Shooting Political Polarization*

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Abstract

This paper studies political polarization on a multidimensional set and its consequences on the democratic process. To do so, I construct a measure of political polarization based on the 1999-2016 congressional speeches of the United States Representatives. Relying on the exogenous feature of politically divisive events, mass shootings (MSE), I implement a dynamic difference-in-differences design exploiting variation across places and time. First, I document that an MSE significantly increases the polarization on the gun rights topic. Second, I explore how the distance between Democrats and Republicans increases over a range of different topics, revealing how contagious polarization may be. I investigate and analyze different mechanisms which may explain these findings. I focus on describing which politicians talk following a salient event and discussing a possible theoretical framework motivating the results. Finally, I explore how the increase in polarization impacts the democratic process. In the days following an MSE, the probability of passing a new law in the House of Representative decreases. These effects are long lasting: bills voted after such divisive events are also less likely to pass in the future.

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1 Introduction

The ideological controversy between political factions is a defining feature of democratic societies, where multiple perspectives and voices coexist. However, recent decades have witnessed a considerable and excessive rise in political conflict, with both citizens and policymakers becoming increasingly divided along ideological and partisan lines. The literature defines this phenomenon as political polarization (DiMaggio et al. (1996)). This fact is particularly clear in a two-parties democratic system such as the United States of America (US). As a matter of fact, in the US, the ideological distance between Republicans and Democrats has sharply increased (Gentzkow, Shapiro, & Taddy (2019)). This evidence stems from congressional voting records (McCarty (2016)), candidate survey responses (Conley (2019), Moskowitz et al. (2018)), congressional speech scores (Gentzkow, Shapiro, & Taddy (2019)), and campaign donation measures (Bonica (2014)). Understanding the origins and impact of political polarization is crucial. It affects policymaking and the likelihood of passing new policies (Epstein & Graham (2007)). Additionally, it influences people's decisions, leading to social divisions (Baldassarri & Gelman (2008), McCarty (2016)).

Existing literature has primarily focused on political polarization as a singular concept, measured using a single metric. However, this approach overlooks the fact that there are multiple political issues and that polarization can vary across these topics at any given moment. The interaction and contagion between polarizations on different topics remain unclear. However, studying this is essential for gaining a comprehensive understanding of societal divisions and developing effective strategies to mitigate the negative impacts of polarization on communities and democracies. This paper aims to fill this gap by exploring the research question: Is political polarization contagious? It investigates whether polarization on a specific issue can trigger a widespread polarization effect across other unrelated political topics. Furthermore, it reveals that this increase in polarization has both short and long-term consequences on the velocity and quality of policy-making.

More precisely, I focus on the topic of gun rights, one of the most divisive topics of the US political landscape (Conley (2019)). By analyzing the impact of mass shooting events

(MSEs), which serve as salient shocks on the divisive topic of guns, the study overcomes endogeneity concerns and demonstrates that polarization not only increases on the focal issue but also spills over to other political topics.

To study this I construct a novel and more flexible measure of polarization by analyzing the 531501 congressional speeches of the US Representatives generated from 1999 to 2016[1]. Drawing upon various text analysis techniques (Ash & Hansen (2023)), I build my measure which I define rhetorical polarization. This measure highlights the stark contrast in the way individuals from different political parties communicate about the same issue.

Exploiting mass shooting events as a quasi-random natural experiment, the paper implements a dynamic differences-in-difference approach. It compares level of polarization among politicians from states directly affected by the shooting and not before and after the occurrence.

The paper reveals that the days after a shooting incident, polarization intensifies not only on gun-related issues but also on topics that are not directly associated with firearms, such as social policy, war and defense, environment, and justice. The effect is particularly pronounced among Democratic and Republican Representatives from states directly impacted by the shooting.This finding underscores the contagious nature of political polarization, with its influence extending beyond a divisive topic to impact other political issues. The spread of political polarization across various issues can be linked to psychological theories such as confirmation bias and cognitive dissonance(Nickerson (1998)).

