates for TANF-related variables. One possible explanation is that TANF cash benefits primarily benefit single mothers with children, making them more likely to evoke empathy. In contrast, the recipients of Medicaid's mental healthcare coverage can be childless adults, for whom the empathy hypothesis may hold less relevance.

[2] The value are calculated by plugging in the average value of the percentage of African Americans across states in our sample period which is 10.34%

Overall, the imprecisely estimated results indicate that desegregation and subsequent interracial exposure can dispel racist stereotypes (empathy hypothesis), potentially leading to more generous welfare policies. However, for certain welfare categories like TANF cash benefits, the effect can be opposite in deep south states, where desegregation and interracial exposure may result in less generous welfare policies due to the larger proportion of African Americans.

2.7.2 Model with instrumental variables

Table 2.3: First stage results

	Exposure Index
Number of Local Governments per 100000 residents	-0.1134** (0.0413)
F -Statistic	7.52
R-Square	0.0991
N	200

[3]

[3]The above table displays the coefficient for the first stage of the two stage least squares (2SLS). The dependent variable is the Exposure Index which is regressed on the instrumental variable, the number of local governments per 100000 residents

Table 2.4: Main results for two stage least squares model

	Anti-Welfare Opinion	TANF Benefit to Income ratio	AFDC/TANF Coverage rate	UI Replacement Rate	Medicaid Inpatient	Medicaid Outpatient	Medicaid Mental health spending
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposure Index	-0.177	0.002	0.104	0.099	0.1291	0.334	0.175
	(5.53)	(0.111)	(3.78)	(2.71)	(5.644)	(11.65)	(5.99)
Exposure Index times Share of African Americans	-0.007	0.0001	0.1964	0.0034	0.0099	0.0182	0.0092
	(0.288)	(0.005)	(0.457)	(0.1413)	(0.293)	(0.606)	(0.3123)
Share of Black population	-0.274	-0.005	-1.87	-0.126	-0.287	-0.564	0.285
	(8.802)	(1.17)	(6.02)	(4.23)	(8.99)	(18.56)	(9.55)
Constant	-0.24	124.9	89.4	2.284	4.79	8.4	100.4
	(5.37)	(4.6)	(48.9)	(64.008)	(133.12)	(0.274)	(421.4)
F-Statistic	0.02	0.05	0.01	0.01	0.01	0.02	0.05
No of Observations	200	100	200	100	100	100	100

Notes: The above table displays the results for the Two-stage least squares regression where the dependent variables are measures of state welfare generosity. The first stage displays the results when the explanatory variable is regressed on the instrumental variable of number of local governments per 100000 residents. Column 1 displays the results when the dependent variable of interest is the share of a state's population who oppose to higher welfare spending. Column 2 displays the estimates when welfare generosity is measured in terms of the ratio between the maximum TANF cash benefit and median income. Column 3 and display the estimates when welfare generosity is measured in terms of the share of poor residents in a state covered under AFDC/TANF and the Unemployment Replacement Rate. Columns 5, 6 and 7 display the estimates when the dependent variable is the share of medicaid spending dedicated to inpatient hospitalization, outpatient hospitalization and mental healthcare. Specification includes socioeconomic controls for all the regressions and political controls for public opinion variable. Standard Errors are clustered at the state level. Stars following coefficients represent p-values less than .10 (*), .05 (**), and .01 (***).

Though the inclusion of fixed effects controls for time and state invariant endogeneity, there may still be some residual endogeity that is time variant. To account for this I run a 2SLS model where the number of local governments per 10000 residents is used as the instrument for the Exposure Index.

Table 2.3 represents the results for the first stage when the Exposure Index is instrumented with the number of local governments per 100000 residents. The regression yields a statistically significant relationship between the instrument and the Exposure Index with an F-statistic of 7.52, indicating a relatively weak instrument.

Table 2.4 displays the estimates for the second stage of our instrumental variables regression.

Of the estimates, most are similar in direction but of a slightly higher magnitude. However there are a few noteworthy differences. First, the sign of the coefficient for Exposure Index is now positive for both the TANF cash benefit and coverage rate. This indicates that after controlling for endogeneity using an instrumental variable, overall effect of increasing exposure is positive for all states, irrespective of the proportion of African Americans, when welfare generosity is measured in terms of cash benefits and coverage rate under TANF. The 'empathy hypotheses' now seems to hold for all states, even those in the deep south. Under the new coefficients, for an average state, a one unit increase is associated with a 0.3% increase in the TANF cash benefit to income ratio, a 2.13% in the coverage rate and a 0.13% increase in the Unemployment Insurance Replacement rate.

Another such as those for Medicaid coverage of mental healthcare, are somewhat puzzling as they have the opposite sign. This implies that higher exposure now has a net positive effect when it comes to Medicaid's coverage of mental healthcare, similar to all the other variables from columns 2 to 6. Though this appears to solve the puzzling estimates of table 2, it must be noted that the instrument is a weak instrument with an F-statistic less than 10 and as such the estimates may not be very meaningful. Overall, the results indicate that desegregation and the corresponding interracial exposure increases the generosity of welfare policies perhaps through dispelling racist stereotypes such as the 'welfare' queen among others.

In the next section I discuss the substantive significance of the aforementioned estimates using California and Florida as examples.

2.8 Discussion and conclusion

Based on all of the previous regressions it is reasonable to conclude that residential Segregation does, in fact have an impact on public opinion, generosity of welfare policies and implementation of said policies. The net effect depends on the share of the African American population of a state, with states with a higher proportion of African Americans more likely to exhibit the threat hypotheses and states with a lower proportion of African Americans more likely to exhibit the empathy hypotheses. The magnitude of the estimates is larger once we instrument for segregation and include year-fixed effects. In line with Schramm et al (2009) Racial Classification Model, we can thus say that residential segregation (and corresponding exposure) contributes to the salience of race and racial biases in the politics of welfare through the perpetuation of stereotypes and subsequently influences welfare policies at the state level.

For the regression involving the TANF Benefit-to-Income ratio, the IV estimate is 0.002 and that of the interaction term is 0.0001. This regression was based on the post-TANF era, it involves two years (2000 and 2010). In these two years, the median value of the exposure index is 8.6. Florida has an exposure index of 11.76 in 2010. This implies that if the average white American in the US had the same level of Exposure to African Americans as White Americans in Florida do, we could expect the average benefit to income ratio across states would change by 11.76(0.002 + 16.37*0.0001) - 8.6(0.002 + 10.34*0.0001) = 0.016 The current median benefit to income ratio across states is approximately 0.0081 and the aforementioned increase would mean it would increase to 0.0241 or that the benefit would be 2.41 percent of the state's median household income. Given that the average of median household income across states is $51710 this implies that the average cash benefit should be approximately $ 1246 which is an increase of $846 dollars from the current national average, if the average White American had the same level of exposure to African Americans as an average White American in Florida.

California has a lower-than-average exposure index of 4.8 . If the average White American had the same level of exposure to African Americans as whites in California then the average TANF Benefit to income ratio across states would decrease by 0.026-0.0182 = 0.0078 or that the benefits would decrease by $ 403 and be approximately $ 606 .

The Southern states have a higher than average Exposure Index and a high proportion of African Americans, have a benefit-to-income ratio between 0.5 to 0.9% and it has declined slightly over the decade as exposure to African Americans increased. Within the South, states with higher exposure indices (the Deep South) have a lower benefit-to-income ratio than those with lower exposure indices (the Upper South). The threat hypothesis seems to at play here and is reasonable, considering the racially charged history of the South. The same appears to hold true for the Upper Midwestern states which have some of the highest levels of segregation (their Exposure Index is low relative to their share of African American population). All the states witnessed a decline in their benefit-to-income ratio as exposure increased.

The states in New England and the West Coast all have lower than average exposure and higher than average benefit-to-income ratio and the ratio has increased from 2000 to 2010 while exposure has increased. The 'empathy hypothesis' appears to be in play here as higher exposure to African Americans seems to mitigate negative racial stereotypes and subsequently lead to more. generous welfare policies

Overall, for most states, welfare generosity declined with increase in exposure to African Americans though for some it increased. The effect seems to be the strongest in the Upper Midwest and New England and the weakest in the South and West Coast. Across states, welfare generosity and exposure are positively correlated for less diverse states (in terms of share of African American population) such as those in the West and New England, while it is negatively correlated for more diverse states such as those in the Deep south and Upper Midwest.

All in all residential segregation does in fact have an impact on the discourse of welfare with the direction of the impact depending on the state in question, its history of race relations and the share of African American population.

The existing Index of Exposure has its limitations in capturing the magnitude of segregation. Firstly, it does not include towns with a population less than 10000. Now while this may not change the index much (since we are weighing in terms of population), it still is important to know what the rural communities' role is in the discourse of welfare. Also rural communities that are predominantly poor and white, may support more re-distributive policies out of self interest regardless of their attitude towards African Americans. Secondly, the exposure index for each city is calculated at the census tract level, and as result does not take into account the level of segregation within a census tract.

Residential segregation may not necessarily lead to lack of contact between different races if schools, social venues and workplaces are not equally segregated. A more composite measure incorporating residential, school and other forms of segregation would be able to shed more light on how much inter-racial contact actually happens.

The use of Maximum TANF benefit as a measure of welfare generosity too has its limitations as it is not clear how many people actually get the maximum amount in a state.Taking the ratio of it in terms of median household income too has its drawback, as the benefits are for a family of 3 while the median household size in a state may be more than three.

There are other factors too that affect the welfare discourse . States with a long tradition of philanthropy and religious charities might feel that it is not the government's job to financially assist the poor resulting in higher anti-welfare sentiments. If most such states are located in a particular region (say the deep south or the west coast) then their levels of exposure index would be similar and their welfare policies may be less generous than states located in different region with a different set of values for the exposure index resulting in the cross state variations arising from such charities and philanthropy rather than exposure. Immigration and associated demographic changes is also another factor that influences both segregation and a state's attitude towards welfare. Increasing diversity due to immigration may lead to more people choosing to self segregate thereby reducing exposure while at the same time increasing opposition to welfare spending. As such it may cause certain states to have higher segregation (lower exposure) and less generous welfare policies at the same time. In such cases, the negative correlation between generosity of welfare policies and segregation would be caused due to immigration (and diversity) affecting both.

As the demographics of the United States of America continue to change the issue of residential segregation and its role in race relations will become more and more salient. As the demand for more generous welfare spending (particularly medicare for all) rises, the role of race in welfare and how segregation contributes to it will need to be analysed in more detail.

Chapter 3

Impact of skilled immigration on attitudes towards welfare generosity

Abstract

Increasing levels of immigration raise questions about the sustainability of the welfare state. While higher immigration would lead to less support for redistribution due to potential fiscal leakage or ethnic antagonism, it can also increase support for redistribution out of self interest due to potential economic competition. This paper explores the relationship between immigration and the politics of redistribution by examining the impact of skilled immigration on support for welfare generosity. Using both individual level survey data and aggregate state level data, the study finds that the level of skilled immigration in a state has a moderately positive impact on support for generous redistribution at both the individual and aggregate level. These results suggest that skilled immigration may have a different impact on the politics of redistribution compared to other forms of immigration and may increase support for welfare generosity among residents.

3.1 Introduction

Two of the most polarizing issues in contemporary Western societies are immigration and the role of the welfare state. These issues are interlinked in what is often called the 'Immigrationization of Welfare,' where attitudes towards welfare are rooted in perceptions of immigrants' 'deservingness' and the fiscal impact they have. However, empirical analyses of the net effect of high levels of immigration on attitudes towards redistribution and the welfare state remain ambiguous. While higher immigration may lead to more opposition to welfare generosity due to the perception of immigrants as a burden, it may also spur support for more generous welfare policies out of self-interest due to perceived economic competition. However, most studies implicitly assume that immigrants are low-skilled and potential welfare recipients, disregarding the potential impact that skilled immigration may have on support for the welfare state.

In the United States, the foreign-born population has grown significantly since 1990, comprising 4.7% of the population in 1970, 9.7% in 1990, and 13.7% in 2021. Approximately 1.25 million immigrants enter the country each year, and six states (California, New York, New Jersey, Florida, Nevada, Hawaii) have a fifth of their population born abroad. This influx of immigrants, primarily from Latin America and often low-skilled or undocumented, has raised concerns about welfare reliance and labor market competition. The passage of the Personal Responsibility and Work Opportunities Reconciliation Act (PRWORA) in 1996 granted states more discretion in setting their own welfare policies, including immigrants' eligibility for welfare. This major reform, coupled with the significant inflow of immigrants, made immigration a salient aspect of the welfare discourse in the United States.

The heterogeneity of immigrant backgrounds and the perception of immigrants as an out-group may reduce the altruistic sentiment necessary to sustain the welfare state. Additionally, the potential tax burden on native taxpayers associated with sustaining higher levels of immigrant welfare reliance may induce anti-welfare sentiment, particularly among educated and wealthy individuals expected to shoulder a larger proportion of the tax burden.

However, the United States also attracts skilled immigrants, with a population of over 20 million skilled foreign-born individuals. Skilled immigrants contribute to entrepreneurial activity and play a significant role in STEM occupations. Unlike low-skilled immigrants, skilled immigrants are less likely to be perceived as fiscal burdens and more likely to be seen as contributors to the welfare system. Moreover, skilled immigration can fuel economic anxiety, which may lead to support for redistribution as a form of insurance against falling through the cracks. Skilled natives who fear job loss to skilled immigrants may also demand other forms of welfare protections, such as universal healthcare and unemployment benefits.