Notably, concerning gun rights, the analysis demonstrates a significant increase of 21% compared to the mean outcome, emphasizing the magnitude of polarization specifically on this issue. This result serves two important purposes. Firstly, it acts as a crucial sanity check by aligning with expectations, validating the hypothesis that polarization would intensify regarding gun rights[2]. Secondly, it serves as a valuable validation of the proxy used to measure

[1]How individuals interact in group discussions can provide essential insights into the position of the politicians and party in a particular topic at a specific time (Karakowsky et al. (2004)). Moreover, who decides to intervene and when a politician speaks are mechanisms for collective decision-making (Blumenau (2019))

[2]MSEs are likely to attract significant media attention and trigger strong emotional responses(Benton et al. (2016)), thereby amplifying existing political divisions.

polarization, affirming the accuracy and reliability of the chosen approach.

However, the extent of impact varies across topics. Certain areas, particularly those related to the economy, remain unaffected by these divisive shocks. To delve deeper, I employ a more specific topic model (Structural Topic Model, STM), to dissect the macro areas[3] into more precise micro topics. The results reveal that the increase in polarization aligns with the specific macro political issues, with some micro topics being more affected than others.

To gain deeper insights, I conduct heterogeneity analyses to uncover the drivers behind these outcomes. One would expect that the salience of these events may play a crucial role in influencing the magnitude of polarization. The severity, the location and the timing of a MSE may change the reaction and the attention a politician and the public opinion direct toward it. I hence examine three different sources of heterogeneity: the number of fatalities, whether the shooting occurred in a school, and whether it took place around an electoral period. This analysis reveals that the increase in the polarization is primarily propelled by shootings with higher numbers of fatalities, whereas incidents within school or university campuses do not yield statistically significant effects. Additionally, the timing of these events does not seem to matter. The analysis indicates no statistically significant difference in the impact during the final six months of a Congressional period, coinciding with electoral campaigns.

Employing an event study approach, I demonstrate that the effect remains present for several weeks following the occurrence of the event. Furthermore, there is no statistical difference in polarization among the treated and non-treated states in the weeks leading up to the mass shooting, providing reasonable evidence for the assumption of parallel trends.

To strengthen the support for my findings and to elucidate the underlying mechanisms, I develop a novel theoretical model which explains the contagious nature of polarization and the varying impact on different topics. This theoretical framework is grounded in the concepts of cultural and economic conflict (Bonomi et al. (2021)) as well as intra-party competition (N. J. Canen et al. (2021)). The model help me in explaining why some topics are responding, while others not.

[3]social policy, environment, war and defense, economy, and justice

I study whether my results may be related to some characteristics of the speakers. Indeed, if, after a salient event, more extreme politicians from both parties are more inclined to speak out compared to their moderate counterparts, this could explain the increase in political polarization. Their heightened involvement may be driving polarization across different topics. I provide suggestive evidence to establish that the observed results are not influenced by the identity of the speakers. Specifically, I find no statistically significant difference in the probability of a more extreme or moderate candidate delivering a speech after a divisive event[4].

Finally, we know from the literature that when dealing with political polarization we should distinguish between ideological and affective polarization (Iyengar et al. (2019)). I demonstrate that a significant portion of the observed increase in polarization can be attributed to the latter. Affective polarization is defined by the literature as the gap between individuals' positive feelings toward their own political party and negative feelings toward the opposing party (Druckman et al. (2021)). To measure affective polarization, I employ a proxy by analyzing the Twitter feeds of each US Representative and constructing a sentiment score. The analysis reveals that after a divisive event, when a treated politician discusses their opponents (candidates from the same state but from another party), they employ more negative terms compared to their previous statements and compared to other members of the House of Representatives.