This paper explores the immigration-redistribution relationship in the United States, focusing on how skilled immigration and welfare usage by poor immigrants influence attitudes towards redistribution. While higher immigrant welfare usage may lead to opposition to welfare spending, skilled immigration may mitigate such sentiments by being perceived as fiscal contributors. Additionally, skilled immigration may increase support for welfare spending due to economic anxiety, leading to higher demand for welfare protections among college-educated Americans. The analysis uses both a state-level panel data approach and an individual-level pooled cross-section approach, using data from various sources to analyze how attitudes towards redistribution vary depending on the level of skilled immigration and welfare dependence of immigrants.

The paper fills gaps in the literature by focusing on cross-state variations in the United States, considering the impact of highly skilled immigrants on support for redistribution, and addressing endogeneity issues through the use of a Bartik-style shift-share instrument.

By studying the correlation between demographic attributes of immigrants (education levels and welfare usage) and support for welfare spending in different states, this analysis sheds light on unexplored channels of the immigration-redistribution relationship. It examines whether skilled immigration strengthens the welfare state by changing perceptions of immigrants from fiscal burdens to fiscal contributors and sources of economic anxiety that necessitate greater welfare protections. The data partially supports this hypothesis.

The remaining sections of the paper are organized as follows: Section 2 discusses the existing literature on immigration and redistribution, Section 3 describes potential hypotheses and causal mechanisms, Section 4 describes the data and variables, Section 5 outlines the empirical specification, Section 6 discusses the main results of the empirical analyses, and Section 7 concludes the paper.

3.2 Immigration and redistribution

The mechanism through which immigration affects welfare generosity is a major theme in the social sciences. There are roughly two strands of literature on the topic. The first one suggests that preferences for redistribution in relation to immigration are primarily guided by self-interest, which is particularly relevant to my paper and aligns with standard political economy models of redistribution. According to the median voter models, Razin, Sadka, and Swagel (2007) explain, using empirical evidence from 11 European countries between 1972 and 1996, how low-skilled immigration leads to "fiscal leakage" and reduces the amount of welfare benefits that the government can provide, thereby making the median voter worse off. Additionally, locals may fear potential future tax increases to support higher welfare spending, as demonstrated by Citrin, Green, Muste, and Wong (1997) using data from the National Election Survey. Another self-interest channel through which immigration can influence preferences for redistribution is the 'Globalization Compensation Theory.' Finceras (2008) shows, using data from the European Social Survey, that under certain circumstances, immigration can actually increase support for welfare spending due to fears of immigrants taking over jobs, particularly in conservative welfare states in European countries. This "compensation hypothesis" holds true for workers who compete with immigrants in the labor market (Dustman, Frattini, and Preston, 2013) and leads to higher welfare spending as a form of insurance against global risk, as shown by Cusack, Iverson, and Rehm (2006) using multiple waves of ISSP survey data. In the United States, many immigrants from poorer countries are less skilled than the average American worker, exerting downward pressure on wages for American workers Borjas (1994). This concentration of immigrants in low-skilled occupations can potentially lead to more support for welfare due to increased competition generated by immigration, causing locals to support a safety net out of self-interest, as shown by Brady and Finnegan (2014) based on International Social Survey data.

The other strand of the immigration-redistribution literature focuses on cultural beliefs about who is deemed a worthy recipient of public generosity. The theory of social comparisons Festinger (1954) and the social identity theory by Tajfel (1981) posit that individuals are more likely to view others in terms of an in-group and out-group and are less likely to cooperate with members of an out-group when it comes to providing public goods (Chen and Li, 2009). Cavaille and Trump (2015) show, using data from the British Longitudinal Survey, that people's support for welfare spending depends on their attitudes towards groups perceived as recipients of welfare benefits. Luttmer (2011) demonstrates, using individual-level survey data, how support for redistribution increases when one's own ethnic group is overrepresented among welfare recipients. Alesina and Glaeser (2004) argue in their seminal work that, aside from fiscal pressures, the main reason why the United States has less generous welfare benefits than Western Europe is due to its higher diversity resulting from its history as a nation of immigrants. Immigrants are therefore seen as a less deserving out-group due to their ethnically different backgrounds, leading to reduced solidarity from locals, a phenomenon referred to as the "anti-solidarity" effect by Romer, Lee, and Van der Straaten (2008). This lack of solidarity with the ethnically different out-group reduces incentives to invest in public goods Habariyama et al., (2007) and undermines class solidarity Hector (2004), both of which are necessary to sustain the welfare state. In the context of Western Europe, Crepaz (2008) shows, using data from the Eurobarometer and the European Social Survey, how rising immigration leads to anti-immigrant and anti-redistributive sentiment. Senik et al (2009) analyze 22 European countries and demonstrate that support for redistribution declines with antagonistic attitudes towards immigrants. Eger (2010) shows, using survey data at the county level in Sweden, how a higher population of foreign-born individuals reduces support for the welfare state. Similarly, Roemer and Van der Straeten (2005, 2006) find, using data from the United States, Britain, Denmark, and France, that anti-immigrant attitudes reduce the preferred level of redistribution, consistent with the anti-solidarity effect induced by ethnic diversity. In Canada, Soroka et al (2016) demonstrate, using data from community surveys, that a higher proportion of the foreign-born population decreases the growth of social policy spending.

In the United States, historically, such anti-solidarity effects and subsequent opposition to welfare due to perceptions of deservingness of the out-group have manifested in prejudice towards African Americans (Schramm et al., 2009; Gillens, 2006). Hurwitz and Pefley (1997) show how when African Americans are perceived as the policy targets, the impact of racial stereotypes enhances, leading to African American welfare recipients being seen as less deserving (Fording, 2003). However, Garand et al. (2015) argue that discourse surrounding welfare in the United States has become increasingly "immigrationalized," with immigrants being viewed as primary recipients of welfare benefits, and opposition to both immigration and redistribution going hand in hand. In fact, Tabellini (2017) shows, using historical data on the Great Migration from the early 19th century, how natives became less favorable towards social policies in cities that received culturally different immigrants. There is abundant evidence that immigrants make greater use of welfare programs than natives (Borjas and Hilton, 1996; Borjas, 1999; Fix and Passel, 2002), which, coupled with immigrants' lack of political voice, makes them prime targets in the politics of redistribution. Hanson, Scheve, and Slaughter (2005) show, using survey data from the NES, that respondents in states with higher welfare usage by immigrants are also more likely to oppose welfare spending. Ybarra, Sanchez, and Sanchez (2016) demonstrate how increasing multiculturalism generates backlash towards sharing public goods with immigrants. Hawes and McCrea (2007) show how higher levels of immigration erode trust and social capital, which, in turn, reduces support for redistribution.

However, an avenue that needs to be explored is how the socioeconomic composition of immigrants influences the discourse surrounding redistribution in the US. Hanson, Scheve, and Slaughter (2007) state that skilled immigrants are more likely to be perceived as net fiscal contributors, which could generate more transfers to low-skilled natives. Given that the link between immigration and support for redistribution often depends on how the immigrant population is *perceived*, it is possible that higher-skilled immigration could shift the perception of immigrants as an undeserving out-group to potential contributors to the welfare system. This shift could potentially lead to more support for welfare generosity, as skilled immigrants can be seen as sharing the burden of taxation for financing the welfare system. Additionally, it could lead to more perceived competition among the middle class, spurring greater support for redistribution out of fear of falling through the cracks. Furthermore, the extent of this effect may vary depending on the skill level and social class of the individual. College-educated natives might be the most likely to support welfare generosity out of self-interest, as they are likely to perceive skilled immigrants as competition and view them as sources of sharing the fiscal burden of the welfare system. Moreover, educated natives are more likely to encounter skilled immigrants in their daily lives, rather than poor immigrants who use welfare benefits, shaping their attitudes towards redistribution.

This paper contributes to the body of literature analyzing individual preferences for redistribution due to immigration using survey data, as well as aggregate public opinion analyses at the state level. Studies on individual preferences are conducted in both cross-country formats (Brady and Finnegan, 2014; Kwon and Curran, 2016) and within-country formats (Eger, 2010; Schmidt, Catran, and Spies, 2016). However, cross-country studies generally suffer from the drawback that international migration is a non-random process, making it difficult to remove confounding variables and establish causality. Within-country studies allow researchers to study variations in preferences for redistribution among respondents under the same national welfare regime, minimizing confounding by country-specific effects. Nevertheless, most of these within-country studies focus on Europe, such as variations across counties in Sweden (Eger, 2010) or Germany (Schmidt, Catran, and Spies, 2016). The United States offers an interesting avenue for within-country studies because all respondents live under the same national welfare regime, but each state has a degree of autonomy in setting its own levels of welfare generosity. Thus, the cross-state variation in immigrant demographics and welfare generosity can be exploited to analyze how immigration affects preferences for redistribution across different welfare regimes in US states. Most studies using survey data on individual attitudes towards redistribution in the US typically compare a respondent's attitude towards redistribution with their views on race (Gillens, 1999) or other group-specific biases (Luttmer and Fong, 2009). In contrast, this paper compares individual-level survey responses to a state's socioeconomic profile of the immigrant community while accounting for endogeneity using an instrumental variables approach. Studies on state-level public opinion generally consider the foreign-born population as a whole at the state level (Hawes and McCrea, 2013). However, in this analysis, I specifically focus on subsets of foreigners, such as those who are highly educated or those who rely on welfare. By doing so, I hope to shed light on how skilled immigration, in particular, shapes the discourse surrounding redistribution across American states.

3.3 Potential hypotheses

Proponents of The 'anti-solidarity' hypotheses (Van Orshoot, 2006) state that higher proportions of immigrants with access to welfare benefits would lower support for redistribution due to immigrants being perceived as an out-group that is less deserving of welfare benefits (Applebaum, 2008)

Hypotheses 1a : *Higher levels of immigrant welfare usage would lead to a decline in support for welfare spending due to the belief that a less-deserving out group disproportionately accesses welfare benefits.*

Proponents of the 'tax burden hypotheses' state that immigration leads to fiscal pressures on native tax payers to provide welfare benefits to immigrants, especially in states with lower levels of welfare spending (Brinkley, 1994). This in turn may generate anti-immigrant sentiments (Citrin et al, 1997) which may further lead to anti-welfare sentiment (Garand et al, 2017). As such we can expect anti-welfare sentiments due to immigrant welfare use to be higher among those expected to shoulder a bigger share of fiscal burden.

Hypotheses 1b: *Higher levels of immigrant welfare usage will reduce support for welfare generosity due to them being limited, particularly among more educated natives who would expect to shoulder a larger share of the potential future tax hike.*

As perceptions of immigrants shape redistributive attitudes more (Alesina, Miano, and Stantcheva, 2018), skilled immigration may shift perceptions of the immigrant population from undeserving fiscal burden to fiscal contributors who could share the fiscal burden of welfare provision and strengthen the welfare state (Guerreiro, Rebelo, and Teles 2020). Further due to the 'compensation hypotheses', skilled immigrants could be perceived as competitors in the labor market which may lead to increased support for redistribution as a form of insurance by natives.

Hypotheses 2a: *Higher levels of skilled immigration will reduce opposition to welfare spending both due to skilled immigrants being viewed as potential fiscal contributors instead of a fiscal burden as they are less likely to use welfare benefits and more likely to pay higher taxes that* *goes into funding the welfare system .*

As stated before, the compensation hypotheses (Cusack, Iverson, and Rehm,2006) states that higher immigration would generate economic anxiety among natives who would demand higher welfare protections out of self interest. Skilled immigration in particular would generate economic anxiety among similarly educated and skilled native workers (Peterson, Pandya, and Leblang, 2014). Now it can be argued that highly skilled and educated Americans would rarely use welfare benefits, which are primarily designed for low-income individuals, themselves and would not be the ones most concerned about welfare benefits. However, in this analyses, by redistribution, I imply any government-provided service that can be a form of social insurance. Aside from cash benefits and food stamps, redistribution can also imply Medicaid and unemployment benefits. An educated individual who fears losing their job to a skilled immigrant may be concerned about losing their health insurance and access to healthcare as well which could lead them to support greater redistribution in the form of expanded Medicare coverage. As a result higher skilled immigration would lead to similarly educated natives supporting redistribution as a form of insurance.

Hypotheses 2b : *Higher levels of skilled immigration will increase support for redistribution as a form of social insurance among equally skilled natives (bachelors degree or higher)*

3.4 Data and variables

I use two approaches, one where I match individual level survey responses to aggregate data at the state level in a pooled cross section format and one where I use state level variables in the form of a state-year panel dataset. The former allows us to analyse the impact of individual level demographic characteristics on the relationship between my immigration variables and attitudes towards support for welfare, while the latter approach allows us to evaluate the aggregate relationship at the level of the state.

For the first approach I obtain the data for attitudes towards immigration and welfare is obtained from the Cumulative American National Election Survey (CANES) dataset. The ANES is an extensive survey based on a stratified population of the US and contains information about a respondent's opinion on social and political matters such as immigration, and redistribution as well as demographic information such as age,education etc. The survey is conducted for every election year with a different set of respondents and the cumulative ANES file contains the survey data for different years combined in a pooled-cross section format. I limit my analyses to the years 2012 and 2016 due to data limitations in constructing the Instrumental Variable which requires data on distribution of immigrants 10 years prior. The resulting truncated sample is quite limited and thus the results obtained may not be fully accurate. The ANES only surveys eligible voters who are US citizens. It may be possible that some survey respondents are of immigrant origin (i.e naturalized citizens) and as such their opinions regarding immigration and redistribution may vary from natural born citizens. Unfortunately, the survey question asking about nativity status was dropped from the surveys conducted after 1994. The resulting sample used in this analysis lacks information about whether a respondent is of immigrant origin which is also another limitation of the analyses. However, I do not expect it to influence the results significantly, as naturalized citizens made up only 6.5% of the total US population in 2016 and 7 % in 2012.

For the main outcome variable, I use a variable denoting a survey question "Do you feel the current levels of welfare spending should be ___ ?" with options being "Increased","Decreased", and "Kept the same". In 2012, 42.91% of respondents favored decreasing welfare spending while 15.53% of respondents favored increasing welfare spending. while in 2016 46.6% of respondents favored decreasing welfare spending while 18.05% of respondents favored increasing it. I generate a new binary variable which is coded 1 for respondents who support higher welfare spending and 0 for those who do not. The reasons for using a binary variable is that I am primarily concerned about the cohort of respondents who support higher welfare spending versus those who do not and whether skilled immigration and immigrant welfare usage lead to a respondent more likely to fall in the cohort of respondents supporting higher welfare spending or not. This use of survey responses as a measure of attitudes has its own limitations as survey questions are interpreted and answered differently by different respondents. For instance, the aforementioned question does not ask respondents about their preferred or ideal level of welfare spending, but rather if they feel the present level of welfare spending should be increased or not. It is possible that an individual may be supportive of generous welfare policies but at the same time feel that the current level of welfare spending is generous enough and thus will not fall in the cohort of respondents supporting higher welfare spending. Also, some respondents may have answered the question with specific welfare policies in mind while others may have answered it in terms of the wider social safety net. Though it may not be an accurate measure of actual attitudes towards redistribution, this survey response variable nonetheless enables us to gauge some of the prevailing sentiment in this regard.

The main explanatory variables in the study are the percentage of a state's population who are skilled immigrants and immigrant welfare users. The data is obtained from the

Census of Government's American Community Survey Integrated Public Use Microdata (ACS-IPUMS). The ACS Microdata is data on individuals and housing units at the level of Geographic areas such as state, region, division that enable data users to create custom tables. The census produces an ACS 1 year estimate and 5 year estimate. For this study I use the ACS 1 year estimate microdata at the state level. The CANES survey contains information about every respondent's state of voter registration to which I code my state-level explanatory and control variables into the dataset.

The first explanatory variable is the percentage of a state's population who are skilled immigrants which I define as foreign born individuals possessing a Bachelors degree or higher. The ACS 1 year estimate has data on education levels broken down by nativity status in a given state. This variable is essentially the percentage of individuals in a state who are foreign born and hold a bachelors degree or higher. In 2016 New Jersey had the highest percentage of skilled immigrants at 9.18% of the state's population followed by California at 8.435% and New York at 7.802%.Mississippi recorded the lowest population of skilled immigrants per capita at 0.45% followed by West Virginia at 0.745% and Alabama at 1.012.%

The other explanatory variable is the percentage of a state's population who are immigrant welfare users which is defined as any individual who is foreign born and used welfare benefits in the preceding 12 months. The ACS has data on welfare usage(Medicaid, TANF and other forms of cash assistance) at the state level broken down by nativity status. Similar to the previous variable this variable is the percentage of individuals in a state who are foreign born welfare users. In 2016, California and New York had the highest percentage of immigrant welfare users at 7.64% and 7.132% respectively.

For the individual level analyses I use a number of control variables at the individual level which are given by :

- Respondent's political orientation which is captured on a Liberal-Conservative Scale of 1-7 with responses being "Extremely Liberal" , "Liberal", "Slightly Liberal", "Moderate", "Slightly Conservative", "Conservative", "Extremely Conservative".
- Respondent's union membership status captured in the form of a dichotomous variable
- Respondent's age
- Respondent's gender

- Respondent's degree of trust in the government which as per Gillens(1999) is an important determinant of an individual's attitude towards redistribution. The variable is captured in the form of a 'Trust in Government index' coded on a 100 point scale ranging from "Least Trusting" to "Most Trusting".
- A Dummy variable denoting whether a respondent has a bachelor's degree or higher

For the second approach which is a state-level panel data approach, the main outcome variable is the share of respondents in a state who support higher welfare spending. The data is obtained from the Correlates of State Policy dataset and is based on the Generalized Social Survey. I regress this variable on both the aforementioned explanatory variables in a state-level panel dataset. I limit my analyses to the years 2008, 2009, 2010, 2011 and 2012 as the data for the two explanatory variables is available in the ACS only from 2008.

In addition, I use a number of state level variables as controls both in the individual-level pooled cross-section specification and the state-level panel specification. Hanson, Scheve and Slaughter (2007) show how immigrant welfare usage impacts preferences for immigration depending on the state's level of welfare generosity. In states with more generous welfare policies financed by progressive taxation, higher immigrant welfare usage would lead to more opposition to immigration due to potential fiscal burden. I account for a state's level of welfare generosity, using the Maximum TANF Benefit amount for a family of 3 as a measure of the state's welfare generosity. The justification for using the Maximum TANF Benefits, as per Hawes and McCrea (2017), Larimer (2005) and Hero and Preuhs (2007) is that benefit levels are set almost entirely by the state Government (as opposed to Food Stamps and Medicaid which are supplemented by the Federal Government) and given their no-strings attached nature are more likely to be criticized by opponents of generous welfare policy. The data is obtained from the Urban Institute's Welfare rules database for 2012 and 2016.

In the United States, race and racial biases play a major role in shaping attitudes towards redistribution (Gillens, 1996). Schramm et al (2009) show how when minorities are over-represented in the welfare discourse, race becomes more salient in shaping welfare policies. In order to account for it, I use the share of welfare recipients in a given state who are not white as a measure of the role of race in shaping a state's attitude towards redistribution. The data is obtained from the American Communities Survey 1 year estimates for 2012 and 2016.

Other control variables used in both approaches include the poverty rate and unemployment rate of a state, data for both which is obtained from the correllates of state policy dataset obtained from the website of Michigan State University's Institute of Public Policy and Social Research. For the state level approach I also use a variable termed as 'citizen ideology' to capture the ideological orientation of a state's respondents. This variable is based on Berry et al (1998) and is calculated based on the ideological score of incumbents and challengers in each congressional district and the share of electorate who support them based on election results.

Table 3.1: Summary statistics for individual level pooled cross section model

	No of Observations	Mean	Standard Deviation	Min	Max
Percentage Skilled Immigrant	100	3.9434	2.343402	0.4	9.12
Percentage Immigrant Welfare Users	100	2.0775	1.999	0.0138	7.6
Support for Welfare	10184	0.16525	0.3714	0	1
State Welfare Generosity	100	440.0742	184.7193	170	1039
Minority Welfare Usage	100	0.3466	0.1124	0.039	0.6103
Age	10143	49.5	17.138	17	90
Union Membership	10143	1.8512	0.3559	1	2
Gender	10143	1.524697	0.501	1	2
College Education Dummy	10184	0.339	0.4736	0	1
Ideology	9521	4.754	2.1222	1	9
Trust in Government Index	10157	19.683	24.517	1	100
Poverty Rate	100	13.86	3.228	0	22
Unemployment Rate	100	2.959	3.84	0	10.4

Table 3.2: Summary statistics for state level panel model

	No of Observations	Mean	Standard Deviation	Min	Max
Support for Welfare	250	22.92	3.239	14.58	34.37
Percentage Skilled Immigrants	250	2.489	1.876	0.3988	7.988
Percentage Welfare using Immigrants	250	1.005	1.090	0.039	5.720
Poverty Rate	250	13.684	3.293	6.6	23.1
Unemployment Rate	250	7.603	2.174	3.1	13.7
Citizen Ideology	250	52.25	16.244	13.48	91.09
State Welfare Generosity	250	387.317	122.214	174	816
Minority Welfare Usage	250	0.345	0.1577	0.0694	0.8594

3.5 Empirical methodology

3.5.1 Individual level pooled cross section

For the individual level pooled cross section specification, I employ a Linear Probability Model with state fixed effects. The inclusion of state fixed effects is due to the fact that certain states may have institutional, cultural and political factors that would contribute to attracting immigrants of a certain socio-economic back ground. The choice of a Linear Probability Model as opposed to a Logit or Probit Model is due to the fact it allows for combining fixed effects with an Instrument.

The equation for the individual level Pooled cross section model is given (for t = 2012,2016) by

$$W_{ist} = \beta_0 + \beta_1 SI_{st} + \beta_2 IW_{st} + \beta_3 G_{st} + \beta_4 M_{st} + \beta_4 X_{st} + \omega_s + \lambda_t + \epsilon_{ist} \tag{3.1}$$

- W_{ist} is a binary outcome variable indicating support for welfare for individual i living in state s in time t.
- SI_{st} represents the percentage of skilled immigrants living in state s at time t.
- IW_{st} represent the percentage of welfare using immigrants living in state s at time t.
- G_{st} represents the level of State welfare generosity.
- M_{st} represents the proportion of welfare users who are people of color.
- X_{st} represents a vector of individual and state level control variables
- ω_{st} denotes state fixed effects.
- λ_t denotes year fixed effects.
- ϵ_{ist} denotes the error term.

As mentioned before, I anticipate a degree of heterogeneity in an individual's attitude towards welfare spending based on their education level. Specifically I am interested in the impact on respondents with a college education or higher since they would be the ones who will anticipate bearing the burden of financing welfare(as education correlates with income) usage by poor immigrants and view skilled immigrants as competition. In order to isolate the impact of my explanatory variables on respondents with a college degree or higher, I interact the main explanatory variables in both my models with a measure of college education attainment. For the individual level pooled cross section model, I interact the percentage of skilled and welfare using immigrants with a dummy variable denoting whether a respondent has a college degree or not

$$W_{ist} = \beta_0 + \beta_1 SI_{st} + \beta_2 IW_{st} + \beta_{11} Si_{st} * Col_{ist} + \beta_{22} IW_{st} * Col_{ist} + \beta_3 G_{st} + \beta_4 M_{st} + \beta_5 X_{st} + \omega_s + \lambda_t + \epsilon_{ist}$$

Where Col_{ist} is dummy variable denoting whether respondent i has a college degree or not. All other variables are as described before.

Endogeneity and instrumental variables

As mentioned before, the percentage of skilled or welfare using immigrants in a given state is not exogenous in this context. Immigrants, whether skilled or otherwise, do not randomly sort into location but are rather attracted to regions where attitudes of citizens are more favourable to immigration and these attitudes are likely to be correlated with support for redistribution (Garand et al 2017). Economic and demographic changes that attract certain types of immigrants such as highly skilled immigrants are also likely to induce changes in attitudes towards redistribution which may in turn further attract certain categories of immigrants. While the inclusion of state fixed effects can certainly account for state specific attributes that may cause endogeneity issues to arise, it may not be sufficient to fully account for endogeneity of immigrants' location choices across both state and time particularly if socio-economic changes over time influence both support for redistribution and the kind of immigrants who are attracted to certain locations. In order to be more thorough in accounting for endogeneity, I use an Instrumental variables approach. The instrument I use is a variation of the Bartik style shift-share instrument obtained by interacting past distribution of immigrants across states with the national level population to predict the present population of immigrants. The Bartik instrument, introduced by Bartik (1991) and popularized by Blanchard and Katz (1992), is widely used in the literature on immigration, where its variant is also referred to as the immigrant enclave instrument. The instrument was first used by Altonji and Card (1991) and later modified by Card (2001) in terms of national origin and uses the same shift share methodology of interacting local distributional variables with national level growth rates and stock. The main intuition behind the instrument is the idea that immigrants' locational choices are influenced by previous settlement patterns of their co-nationals (Bartel, 1989). Examples include settlement of Irish immigrants in Boston, Italian immigrants in New York, Mexicans in Los Angeles and Indians in the San Francisco Bay area. So if a state had a high fraction of immigrants from a certain nationality then subsequent waves of immigrants from the same nationality are more likely to move to that state where their compatriots reside. This shift share methodology is widely used in the immigration literature and has reasonable power since networks of existing immigrants do attract new immigrants.

To illustrate this, let us consider a hypothetical scenario where there is one group of immigrants, Indian, and two states where they reside: California and Florida. Let us assume that 10 years prior 60% of the Indian immigrant population lived in California and 40% lived in Florida. Now at present there are 100 Indian immigrants in the United States who reside in either California or Florida, out of which 50 were already in the US 10 years ago while the other 50 moved to the US since then. Based on the distributions across the two states 10 years prior, 30 out of 50 Indian immigrants lived in California while the other 20 lived in Florida. As per the intuition of the immigrant enclave instrument, immigrants entering the country sort according to the distribution of their co-nationals across regions. So of the 50 Indian immigrants who entered the US over the past 10 years, 60% or 30 individuals would likely move to California while the remaining 40 % or 20 individuals would likely move to Florida. The predicted Indian immigrant population in California would be 60 (30 who lived 10 years prior and 30 who entered the country since then) or 60% of 100 (the total national population) while for Florida it would be 40 by the same token. The predicted population of Indian immigrants in a state is the proportion who lived 10 years prior times the present national population. Since in the example, 60% of Indian immigrants lived in California 10 years ago, California today would be predicted to have 60% of the total Indian immigrant population which includes those who already lived in California 10 years prior and those who moved since then. Aggregating across all major immigrant groups would give us the predicted immigrant population of California at present. Since I am considering two distinct groups of immigrants(skilled and welfare users) I create my own variations of the shift share instrument which is the closest to Mayda, Peri and Steingress (2013). For the percentage of skilled immigrants, I begin by taking the total stock of skilled immigrant population of a particular nationality(say Indian) and multiply it with the proportion of skilled Indian immigrants who lived in a given state 10 years prior as based on the previous settlement pattern idea, skilled Indian immigrants who moved to the US over that past 10 year would more likely settle in states with a higher existing population of skilled Indian immigrants. I then sum across all major nationalities which for this study includes India, Mexico, China, Phillipines, Vietnam and the Rest of Spanish Speaking Latin America aggregated into one. I restrict my analyses to these nationalities as they account for 65.4% and 70.9% of the Skilled immigrant population in 2012 and 2016 respectively. This instrument is essentially a weighted average of the skilled immigrant population of various nationalities, with weights being the distribution across states from 10 years prior. The value of this variable for a given state is the predicted skilled immigrant population which should be correlated to our explanatory variable of skilled immigrants per capita. The data for the distribution of immigrants by country of origin across states 10 years prior is obtained from the Current Population Survey's Integrated Public Use Micro-data Samples. This data is only available from 2002 onwards due to which I am only able to use this instrument for the individual level pooled cross section specification where the years in question are 2002 and 2016. For the state level panel specification from years 2008 to 2012 I rely mostly on fixed effects to account for endogeneity.

Mathematically, let H_{ct} denote the population of skilled immigrants from country of origin 'c' at time 't' residing in the nation. Let λ_{sct10}denote the proportion of skilled immigrants from country of origin 'c' residing in state 's' 10 years prior.The Bartik Instrument is given by

$$\hat{H_{st}} = \sum_{c} (H_{ct}) * (\lambda_{sct10}) \tag{3.2}$$

Where $\hat{H_{st}}$ represents the predicted population of skilled immigrants in state 's' at time 't' based on the distribution of skilled immigrants in state 's' ten years prior based on previous settlement patterns. As I am interested in the percentage of a state's population who are skilled immigrants I take the percentage of predicted skilled immigrants based on the population of a state.

The instrument is correlated with the population of skilled immigrants per capita with a coefficient of 0.00046(p-value =0.000) and an F-statistic of 1247 which indicates that it is a strong instrument.

In a similar fashion I create the corresponding Bartik instrument for the percentage of immigrant welfare usage. However, I restrict the countries of origin to Mexico and Central America as immigrants from Mexico and Central America make up close to 70% of immigrant welfare users. Let W_{ct} denote the population of immigrant welfare users from country of origin 'c' at time 't' residing in the nation. Let $lambda_{sct10}$ denote the proportion of immigrant welfare users from country of origin 'c' residing in state 's' 10 years prior. The Bartik instrument is given by

$$\hat{W_{st}} = \sum_{c}(W_{ct}) * (\lambda_{sct10}) \tag{3.3}$$

Just as the previous case, $\hat{W_{st}}$ is also essentially the predicted population of immigrant welfare users in state 's' which I then convert to a percentage of the state's population. The instrument is correlated with the population of skilled immigrants per capita with a coefficient of 0.00023(p-value =0.000) and an F-statistic of 1647 which indicates that it is a strong instrument.

In terms of exogeneity, it is plausible to assume that the national population of immigrants, both skilled and unskilled, from a particular nationality will not be correlated with attitudes towards redistribution in a particular state. Also I assume the distribution of immigrants across states 10 years before the period of analyses is unlikely to be correlated with socio-economic factors that influence support for redistribution in the current period except through the explanatory variables. This latter assumption is quite debatable as past levels of immigration can indeed influence present attitudes towards political issues such as redistribution particularly if a particular nationality of immigrants are viewed as welfare magnets. This is admittedly a drawback of the instrument which I intend to somewhat mitigate by choosing the distribution from 10 years prior in the hopes that it will be less correlated with present redistributive attitudes than say the distribution from 5 years prior. The distribution of immigrants of any nationality is a state can also be correlated across time since states can have certain persistent economic, institutional and cultural factors which can both attract certain types of immigrants, and also influence support for redistribution, the inclusion of state fixed effects would hopefully eliminate some of these concerns.

3.5.2 State level panel model

In the state level panel model, I regress the public opinion variable of welfare spending in state on my main explanatory variables with suitable controls in the form of a Fixed Effects Panel Regression. The equation for the State Level Panel Model is given (for t=2008 to 2012) by

$$W_{st} = \beta_0 + \beta_1 SI_{st} + \beta_2 IW_{st} + \beta_3 G_{st} + \beta_4 M_{st} + \beta_5 P_{st} + \beta_6 U_{st} + \gamma CI_{st} + \omega_s + \lambda_t + \epsilon_{st} \quad (3.4)$$

Where W_{st} denotes the percentage of residents in a state who support higher welfare spending. The variable CI_{st} denotes Citizen ideology which is a measure of a state's ideological orientation. All other variables are as described in equation 1.

To investigate the heterogeneity of impact for college educated respondents, I interact the percentage of college graduates in a state with my explanatory variable.

$$W_{st} = \beta_0 + \beta_1 SI_{st} + \beta_{11} SI_{st} * Col_{st} + \beta_2 IW_{st} + \beta_{22} IW_{st} * Col_{st} + \beta_3 G_{st} + \beta_4 M_{st} + \beta_5 P_{st} + \beta_6 U_{st} + \beta_7 CI_{st} + \omega_s + \lambda_t + \epsilon_{st}$$

Where Col_{st} denotes the percentage of residents in a state with a college degree(Bachelors or higher)

3.6 Results

3.6.1 Baseline model

Pooled cross section model with individual level data

Table 3.3 represents the results of the pooled cross section model where I match individual level opinions with state level data on skilled immigrants and welfare using immigrants. Model 1 is the baseline model Pooled OLS model, Model 2 includes fixed effects while Model 3 includes the IV alongside Fixed Effects

Under the OLS specification with no fixed effects, a 1 percentage point increase in the percentage of skilled immigrants in a state leads to a 1.17 % increase in the probability of a respondent supporting higher welfare spending. This estimate is significant at the 5 % level(p-value=0.059). Once Fixed effects are included, a 1 percentage increase in the percentage of skilled immigrants in a state causes a 0.46 % increase in the probability that a respondent in the state will support higher welfare spending but the estimate is no longer statistically significant. Once the Bartik IV is used, the coefficient increases to 0.032 (or a 3.2 % increase in the probability of supporting higher welfare spending but is not statistically significant). This shows that once we account for endogeneity in location choices of immigrants by using Fixed effects or an Instrumental Variable, the negative relationship between the percentage of skilled immigrants in a state and the probability of a respondent supporting higher welfare spending is not statistically signifcant.

To illustrate the substantive significance of the results, let us consider the data for Alabama and California. In 2012, skilled immigrants accounted for 1.03 % of Alabama's population and 7.7 % of California's population. Based on the estimates obtained using an Instrumental Variable along with Fixed effects, if respondents in Alabama had the same level of exposure to skilled immigrants as California, their probability of supporting higher welfare spending would rise by (7.7- 1.03)*3.2 per cent or 21.344 %. In other words, assuming all other individual and state level control variables being constant, if a respondent from Alabama were to be placed in California, their probability of supporting higher welfare spending would rise by 21.344%.

Table 3.3: Individual level pooled cross section

	OLS	OLS with FE	IV with FE
Percentage skilled immigrants	0.0117*	0.0046	0.032
	(0.0048)	(0.0054)	(0.024)
Percentage welfare using immigrants	-0.0264*	-0.007	-0.0422
	(0.006)	(0.006)	(0.0366)
State welfare generosity	0.00012	0.00024	0.000924
	(0.00004)	(0.0002)	(0.00015)
Minority welfare usage	-0.144	-0.126	-0.058
	(0.054)	(0.045)	(0.138)
Poverty rate	0.0086	0.0011	0.0081
	(0.002)	(0.0022)	(0.0089)
Unemployment rate	0.0011	0.0019	-0.0082
	(0.0013)	(0.0031)	(0.0061)
Age	-0.0012	-0.0016	-0.0016***
	(0.0002)	(0.0021)	(0.0002)
Gender	0.018	0.0214	0.0227
	(0.0096)	(0.063)	(0.0067)
Ideology	-0.0227	-0.0215	-0.021
	(0.0027)	(0.0025)	(0.002)
Trust in Government Index	0.0015	0.0019	0.00194
	(0.0002)	(0.0002)	(0.00021)
Union membership	0.0166	0.0311	0.03
	(0.013)	(0.0102)	(0.0109)
College education dummy	-0.066	-0.702	-0.071
	(0.0089)	(0.088)	(0.0082)
Constant	0.377	23.74	0.716
N	9297	9297	9297
Fixed Effects	No	State,Year	State, Year
F-Statistic	77.62	54.66	54.71
R-Squared	0.0479	0.0448	0.0379

*: significant at 5%. **: significant at 1%. Standard errors are clustered at the state level.

For immigrant welfare usage the baseline OLS coefficient is -0.0264 and is statistically significant at 5 % (p-value = 0.028). Once Fixed effects are introduced the coefficient declines slightly to -0.007 but is no longer statistically significant. In the Model with the Bartik instrument, the coefficient is -0.042 implying that a 1 % increase in the percentage of immigrant welfare users in a state leads to a 4.2 % decline in the probability that a respondent in the state will support higher spending.

For the substantive significance of the coefficients, I once again use the example of California and Alabama. In 2012, 0.2 % of Alabama's population was welfare using immigrants while for California the figure was 4.79 %. Based on the estimates for the model with the instrument and fixed effects, all other variables being equal, if Alabama had the same level of immigrant welfare usage as California, then Alabama's respondents would be (4.79 -0.2)*4.2 = 19.278 % less likely to support higher welfare spending. In other words, if a respondent from Alabama were to be placed in California then their probability of supporting higher welfare spending would decline by 19.28%.

For the individual level control variables, age is negatively correlated with support for redistribution with older respondents being less likely to support generous welfare spending while gender is positively correlated with women being more likely to support welfare generosity. Both these are in line with previous research (Cusack et al, 2006; Iverson and Soskice, 2001). For ideology, the coefficient is negative which is a bit puzzling as it implies that respondents identifying as conservative were more likely to support higher welfare spending. Respondents who are union members were more supportive of redistribution as were respondents with higher levels of trust in the government. All these results are largely as expected with the only puzzling result being that college educated respondents were less likely to support higher welfare spending. This is interesting to me as I anticipated college educated people to lean more liberal and support higher welfare generosity. However the reason could also be that as education correlates with income, respondents with a college degree could be wary of having to pay higher income taxes to finance more redistribution.

Overall, the substantive significance of the results of the individual level pooled cross section analyses lends a certain degree of support to Hypotheses 1a and 2a. Skilled immigration does have a positive impact on the probability that a respondent will support higher welfare spending while immigrant welfare usage reduces the probability of a respondent supporting higher welfare spending. However, it must be noted that the estimates obtained after including the Instrumental Variable are not sizeable higher than the estimates obtained under the OLS framework suggesting that the Instrument may not have been very effective at accounting for endogeneity. As such the estimates may still suffer from simultaneity bias due to endogeneity and cannot be treated as conclusive evidence for the hypotheses being tested.

State level panel

Table 3.4 represents the results of the state level panel model.

In the Baseline OLS model without Fixed Effects, an increase in the percentage of skilled immigrants in a state by 1 % leads to a 0.506 % increase in support for higher welfare spending with the result being statistically significant at 5% level(p-value of 0.032). For immigrant welfare usage, a 1 unit increase in the percentage of immigrant welfare users in a state leads to a 0.167 % decline in support for welfare spending though it is not statistically significant. In the model with state and year fixed effects a 1 percentage increase in the percentage of skilled immigrants leads to a 3.243 % increase in support for welfare spending with the estimate being statistically significant at 1% (p-value ¡0.01). For percentage of immigrant welfare users, a 1 % increase causes a 4.061% decline in support for welfare spending with the coefficient being statistically significant at 1%. The fixed effects estimates are larger than the OLS estimates and are both statistically significant at the 1% level indicating a greater likelihood of rejecting the null hypotheses.

To illustrate the substantive significance of the results I compare the values for New Jersey and Texas. In the time frame from 2008 to 2012, the average level of skilled immigrants as a percentage of a state's population was 6.953 % for New Jersey and 3.364 % for Texas. If skilled immigrants constituted the same percentage of Texas' population as that of New Jersey, support for welfare among Texas' residents would rise by (6.698 - 3.364)*3.243 or 11.639 %. In other words, all other variables being unchanged, if Texas had the same share of skilled immigrants as New Jersey, an additional 11.639 % of its residents would be in favor of more generous welfare policies.

Overall, the results from the state level panel analysis demonstrate that a higher percentage of skilled immigrants correlates with greater support for welfare spending while a higher percentage of immigrant welfare users correlates with declining support for welfare spending. The estimates here are both statistically and substantively significant and thus lend a certain degree of credibility to the anti-solidarity hypotheses (Hypotheses 1a) and the compensation hypotheses (Hypotheses 2a). However the limited time frame of 5 years and insufficient number of control variables implies that we cannot strongly conclude that either of the

Table 3.4: State level panel

	OLS	OLS with Fixed Effects
Percentage	0.506*	3.243**
skilled immigrants	(0.240)	(1.819)
Percentage welfare	-0.167	-4.061**
using immigrants	(0.377)	(1.062)
Poverty rate	-0.035	-3.55
	(0.094)	(0.1454)
Unemployment	0.225	0.323
rate	(0.106)	(0.128)
State welfare	0.0000267	0.0064
generosity	(0.021)	(0.012)
Minority welfare	-2.399	-16.438
usage	(1.583)	(14.797)
Citizen ideology	0.0329	0.0052
	(0.012)	(0.0112)
Constant	18.095	40.891
	(1.889)	(9.005)
N	250	250
F-Statistic	16.77	15.39
R-Square	0.1652	0.1054
Fixed Effects	No	State, Year

* :significant at 5%, ** :significant at 1%.
Standard errors reported are clustered at the state.

hypotheses are at play.

3.6.2 Heterogenous impacts

In order to investigate the hetereogeneity of impact for respondent's with a college degree in the individual level model and share of college graduates in the state level model I estimated equations 3 and 4 using interaction terms.

Individual level pooled cross section

Table 3.5 represents the results for Equation 3 where a dichotomous indicator variable denoting whether a respondent has a Bachelors degree or higher is interacted with the percentage of Skilled and Welfare using immigrants in a respondent's state.

In the OLS model without any fixed effects the coefficient for the percentage of skilled immigrants is 0.0087 and that of the interaction term involving the college education dummy and percentage of skilled immigrants is 0.0064 with neither being statistically significant. The estimate of the interaction term is however positive suggesting that a positive effect of increased skilled immigration on support for redistribution among college graduates. As per the estimates, the overall effect of a 1 unit increase in the percentage of skilled immigrants on probability of a college graduate supporting higher welfare spending is 0.0087 + 0.0064 = 0.0151 or 1.51%. Once State and Year Fixed effects are incorporated the estimate on the percentage of skilled immigrants is 0.0017 and that of the interaction term is 0.0063 with neither coefficient being statistically significant. The overall effect under the fixed effects specification is 0.00177 +0.0063 = 0.00807 or 0.87 % increase in the probability of supporting higher welfare spending for a college educated respondent. In other words, when we control for state and year specific unobservables the probability of a college educated respondent supporting higher welfare spending in response to skilled immigration rises by 0.87 % which is less than the specification without fixed effects. None of the coefficients is statistically significant but the direction of the coefficients are consistent with the hypotheses that higher immigrant welfare usage induces greater support for welfare generosity among college educated respondents as they are more likely to view skilled immigrants as competition and subsequently support higher welfare generosity out of self interest.

Under the Instrumental Variables specification with fixed effects, the estimate for percentage of skilled immigrants is 0.0031 and that of the interaction term is -0.00438 with neither being statistically significant. The overall effect after accounting for endogeneity by combining an Instrument with fixed effects is a 0.0331-0.0048=0.0283 or a 2.83 % increase in the probability of supporting higher welfare spending for a college educated respondent. Though the overall effect is positive, the negative coefficient on the interaction term is nonetheless puzzling, especially since the IV combined with Fixed effects should have been more thorough in accounting for endogeneity in location choices of immigrants. Possible reasons could be that the instrument is not sufficiently exogenous to account for endogeneity or that the sample size of two survey years is too limited.

For percentage of immigrant welfare users, the baseline OLS estimates are -0.0129 for main variable and -0.0138 for the interaction term. Under the specification with Fixed Effects, the estimates are -0.0015 for the main variable and -0.0137 for the interaction term. The overall effect of a 1% increase in the percentage of immigrant welfare users in a state on the probability of a college educated respondent supporting higher welfare spending is a decline of 2.677 % under the Baseline OLS specification and 1.52 % under the Fixed Effects specification. Controlling for time invariant unobservables at the state level using Fixed effects thus reduces the magnitude of the estimates. None of the coefficients are statistically significant but the direction consistent with the hypotheses that higher immigrant welfare usage induces less support for welfare generosity among college educated respondents owing to fears of having to shoulder a greater share of the fiscal burden of financing welfare provisions for immigrants.

Once the Bartik IV included alongside fixed effects to account for endogeneity, the estimates are -0.046 for the main variable and 0.0133 for the interaction term. Once again the IV estimate for the interaction has an opposite sign than that of the main variable. Though the overall effect is still negative, the positive sign on the interaction term is, nonetheless, puzzling. The lack of overall statistical significance however rules out any evidence for a significant linear relationship between the level of immigrant welfare usage and support for redistribution among college educated respondents.

Overall, the estimates obtained do not provide adequate support for Hypotheses 1b and 2b..

Table 3.5: Individual level pooled cross section

	OLS	OLS with Fixed Effects	IV with Fixed Effects
Percentage skilled immigrants	0.0087	0.00177	0.0331
	(0.007)	(0.0063)	(0.0226)
Percentage skilled immigrants times Share of College graduates	0.0064	0.0063	-0.00438
	(0.0057)	(0.0055)	(0.0049)
Share of college graduates	0.0172	0.0737	-0.0186
	(0.4943)	(0.0168)	(0.0206)
Percentage welfare using immigrants	-0.0129	-0.0015	-0.046
	(0.009)	(0.0072)	(0.0356)
Percentage welfare using immigrants times share of college graduates	-0.01387	-0.0137	0.0133*
	(0.074)	(0.007)	(0.005)
Individual Level Controls	Yes	Yes	Yes
State Level Controls	Yes	Yes	Yes
Fixed Effects	No	State,Year	State,Year
Constant	0.7163	23.478	-34.478
	(0.498)	(5.549)	(14.624)
N	9297	9297	9297
R-Squared	0.0277	0.0452	0.0389
F-Statistic	45.38	60.96	122.19

*: significant at 5%. **: significant at 1%.
Standard errors are clustered at the state level.

Table 3.6 represents the result for the state level panel model with the interaction terms involving the share of college graduates in a state with the explanatory variables as in equation 4.

For the percentage of skilled immigrants, the baseline OLS estimate is 2.188 for the main variable and -0.039 for the interaction term. After the inclusion of State and Year Fixed Effects, the estimates are 1.605 for the main variable and -0.709 for the interaction term. The coefficient on the interaction term is once again negative, which is a puzzling result. Coupled with none of the coefficients being statistically significant implies that there is no evidence to indicate that increase in support for welfare due to higher levels of skilled immigration will be higher in states with a greater share of college graduates. The compensation hypotheses of college graduates supporting higher welfare protections out of self interest due to perceived competition from skilled immigrants does not appear to be supported by the data at the state level in the years 2008 to 2012.

For the percentage of immigrant welfare users, the baseline OLS coefficient is -6.308 for the main variable and 0.1521 for the interaction term. Once unobservables are controlled for using state and year fixed effects the coefficient rises to -18.937 for the main variable and 0.3529 for the interaction term. Here again the coefficients on the interaction terms have an opposite sign to the main variable which is also quite puzzling. Similar to the instance of the level of skilled immigration, the magnitude of the anticipated effect does not appear to be higher for college graduates with regards to higher levels of immigrant welfare usage. The data does not seem to support the hypotheses that the decline in support for redistribution due to higher levels of immigrant welfare usage will be higher for college graduates due to expectations of sharing the fiscal burden.

Overall, the results from the state level panel analyses, even after accounting for endogeneity with fixed effects, do not lend any support to the anticipated heterogenous impact for college educated citizens. Neither the percentage of skilled immigrants nor the percentage of immigrant welfare users seem to have a higher effect on support for welfare spending when the share of college graduates in a state increases.

Table 3.6: Heterogenous impact for state level panel

	OLS	OLS with Fixed Effects
Percentage skilled immigrants	2.188 (3.088)	1.605 (7.199)
Percentage skilled immigrants times Share of College graduates	-0.039 (0.0767)	-0.709 (0.1815)
Share of College graduates	-0.192* (0.0886)	-1.616* (0.4943)
Percentage welfare using immigrants	-6.308 (5.525)	-18.93772 (10.419)
Percentage welfare using immigrants times Share of college graduates	0.1521 (0.1313)	0.3599 (0.2378)
State Level Controls	Yes	Yes
Constant	25.705 (3.907)	23.141 (2.107)
N	250	250
R-Squared	0.1915	0.0277
F-Statistic	6.21	16.14

*:significant at 5%. ** : significant at 1%.
Standard errors reported are clustered at the state level.

3.7 Discussion and conclusion

This paper sets out to explore a different dimension of the immigration-redistribution relationship, namely how the presence of skilled immigrants alongside the welfare usage of poor, low-skilled immigrants in the United States shapes attitudes towards redistribution through the compensation hypotheses. The increasing population of low-skilled, welfare-reliant immigrants has already been known to generate opposition to redistribution, both due to fiscal leakage and perceptions of 'deservingness' based on ethnic antagonism. On the other hand, skilled immigration could not only mitigate some of this opposition, as they are more likely to be perceived as fiscal contributors to the welfare system, but also generate support for more generous redistribution out of self-interest due to perceived economic anxiety.

The results of both the pooled cross-section and the state-level panel model lend a certain degree of support to this paper's ideas about how skilled immigration can potentially generate more support for welfare generosity. In the individual-level pooled cross-section specification, the paper attempted to be thorough in accounting for endogeneity by combining fixed effects with a Bartik-Style Instrument based on previous settlement patterns. The results obtained are sizable in magnitude and substantively significant, revealing how respondents in states with higher levels of skilled immigrants are more likely to support more generous welfare policies. As per my hypotheses, this is possibly due to the compensation hypotheses of skilled immigrants being viewed as sources of economic anxiety by natives who demand generous welfare protections out of self-interest. The analysis thus lends a certain degree of possible support to the aforementioned hypotheses. However, the sample size of the data is limited to only two years with a total of 9,289 respondents, and thus we cannot draw any strong inferences based on the results.

In the state-level panel model based on data from 2008 to 2012, the paper attempted to study the hypotheses of skilled immigration generating support for redistribution at the aggregate level of the state. Using fixed effects to control for state-specific attributes that are more likely to attract certain types of immigrants, the results reveal a 3.23% increase in support for welfare generosity due to a 1 unit increase in the level of skilled immigration and a 4.06% decline in support for welfare spending due to a 1 unit increase in the level of immigrant welfare usage. The estimates are both statistically and substantively significant, suggesting that skilled immigration does have a sizable positive impact on attitudes towards redistribution at the aggregate state level in the period from 2008 to 2012. However, the number of panels is still not sizable, and the limited number of control variables employed prevents us from drawing any strong conclusions in this regard either.

An extension of the hypotheses, the paper intended to explore, was whether the magnitude of the increase (decrease) in support for welfare spending due to skilled immigration (immigrant welfare usage) would be higher for college-educated Americans. Since skilled immigrants are defined as foreigners with a Bachelor's degree or higher, college-educated natives would be the ones most likely to view them as direct competition in the labor market and could possibly support a more generous social safety net (such as state-financed healthcare services that are not tied to employment) as a form of insurance. They are also more likely to anticipate shouldering a greater share of the tax burden of financing the welfare usage of poor immigrants. However, the estimates obtained are somewhat puzzling. In the individual-level pooled cross-section framework, the direction of the coefficient of the interaction term involving the percentage of skilled/welfare-using immigrants and the respondent's education level is positive under the OLS model but negative once the instrument is introduced. In the state-level panel model, the direction of the coefficient of the interaction term is negative while that of the main variable is positive, suggesting that the magnitude of the impact is lower for states with a higher share of college graduates. Coupled with neither of the estimates in any of the models being statistically significant, the analysis finds no evidence that college-educated natives would be more likely than others to support higher welfare spending out of self-interest due to increasing skilled immigration.

Overall, the findings reveal a modest amount of support for both the compensation hypotheses with respect to skilled immigration and the fiscal burden hypotheses with respect to immigrant welfare usage, both in terms of individual preferences and aggregate attitudes at the state level. Despite the relatively limited sample size, the substantive significance of the estimates obtained under the baseline models reveals an additional channel of the immigration-redistribution causal relationship, namely the role of skilled immigration. The findings portray the immigration-redistribution relationship as being more complex than previously imagined, as low-skill, reliant immigrants and their perceived "deservingness" are not the only channels through which immigration impacts the politics and sustainability of the welfare state. Skilled immigrants, despite their relatively smaller population, can also alter the political-economic discourse surrounding the welfare state as they can shift perceptions of foreigners from being fiscal burdens on the state to fiscal contributors to the welfare system.

The results have significant ramifications on the debate surrounding both immigration and welfare policy. One of the major sources of contention in the debate surrounding immigration policy is whether the present family reunification-based immigration system should be replaced with a merit-based system that would select in favor of more educated and skilled immigrants, while on the redistribution sphere, the debate rages on about whether the social safety net should be expanded. As my findings illustrate, higher skilled immigration would not only mitigate opposition to expanding the social safety net but may also increase support for it. Coupled with the fact that skilled immigrants would contribute more to the social safety net than take from it, it shows that shifting to a more skill-focused and merit-based immigration policy could actually strengthen the social safety net by both providing a wider tax base and also by changing the public attitude towards welfare. A merit-based immigration policy can significantly alter the discourse on redistribution.

The reliance on survey responses for capturing public opinion towards a polarizing and nuanced topic such as redistribution has its limitations. As mentioned before, survey questions can be interpreted by respondents in different ways, with the question regarding welfare spending being possibly interpreted by some respondents in terms of specific welfare policies such as cash benefits and by other respondents more generically in terms of the wider safety net. Similarly, aggregate public opinion at the state level too does not reveal much about how residents specifically feel about different facets of the welfare system. A more nuanced survey where respondents are asked questions specifically about different welfare programs or about immigrant eligibility would be more useful in grasping public opinion surrounding redistribution.

The choice of the state as the unit of analysis has its own drawbacks, as immigrants (regardless of their skill level) often congregate in certain parts of a state (such as large cities), while public opinion surveys involve respondents from all across the state. The attitude towards welfare for an individual living in Lake Elsinore is unlikely to be influenced by skilled immigrants in Palo Alto. Counties or Congressional Districts may serve as better units of analysis in this regard if sufficient data is available. Also, as skilled immigrants tend to be heavily concentrated in certain industries such as IT or healthcare, using a respondent's occupation as the unit of analysis can also be useful.

The variable denoting immigrant welfare usage includes any foreign-born individual using any form of government assistance, such as Medicaid, Food Stamp, Cash Benefits, etc. It is possible that some respondents may be okay with immigrants accessing emergency medical treatment via Medicaid or food stamps but not, say, cash benefits. More detailed data on immigrant usage of different kinds of welfare benefits, such as Medicaid or cash assistance, could prove to be more useful.

Though I have attempted to account for endogeneity using a Bartik-style IV and fixed effects, some endogeneity may remain, as can be seen from the estimates not changing significantly with the addition of the IV and fixed effects. The Bartik instrument has a drawback in that past immigration from certain nationalities can shape redistributive attitudes in the present. The use of a different instrument that does not rely on past immigration may be more useful.

The role of racism and ethnic diversity in the American welfare discourse is still pretty significant, which my analysis does not delve deep into apart from controlling for minority welfare usage. A more detailed analysis involving welfare usage by immigrants of different nationalities could shed more light on how racial biases play a role in shaping the immigration-redistribution relationship.

Finally, the sample size in both the individual-level pooled cross-section framework and the state-level panel framework is quite limited, with only two panel years for the former and five for the latter. A wider dataset with more panel years is necessary to fully grasp the impact of immigrant demographics on the discourse surrounding redistribution.

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Appendix A

Impact of mass shootings on mental health policy

A.1 Appendix A1 : Robustness checks

In this section, I perform four checks of robustness to ensure that the main results are not sensitive to the definition of mass shootings, spillover effects of mass shootings on other states, and trends in past legislation.

A.1.1 Alternative definitions

The paper's definition of mass shootings is relatively broad compared to certain other databases (see Table 2). To ensure that the findings thus far are not sensitive to fatality thresholds or other key defining attributes of mass shootings I run robustness checks with alternative definitions. I use the criteria of Luca, Malhotra, Poliquin (2020) and *Mother Jones* magazine to define mass shootings. This alternative definition restricts the fatality threshold to four or more fatalities (as opposed to 3 or more fatalities that I used) and excludes shootings that occurred in private residences and where the victims and the perpetrator shared any personal relationship. This restricted criterion filters out 76 mass shootings. Using this restricted definition of mass shootings I estimate equation 1 using fixed effects poisson model. The results for bills are :

Table A.1: Effect of mass shootings on the number of mental health related bills introduced using the alternative definition

Dependent Variable:	*Count of bills introduced in different categories*			
	Insurance Bills	School Bills	Community Bills	Firearm Bills
	(1)	(2)	(3) Poisson	(4)
Mass shooting indicator	0.2923** (0.099)	0.676*** (0.0817)	0.033 (0.0835)	0.8423*** (0.177)
No of Observations	996	996	956	796

Notes: The table denotes regression output for estimating a fixed effects poisson model on the count of mental health related bills enacted into laws. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). The specification includes Political, Demographic, Institutional and Mental Health related controls. The main explanatory variables are an indicator for mass shootings at the state year level Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations without any within cluster variation.

The magnitude and direction of the estimates from table A.1 are largely similar to those obtained in table 6 of the main results section. Mass shootings have a positive and statistically significant impact on the introduction of bills related to insurance coverage of mental illness, mental healthcare in schools and firearm restriction on grounds of mental illness with the magnitude being highest for bills related to firearm restriction. The overall legislative impact for introduction of bills is similar to the those obtained under the definition of mass shootings used in the paper and are not sensitive to fatality thresholds and the exclusion of family murders.

Next, I estimate the impact of mass shootings on laws enacted using the more restrictive definition of mass shooting. The corresponding estimates in table A.2 are mostly similar in magnitude and direction to those obtained using the paper's criterion for mass shootings (see table 1.9). Mass shootings have a positive and statistically significant impact on bills enacted into law for school and community related legislation. For laws related to insurance coverage, the estimate is also similar in magnitude and direction to that obtained in table 6 but is slightly less precise and not statistically significant. Overall, the legislative impact of mass shootings in terms of bills enacted to law remains the same under this more restrictive definition.

Table A.2: Effect of mass shootings on the number of mental health related bills enacted into law using the alternative definition

Dependent Variable: Count of bills enacted into law in different categories				
	Insurance Laws	School Laws	Community Laws	Firearm Laws
	(1)	(2)	(3)	(4)
Mass shooting indicator	0.145 (0.203)	0.424* (0.0817)	0.342** (0.128)	0.525 (0.339)
No of Observations	956	797	896	560

Notes: The table denotes regression output for estimating a fixed effects Poisson model on the count of mental health related bills enacted into laws.The specification includes Political, Demographic, Institutional and Mental Health related controls. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***) The main explanatory variables are an indicator for mass shootings at the state year level Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations without any within cluster variation.

A.1.2 Spillover effects of neighboring states

Identifying the causal impact of mass shootings on mental health legislation rests on the assumption that mass shootings influence mental health policy only in the state in which it occurred and not on neighboring states. To ensure that the results are not affected by spillover effects on neighboring states, I introduce an indicator variable that indicated whether there was any mass shooting in any of a state's neighbors (defined as states that share a common border) and estimate equation 1 using the Poisson model for both bills and laws

Table A.3: Effect of mass shootings on neighboring states

Dependent Variable: Count of bills introduced and laws enacted in each category										
	Insurance		School		Community		Firearm		Total	
	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws
Mass shooting	0.285**	0.385*	0.5309***	0.391*	0.044	0.34**	0.817***	0.6513*	0.304***	0.396***
	(0.089)	(0.027)	(0.226)	(0.207)	(0.075)	(0.129)	(0.168)	(0.339)	(0.044)	(0.088)
Marginal effect	49.7%↑	46.9%↑	70.04%↑	47.8%↑	4.4%↑	40.4%↑	126.3%↑	91.8%↑	35.5%↑	48.5%↑
Mass shooting in	-0.0245	0.016	0.05	-0.002	-0.0099	0.1056	-0.079	-0.0175	0.0119	-0.0818
neighboring states	(0.077)	(0.912)	(0.0703)	(0.184)	(0.0613)	(0.333)	(0.1554)	(0.303)	(0.038)	(0.076)
Sample mean	0.951	0.232	1.109	0.198	1.448	0.465	0.281	0.09	3.664	0.8619
No of Observations	996	956	996	797	976	896	796	560	996	996

Tables A.3 and A.4 displays the results when indicators for mass shootings in a neighboring state and the same Census division are introduced into the regression. Mass shootings continue to have a positive and statistically significant impact on the same categories of bills and laws as Tables 1.6 and 1.7 with the magnitudes being approximately similar. However, the occurrence of a mass shooting in a neighboring state or the same Census division has no statistically significant impact on most categories of bills and laws. Only the estimate for shootings in the Census division for the total number of bills enacted into law is significant at 10% but the magnitude is similar to that of the baseline model in table 7. The results rule out any spillover effects of mass shootings on neighboring states and states in the same census division which could bias the estimates of the baseline model.

Table A.4: Effect of mass shootings on states in the same Census division

Dependent Variable: Count of bills introduced and laws enacted in each category	Insurance		School		Community		Firearm		Total	
	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws
Mass shooting	0.2875**	0.401*	0.5322***	0.428*	0.0474	0.3614**	0.815***	0.6716*	0.308***	0.404***
	(0.089)	(0.175)	(0.0789)	(0.207)	(0.0753)	(0.129)	(0.168)	(0.341)	(0.0439)	(0.088)
Marginal effect	33.3%↑	49.3%↑	70.2%↑	53.4%↑	4.8%↑	43.5%↑	125.9%↑	95.87%↑	36.1%↑	49.7%↑
Mass shooting in Census division	-0.031	-0.117	0.0229	-0.2002	-0.0429	-0.145	-0.2404	-0.416	0.0119	-0.132
	(0.0737)	(0.145)	(0.069)	(0.184)	(0.0594)	(0.106)	(0.1536)	(0.299)	(0.038)	(0.074)
Sample mean	0.951	0.232	1.109	0.198	1.448	0.465	0.281	0.09	3.664	0.8619
No of Observations	996	956	996	797	976	896	796	560	996	996

Overall, the results from the robustness checks imply that the key findings of the paper for the legislative impact of mass shootings are not sensitive to the fatality threshold and the exclusion of shootings occurring in private residences.

A.1.3 Time dependency

The main specification so far has assumed that mental health-related legislation enacted by a state does not depend on legislation enacted by the said state in prior years. To further ensure that past legislation does not affect current legislation, I incorporate state-specific time trends in equation 1 and estimate a Linear Probability Model (for the extensive margin) and an OLS model for the number of bills and laws. For bills, the results are given in table 15.

Table A.5: Effect of mass shootings on the introduction of mental health bills using a fixed effects OLS and linear probability model (LPM) after controlling for state-specific time trends

Dependent Variable:	*Dummy variable indicating whether any bills were introduced and the count of bills introduced in a state-year in each of the categories*							
	Insurance Bills		School Bills		Community Bills		Firearm Bills	
	OLS	LPM	OLS	LPM	OLS	LPM	OLS	LPM
Mass shooting	0.254*	0.0324	0.6401**	0.087*	0.1048	0.0567	0.214**	0.0677*
	(0.2467)	(0.045)	(0.214)	(0.0439)	(0.174)	(0.0452)	(0.064)	(0.0321)
Sample Mean	0.951	0.948	1.109	1.105	1.448	1.385	0.281	0.224
No of Observations	996	1000	996	1000	956	1000	796	1000

Notes: The table denotes regression output for estimating a fixed effects OLS and Linear Probability model on the count of mental health-related laws and a dummy variable for whether a law was enacted respectively. The specification includes state-specific time trends. The specification also includes Political, Demographic, Institutional, and Mental Health related controls. Stars following coefficients represent p-values less than .10 (*), .05 (**), and .01 (***) The main explanatory variables are an indicator for mass shootings at the state-year level Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations without any within-cluster variation.

Based on the estimates in table A.5 , we can see that the estimates of the Linear Probability model are similar in magnitude and direction to those obtained in table 7 with the coefficients for school and firearm bills being statistically significant. The coefficients of the OLS model are also quantitatively similar to those obtained under the Poisson specification in table 9. There does not appear to be any evidence of past legislation influencing present bills. Overall the results are robust to the inclusion of state-specific time trends.

Next, I apply the same model to laws enacted. The results are:

Table A.6: Effect of mass shootings on mental health bills enacted into law using fixed effects OLS and LPM, controlling for state specific time trends

Dependent Variable:	*Dummy variable indicating whether any bills were enacted into law and the count of laws enacted in a state-year in each of the categories*							
	Insurance Laws		School Laws		Community Laws		Firearm Laws	
	OLS	LPM	OLS	LPM	OLS	LPM	OLS	LPM
Mass shooting	0.119*	0.0401	0.0483	0.017	0.247**	0.109	0.0409	0.0352
	(0.0503)	(0.038)	(0.214)	(0.028)	(0.079)	(0.0424)	(0.116)	(0.0229)
No of Observations	996	1000	996	1000	956	1000	796	1000

Notes: The table denotes regression output for estimating a fixed effects OLS and Linear Probability Model on the count of mental health related bills and a dummy variable for whether a bill was introduced respectively. The specification includes state specific time trends. The specification also includes Political, Demographic, Institutional and Mental Health related controls. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). The main explanatory variables are an indicator for mass shootings at the state year level Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations without any within cluster variation.

The estimates from table A.6 are by and large quantitatively similar to those obtained in table 8 (for the LPM) and table 1.10 (for the OLS). Only the coefficient for school related laws under the linear probability model being slightly less precise. Similar to introduction of bills, enactment of laws do not appear to be influenced by laws enacted in years prior.

Altogether, the estimates for mass shootings obtained in the main results are robust to controlling for state-specific time trends.

A.1.4 Appendix A2: Impact of mass shootings on passage of mental health related bills and laws at the extensive margin by category

In this section I begin by analyzing whether mass shootings affect the probability of state governments introducing any bill related to mental healthcare the following year in each category. For this purpose I estimate equation 1 using a conditional fixed effects Logit and Linear probability model (LPM) for both bills introduced and enacted into law.

Introduction of bills

Table A.7: Effect of mass shootings on the introduction of mental health bills at the extensive margin

Dependent Variable: Dummy variable indicating whether any bills were introduced in a state-year								
	Insurance Bills		School Bills		Community Bills		Firearm Bills	
	Logit	LPM	Logit	LPM	Logit	LPM	Logit	LPM
Mass shooting	0.3288 (0.2188)	0.0695 (0.4501)	0.4934* (0.226)	0.1006* (0.0426)	0.2127 (0.2284)	0.039 (0.043)	0.6586* (0.2817)	0.0817* (0.031)
Exponentiated coefficient	38.9%↑	-	63.8%↑	-	23.7%↑	-	93.2%↑	-
No of Observations	996	1000	996	1000	956	1000	796	1000

Notes: The table denotes the regression output for estimating a fixed effects Logit and Linear probability model (LPM) on dummies indicating whether any mental health related bills were introduced. The Logit coefficients are depicted as log-odds. The specification includes Political, Demographic, Institutional and Mental Health related controls. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). The main explanatory variables are an indicator for mass shootings at the state-year level. Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations which have all zeros in the dependant variable.

Table A.7 reports the estimates from running a fixed effects Logit and a Linear Probability Model where the indicator for mass shootings is the main explanatory variable. The specification includes all control variables along with state and year fixed effects and the standard errors clustered by state. The results across both specifications indicate that a mass shooting has a positive impact on the probability of introducing any bill in some of the categories, namely for school and firearm related bills, which are the highest in magnitude and also statistically significant. Interpreting the Logit model coefficients in terms of odds ratios, a mass shooting increases the odds of a state introducing a school related mental health bill by 63.8 % and that of firearm bills by 93.2 %. The results reveal that bills restricting firearm access on grounds of mental illness appears to be the most likely political response following a mass shooting closely followed by bills mandating better mental health facilities in schools.

Table A.8: Effect of mass shootings on mental health related bills enacted into law

Dependent Variable: Dummy variable indicating whether any bills were enacted into law in a state-year								
	Insurance Laws		School Laws		Community Laws		Firearm Laws	
	Logit	LPM	Logit	LPM	Logit	LPM	Logit	LPM
Mass shooting	0.279 (0.245)	0.0475 (0.037)	0.522* (0.312)	0.0554* (0.0289)	0.3688 (0.233)	0.067 (0.0518)	0.5439 (0.2817)	0.0341 (0.0223)
Exponentiated Coefficient	32.1%↑		68.5%↑		44.5%↑		72.2%↑	
No of Observations	996	1000	797	1000	896	1000	560	1000

Notes: The table displays the regression output for estimating a fixed effects Logit and Linear probability model (LPM) on dummy variables indicating whether any mental health related bills were enacted into law by category. The specification includes Political, Demographic, Institutional and Mental Health related controls. The logit coefficients are displayed as log-odds Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***) The main explanatory variables are an indicator for mass shootings at the state year level. Standard errors are robust and clustered at the state level. The different sample sizes are due to the fixed effects model dropping observations which have all zeros in the dependant variable.

Enactment of laws

Table A.8 shows the estimates for a conditional fixed effects Logit and Linear probability models where the dependent variable is a dummy indicator for whether any laws were passed in any of the categories. Mass shootings appear to only have a statistically significant effect on the probability of introduction of any laws related to school based mental healthcare based on both the fixed effects Logit and the linear probability model. In terms of odds ratios, a mass shooting leads to a 68.5 % increase in odds of a state enacting any school based mental health law. Compared to the estimates for bills under the binary models (see Table 1.4), mass shootings do not affect laws restricting firearm access unlike the specification involving bills where mass shootings had a positive impact. The reason could be due to firearm restriction emerging as a hot button issue in the aftermath of many a mass shooting leading to a higher probability of politicians introducing such bills to appease their constituents. But there ends up being no such impact on laws enacted owing to the divisive nature of firearm restriction and the organized opposition it faces from interest groups like the National Rifle Association. This result is in line with Schildkraut et al (2018) where the authors describe this phenomenon as feel-good legislation aimed at appeasing their constituents. On the other hand, school-related mental healthcare is less divisive in nature and faces no organized opposition comparable to the NRA resulting in them being more likely to be enacted into law.

A.2 Appendix A3: Cumulative impact by category

The identification strategy in section 6.2 relies upon the assumption that mass shootings can only impact mental health policy the year after and not have any sort of cumulative impact over the years. To test whether our estimates for each category are not affected by any 'stock effect' state's cumulative experience with mass shootings over the years, I introduce a variable capturing the cumulative number of mass shootings that occurred in the state over the years prior.

Table A.9: Effect of cumulative count of mass shootings

Dependent Variable: Count of bills introduced and laws enacted in each category										
	Insurance		School		Community		Firearm		Total	
	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws
Mass shooting	0.243**	0.341*	0.439***	0.2809	0.009	0.3215*	0.716***	0.6009*	0.224***	0.324***
	(0.093)	(0.182)	(0.082)	(0.216)	(0.0784)	(0.135)	(0.175)	(0.3515)	(0.046)	(0.093)
Marginal effect	27.5%↑	40.6%↑	70.2%↑	32.4%↑	0.94%↑	37.9%↑	104.6%↑	82.3%↑	25.1%↑	38.9%↑
Cumulative count	0.0259	0.027	0.063***	0.086*	0.0219	0.012	0.074*	0.037	0.0501***	0.0368*
of mass shootings	(0.016)	(0.029)	(0.012)	(0.038)	(0.0134)	(0.022)	(0.032)	(0.063)	(0.007)	(0.015)
Marginal effect	2.6%↑	2.7%↑	6.5%↑	8.9%↑	2.94%↑	1.2%↑	7.6%↑	3.76%↑	5.13%↑	3.74%↑
Sample mean	0.951	0.232	1.109	0.198	1.448	0.465	0.281	0.09	3.664	0.8619
No of Observations	996	956	996	797	976	896	796	560	996	996

The estimates from table A.9 for the mass shooting indicator are slightly lower than those obtained in the baseline specification but not by a huge amount in substantive terms. The largest decline is for the estimate of the total number of bills where the substantive impact of a mass shooting declines from 1.308 additional bills for the mean state versus a 0.919 bill increase after the cumulative count of mass shootings is taken into account. The coefficients for firearm laws are more precisely estimated than in table 1.6 (t-statistic of 1.7 vs 1.54) while that of school-related laws is less precisely estimated (t-statistic of 1.3 vs 2.11). The cumulative count of mass shootings also appears to have a positive and statistically significant for both school-related and the total count of bills and laws while firearm legislation, only affects bills. However, in substantive terms, the magnitude of the estimates is very small, ranging from a 1.2% increase from a sample mean of 0.465 enacted laws for community mental health-related legislation to an 8.9% increase from a sample mean of 0.198 enacted laws for school-related mental healthcare legislation. On the whole, the cumulative count of mass shootings in the years prior does impact the total volume of bills introduced and enacted into law, with the estimates being slightly more precise for school and firearm-related bills. However, the magnitude of said impact is relatively low in substantive terms and as a result, I do not find the baseline estimates to be significantly skewed by a state's aggregate count of shootings over the years.

A.3 Appendix A4: Mass shootings with positive news coverage

The specification so far has assumed that mass shootings can potentially impact mental health policy even when it received no media coverage. However, it can be argued that as media coverage functions as a vehicle for the issue of mental healthcare to be salient among the general public, mass shootings that receive no media coverage (usually ones at private residences) are unlikely to generate the necessary impetus. To test whether the results so far are driven largely by only those shootings that received a position amount of media coverage, I estimate the main set of regressions in tables 8 and 9 with the sample of mass shootings restricted to those with positive media coverage.

Table A.10: Effect of mass shootings that receive any form of media coverage

Dependent Variable: Count of bills introduced and laws enacted in each category	Insurance		School		Community		Firearm		Total	
	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws	Bills	Laws
Mass shooting	0.317**	0.2009	0.573***	0.359	0.0288	0.168	0.942***	0.675*	0.329***	0.262***
	(0.095)	(0.193)	(0.082)	(0.219)	(0.0812)	(0.144)	(0.175)	(0.3647)	(0.046)	(0.096)
Marginal effect	37.3%↑	22.2%↑	77.3%↑	43.18%↑	2.9%↑	18.2%↑	156.5%↑	96.4%↑	38.9%↑	29.9%↑
Sample mean	0.951	0.232	1.109	0.198	1.448	0.465	0.281	0.09	3.664	0.8619
No of Observations	996	956	996	797	976	896	796	560	996	996

Table A.10 displays the results for shootings that received any amount of media coverage. Compared to table 8, the marginal effect of mass shootings with positive media coverage is statistically significant for all categories except community bills. Firearm bills appear to have the highest percentage increase going from 122.1% to 156.5 %. In substantive terms, school bills witness the highest, albeit of a low magnitude, increase going from 0.768 to 0.857 additional bills introduced by the average state. The legislative impact in terms of bills is higher when the analysis only considers mass shootings with positive media coverage but is relatively low in substantive terms. Compared to the estimates in table 9 for laws, the legislative impact on the total count of laws and insurance, school, and community laws is lower with the latter three categories being imprecisely estimated. The impact seems to be higher and statistically significant at 10% for firearm laws. It seems that restricting the sample to just mass shootings with positive media coverage leads to a higher substantive impact only for firearm restrictive bills enacted into law. The issue of firearm restriction could be swayed by the disproportionately high coverage received by shootings like Sandyhook, Parkland, and Virginia Tech, among others. The result for all other categories is in line with those obtained from the section on media coverage, in which media coverage has a symbolic effect on bills by generating public angst, but has no impact on laws. Overall, restricting the analysis to only shootings with positive media coverage does lead to a noticeable yet substantively small impact on mental health policy.

A.4 Appendix A5: Impact of media coverage at the extensive margin

In this section, I analyze how media coverage affects the introduction of bills and enactment of laws at the extensive margin using a conditional fixed effects Logit and Linear Probability Model.

Table A.11 shows the results for the conditional fixed effects Logit and Linear Probability Models when the media coverage variable interacted with the mass shooting indicator in equation 1. The results are for the most part similar to those obtained under the fixed effects Poisson specification. The estimate for the interaction involving media coverage without FOX news is statistically significant only for firearm-related bills. The conditional Logit model estimates reveal that every 30 minutes of media coverage is associated with an 8.6 % increase in the odds of a state introducing any mental health-related firearm restrictive bills. In the specification involving coverage by FOX news, the corresponding estimate indicates a 3.97 % increase in the odds of any firearm-related bill introduction for every 30 minutes of media coverage. Compared to the estimates for media coverage without FOX news, the estimate is smaller and not statistically significant. This is similar to what was obtained under the count model and could be attributed to FOX news' larger viewer base and the possibility they may have covered mass shootings in a way that discouraged any form of gun control. The estimate for the school-related bills is also positive like those obtained from the count model but not statistically significant by conventional means.

The media coverage estimates for insurance-related bills are negative but are not statistically different from zero under both specifications in Table 1.4 (with or without FOX news). Recall that the media coverage estimates under the count model were both positive and statistically significant in the case of insurance bills. This appears to indicate that media coverage increases the number of insurance-related bills introduced but has no such effect on the probability of introducing any insurance-related bill under the binary models. For this category, the media coverage operates on the intensive margin of the number of bills introduced but not on the extensive margin (probability of any bill being introduced). A possible reason could be that the binary model is somewhat noisy and suffers from much randomness. Many legislators may introduce minor bills in order to signal that they are making an effort despite the said bills having little chance to be discussed by the relevant committees and codified into law. For insurance related bills, a legislator can introduce any minor bill at the behest of advocacy groups. Unlike the count models, the binary model would not be able to distinguish between a single minor proposal introduced and a number of bills introduced (which would signify a concerted effort by the state legislatures at improving insurance coverage of mental illnesses). These could be potential reasons why the estimate for the media coverage has no impact on the extensive margin but does appear to have an impact on the number of bills introduced.

Table A.11: Effect of media coverage of mass shootings on the introduction of mental health bills using a fixed effects Logit and Linear Probability Model (LPM)

Dependent Variable: Dummy variable indicating whether a bill was introduced in any of the categories								
	Insurance Bills		School Bills		Community Bills		Firearm Bills	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A : Conditional fixed effects Logit Model								
Mass shooting Indicator	0.34157 (0.2311)	0.1182 (0.3453)	0.443* (0.242)	0.209 (0.352)	0.2439 (0.2427)	0.3765 (0.3466)	0.4697 (0.3006)	0.5235 (0.364)
Mass shooting times Media coverage excluding FOX	-0.000234 (0.00139)		0.00096 (0.00169)		-0.00005 (0.00133)		0.00277* (0.0014)	
Mass shooting times Media coverage including FOX		-0.00034 (0.0022)		0.00074 (0.00161)		-0.000342 (0.00149)		0.0013 (0.00137)
No of Observations	996	500	996	500	956	500	796	400
Panel B: Linear Probability Model								
Mass shooting indicator	0.07222 (0.0476)	0.0197 (0.0656)	0.0894* (0.0450)	0.0357 (0.0653)	0.0459 (0.0459)	0.0687 (0.0639)	0.0530 (0.0327)	0.07715 (0.0552)
Mass shooting times Media coverage excluding FOX	-0.00005 (0.00029)		0.000216 (0.00028)		-0.000113 (0.00028)		0.00054** (0.002)	
Mass shooting times Media coverage including FOX		-0.000424 (0.00029)		0.00002 (0.00029)		-0.00077 (0.0002)		0.0002 (0.00024)
No of observations	1000	500	1000	500	1000	500	1000	500

Table A.12: Effect of media coverage of mass shootings on mental health bills enacted into law at the extensive margin

Dependent Variable : Dummy variable indicating whether a bill was introduced in any of the categories								
	Insurance Laws		School Laws		Community Laws		Firearm Laws	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A : Conditional fixed effects Logit Model								
Mass shooting indicator	0.4198 (0.2644)	0.1939 (0.3887)	0.5131 (0.331)	0.4716 (0.372)	0.3264 (0.2428)	0.5194 (0.353)	0.5201 (0.4096)	0.539 (0.4087)
Mass shooting times Media coverage excluding FOX	-0.000302 (0.00257)		0.000106 (0.00145)		0.00066 (0.00131)		0.000426 (0.00253)	
Mass shooting times Media coverage including FOX		-0.0034 (0.0032)		-0.00017 (0.0014)		-0.00006 (0.0014)		-0.0062 (0.00665)
No of Observations	956	400	797	400	956	500	796	260
Panel B: Linear Probability Model								
Mass shooting indicator	0.0671 (0.0412)	0.0217 (0.0566)	0.0487 (0.0353)	0.0599 (0.0555)	0.0578 (0.0429)	0.0908 (0.0596)	0.0334 (0.0230)	0.0345 (0.0228)
Mass shooting times Media coverage excluding FOX	-0.00036 (0.000024)		0.00012 (0.00029)		0.000172 (0.000262)		0.00012 (0.0014)	
Mass shooting times Media coverage including FOX		-0.000301 (0.00025)		0.000015 (0.00025)		0.00003 (0.000161)		-0.000076 (0.000161)
No of observations	1000	500	1000	500	1000	500	1000	500

Table A.12 shows the estimates once the media coverage variables (with or without FOX news) are included in the regression. The results for the media coverage are similar to those obtained under the count models (see Table 1.7) where the media coverage does not have any impact on the probability of laws enacted unlike the case with bills where there was a statistically significant positive impact for firearm bills (see Table 1.13). This suggests that the increase in the probability of introducing firearm bills due to higher media coverage is more of a symbolic attempt by politicians to appease their constituents. It is also possible that the media coverage may galvanize opponents of such legislation (firearm restrictions in this case) which may lead to no such effect on laws.

A.5 Appendix A6: Heterogeneity by political party at the extensive margin

In this section, I attempt to analyze whether the political party in power influences the impact of a mass shooting on the enactment of laws at the extensive margin using a conditional fixed effects Logit and Linear Probability Model.

Table A.13: Effect of mass shootings on mental health bills at the extensive margin using a Logit and Linear Probability Model

Dependent Variable: Dummy variable indicating whether any bills were introduced in a state-year

	Insurance Laws		School Laws		Community Laws		Firearm Laws	
	Logit	LPM	Logit	LPM	Logit	LPM	Logit	LPM
Mass Shooting	0.0906	0.018	0.1003	0.0053	0.5301	0.0882	0.5409	0.033
	(0.3855)	(0.053)	(0.5095)	(0.039)	(0.338)	(0.057)	(0.5609)	(0.031)
Dem Leg * Shooting	0.0822	0.0197	0.7117	0.1309*	-0.066	0.009	0.1063	0.004
	(0.548)	(0.0829)	(0.7151)	(0.062)	(0.5082)	(0.0907)	(0.8403)	(0.048)
Split Leg * Shooting	2.008*	0.339**	-1.32*	0.1819*	-0.727	-0.113	-0.074	0.0028
	(0.8211)	(0.1284)	(1.0627)	(0.096)	(0.838)	(0.1404)	(1.337)	(0.075)
Democrat Legislature	0.1123	0.0237	-0.8003	-0.0753*	0.09744	0.0188	-0.8961	-0.0316
	(0.343)	(0.0464)	(0.5477)	(0.0347)	(0.2896)	(0.0508)	(0.6511)	(0.0272)
Split Legislature	-0.9986*	-0.124*	2.341*	-0.0963*	-0.205	-0.039	-0.1466	-0.0094
	(0.3941)	(0.049)	(1.15)	(0.0367)	(0.3067)	(0.053)	(0.6898)	(0.0288)
No of Observations	889	1000	738	1000	851	1000	513	1000

Notes: The table denotes regression output for estimating a fixed effects Logit and Linear probability Model on whether any mental health related laws were enacted in each category when the mass shooting variable is interacted with dummies for Democrat and split control of state legislatures. The specification includes Political, Demographic, Institutional and Mental health related controls. The omitted group is Republican controlled state legislatures. Stars following coefficients represent p-values less than .10 (*), .05 (**) and .01 (***). Standard errors are robust and clustered at the state level

Table A13 shows the results for estimating a fixed effects Logit and Linear Probability Model where the mass shooting indicator is interacted with dummies for democrat controlled and split legislatures. Similar to the results obtained from the count model, split legislatures are more likely to enact laws related to insurance coverage following a mass shooting. Split legislatures are also less likely to enact laws related to access to mental healthcare in schools. Both these results however are driven by a single state (Washington). When the model is estimated without the state of Washington, the coefficients are no longer statistically significant. Overall, similar to the count model, the results from the binary models also do not show any conclusive evidence of partisanship.

A.6 Appendix A5: Data appendix

This section of the appendix, describes in detail the process by which I have collected the data and created the variables.

A.6.1 Mental health legislation

The variables for mental health legislation denote the number of bills introduced and laws enacted (bills passed by both houses of a state legislature) by a state in a certain year. There are a total of eight such variables depicting the number of bills and laws in a state-year by each of the four categories of mental health legislation (Insurance, Community, Firearm, School)

The data for mental health legislation is obtained from the Bill Tracker provision of the Lexis Nexis Database. The Bill tracker provision contains a list of bill introduced in state legislatures across all fifty states along with a brief synopsis and timeline of the bills progress from its introduction to whether it finally passes both houses and is signed by the governor into law. I first search for mental health related bills using a list of keywords in table 1 such as 'mental health', 'behavioral health' etc and obtain a list of all mental health related bills introduced in state legislatures of all fifty states from 1989 till the present. As the analyses is restricted from 2000 to 2020, I filter by date to obtain the relevant bills in the time frame of the study. The database has an additional search feature that enables one to further filter among bills using keywords.

As the paper restricts the analyses to four categories of bills, i.e, insurance, firearm, school and community, I use keywords related to each category (listed in Table 1) to obtain a list of mental health related bills that somehow pertain to each category. For example, for insurance related bills, I use key words like 'insurance coverage', 'parity', 'medicaid' and obtain a list of bills related to mental health that contain any of the keywords. I then go over the synopsis of each bill to see if it fits the criteria of a bill that aims to improve insurance coverage of mental illness. An example of such a bill that aims to improve insurance coverage of mental illness is a bill introduced in the Iowa Senate in 2008.

"*Provides that an insurance policy, contract, or plan providing for third-party payment or prepayment of health or medical expenses must provide coverage benefits for mental health conditions based on rates, terms, and conditions which are no more restrictive than the rates, terms, and conditions associated with coverage benefits provided for other health conditions*"

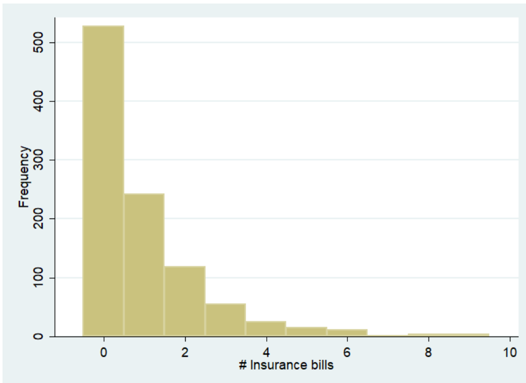
I count the number of such bills aimed at improving insurance coverage by state and year and create the associated variable of insurance bills introduced by state and year.

I then repeat the same process for the other three categories of bills and create multiple variables for the number of bills introduced by state and year that pertain to improving access to mental healthcare in the four domains.

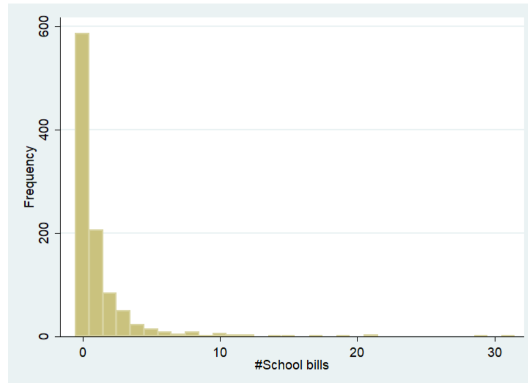
I also go over the timeline of each bill to see if the bill eventually passed both houses and became a law. I then count the number of such laws enacted by state and year in each of the four categories and create the relevant variables for the count of laws by category.

Figure A.1: Histograms of mental health bills

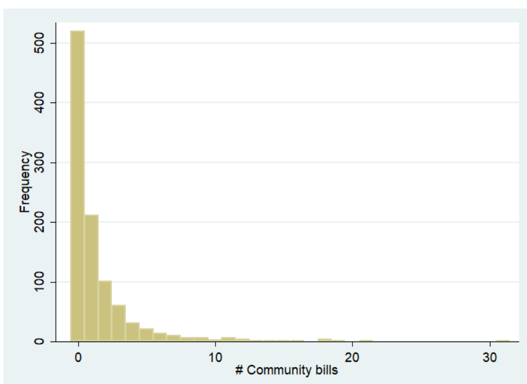
(a) Insurance related bills



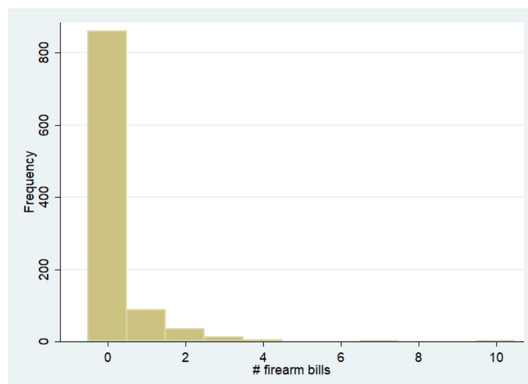
(b) School related bills



(c) Community mental healthcare related bills



(d) Firearm related bills



A.6.2 Mass shootings

As mentioned in the data and variables section, the data for mass shootings related variables is collected primarily from newspaper articles and the FBI's Supplementary Homicide Reports.

I first use the advanced search feature in newspapers like New York Times, LA Times, Chicago Tribune and Washington Post. I begin by setting the date filter to a particular year and search using keywords like 'mass shooting in Nevada' or 'multiple homicide in Tennessee'. If any article describes an incident that meets the criteria of a mass shooting as described by my paper, I record it in the dataset along with the number of fatalities, injuries as well as whether the incident occurred in a private or public location, was a school shooting or classified as a terrorist act etc.

I then corroborate each incident using the FBI-SHR which contains detailed data for homicides reported to the FBI including the location, the jurisdiction of the relevant police department, the type of murder weapon and characteristics of victims and perpetrators such as race, gender, and ethnicity. I first filter the dataset by restricting it to homicide incidents with multiple fatalities committed by a lone perpetrator using firearms. Using the date and location (county and city) of a mass shooting incident from newspaper reports, I look up each incident and record information such as the race of the perpetrators and victims.

Media coverage of mass shootings

The media coverage related variable denote the total media coverage in minutes for all mass shootings in a state in a certain year. The variable is calculated using the Vanderbilt Television News Archive (VTNA). The VTNA is a database of news segments from major Television networks such as ABC, NBC, CNN etc. I use their advanced search feature to type in keywords related to a mass shooting such as ”Sandyhook shooting Connecticut” and set the search dates to the 10 days after the mass shootings. This gives me a list of news clips dedicated to the mass shootings in question. I then add the total time of all the news clips in seconds and obtain data on the media coverage for mass shootings by networks like CNN, NBC, ABC. As the unit of observation is a state-year, I add the media coverage of mass shootings that occurred in a given state in a given year.

The VTNA however does not have clips from FOX News. For coverage by FOX news I rely on their website's media archive section. I use the same approach where I search using keywords related to a certain mass shooting and filter by the dates of the 10 days following a mass shooting. This allows me to obtain a list of clips of FOX's coverage of a certain mass shootings which I use to calculate the total coverage by FOX in seconds.

A.6.3 Control variables

Political controls

The political control variables include dummies for whether a state's legislature is democrat or Republican controlled and the share of female legislators in a state. The data is obtained from the National Conference of State Legislatures (NCSL). The NCSL's website has webpages with detailed tables on the number of Democrat and Republican members in a state's house and senate as well as the number of legislators by race and gender. Using the information on party affiliation, I first calculate the shares of senators and congressmen in a state-year by political party. Using this information, I code a legislature as Democrat or Republican controlled if a majority of legislators in both houses belong to the respective party and split legislature if each party has a majority in one of the houses. For the share of female legislators, I add the number of female legislators in the house and senate for each state for every year and the then divide it by the combined size of the legislatures(size of house plus size of senate)

Mental healthcare related controls

14.3.2.1 Mental healthcare capacity

For the mental healthcare related controls I begin with a covariate which captures the mental health capacity of a state. This variable captures the share of a state's workforce employed in Mental health care establishments. The data is drawn for the US Census Bureau's County Business Patterns (CBP) data. In the CBP data an establishment is 'A single physical location where business is conducted or where services or industrial operations are performed.' For the purposes of this paper an establishment is a physical location where mental healthcare services are delivered. The CBP contains the near universe of establishments in the US from 1998 to 2019. Using the North American Industrial Classification system (NAICS) codes for different industries, I extract data on the number of firms and level of employment in different mental health related establishments. This approach of using CBP data on mental healthcare establishments has been used by Deza et al (2020) to study the effect of local access to mental health care on crime and by Swensen (2015) to study the impact of access to substance abuse treatment facilities on crime. The main types of mental health care establishments along with their associated NAICS codes are:

- Office of psychiatrists. (NAICS code : 621112)
- Office of mental health professionals other than psychiatrists (NAICS code: 621330)
- Psychiatric hospitals (NAICS code 622210)
- Outpatient mental health and substance abuse centres (NAICS code: 621420)

- Residential intellectual and development disability facilities (NAICS code: 623210)
- Residential mental health and substance abuse facilities (NAICS: 623220)

Upon adding the total number of employees in all mental health establishments in a given state in a given year, and dividing it by the state's labor force population, I obtain the share of labor force employed in mental healthcare establishments is state. The CBP data however had many missing values for the level of employment in certain establishments in certain states as they are suppressed due to confidentiality reasons (for instance the number of employees in psychiatric hospitals are suppressed for North Dakota and Minnesota for most of the years so far). In such cases I calculated the values by subtracting from the parent establishment. For instance, in order to calculate the employment in psychiatric hospitals in a state, I first take the total employment in all Hospitals and subtract the employment levels in non-psychiatric hospitals such as general hospitals, surgical Hospitals, specialty Hospitals(the data for which I obtain using the relevant NAICS codes). In doing so I fill in the missing values, and create a dataset of the share of workforce employed in mental health establishments in a given state year.

14.3.2.1 **Suicide rates**

The paper uses suicide rates as a proxy for the prevalence of mental illness in a state. The data for suicide rates is obtained using the CDC's Web Based Injury Statistics and Query System (WISQARS). The WISQAR's database of the CDC is an interactive online database that contains data on fatal injury related deaths by age, ethnicity, state, region and for the nation as a whole as well as the cause and nature of the fatal injury. Using the interactive query system and setting 'suicide' as the cause of fatal injury and including additional filters for state and year I obtain the number of suicide related deaths for each state for the duration of the sample period. By dividing it by the state's population I create a measure of suicide rate which is defined as the number of suicide related deaths for 100000 people in a state.