After establishing the role of salient and divisive events in driving rhetorical polarization and exploring the mechanisms behind this phenomenon, I delve into the consequences of increased polarization within the political system and its impact on policy-making. Building upon previous research (?, ?), one would naturally anticipate that an increase in political polarization would lead to a heightened inability to pass legislation, resulting in congressional gridlock. While existing literature has explored this phenomenon, there remains a significant knowledge gap concerning the potential impacts of polarization on congressional gridlock in the medium to long term. Additionally, it remains uncertain whether all policies are equally affected by this polarization.

[4]Measured using the DW-nominate suggested by Poole & Rosenthal (1985)

This study aims to address these gaps. Specifically, I find that the probability of passing new policies decreases following a divisive event, such as a mass shooting, confirming the already existing relationship between polarization and congressional gridlock. Notably, this effect is particularly pronounced for moderate policies. However, extreme policies, whether conservative or liberal, appear to be less affected or even unaffected by this polarization. Furthermore, by tracking the trajectory of these policies over time, I observe that they face even lower probabilities of passing in the future compared to other policies that were not passed during less polarized periods.

These discoveries offer some insights into the medium to long-term effects of polarization on policy-making and introduces a new understanding of the heterogeneous ways in which policies are more impacted by political polarization.

To further explore the long-term implications, I investigate how these divisive events may impact the future composition of the House of Representatives. In the congressional districts affected by such shocks, I find a higher probability of electing an extreme candidate in the future compared to non-treated districts. However, I do not observe a statistical difference in the likelihood of electing a Republican or Democrat representative. This observation may suggest that the change occurs primarily on the supply side of the political environment, indicating an impact on the type of candidates running for office rather than a shift in the preferences of voters between the two parties.

This paper relates to three different strands of the literature. First, it contributes to a growing literature that argues that, in addition to historical and cultural motivations, political polarization also reacts to unrelated and specific events (Demszky et al. (2019)). The findings in this paper also suggest that salient and local events shift the polarization among politicians (Burden (2001)). To the best of my knowledge, this is the first paper showing how contagious polarization is across topics. Indeed, a salient shock on a divisive topic triggers polarization not just on the specific topic but also on other issues not directly related to the former one.

This paper also relates to the new literature on text as data (Gentzkow, Shapiro, & Taddy

(2019)). Using text analysis techniques, I compute polarization in different topics identified using a topic model (Martin & McCrain (2019)). I follow a dictionary-based sentiment analysis (Fei et al. (2012), Mohammad & Turney (2013)) to compute a measure of polarization through the sentiment of the words used by the individual. This paper contributes to this literature by introducing the multidimensional concept of rhetorical polarization. Indeed, previous works on this field consider it as a general phenomenon. In contrast, with this work, I show that political polarization can have different dimensions and movements based on the topic.

This work also contributes to the political economy literature on public attention, policymaking, and law. Empirical research on policymaking emphasizes that factors beyond social welfare influence policy (Luca et al. (2020), Bardhan & Mookherjee (2010), Makowsky & Stratmann (2009)). As I show in the last part of the paper, the days immediately after an MSE register a reduction in the Congress' legislative activity, suggesting a decrease in the probability of voting and introducing a new law.

The paper proceeds as follows. In the next two sections, I give an overview of the causes and consequences of political polarization and which data I use. Section 4 explains how I construct my outcome variable for measuring political polarization through text analysis. Section 5 outlines the estimation strategy, and Section 6 describes the main results. Section 7 presents the mechanisms behind my results. Finally, Section 8 shows how polarization impacts legislative activity and the future composition of the House of Representatives, and Section 9 concludes.

2 Institutional Context

This study aims to demonstrate how a divisive topic shock can heighten polarization and how this polarization spreads to other political topics. In this section, I explain how the literature define political polarizationa and how I refer to it in this paper. Moreover, I describe the divisive topic I analyze and the main shock to it used in the paper.

2.1 Political Polarization in the US

Definition. Political polarization is a widespread and significant phenomenon in almost all the Western democratic systems today. Its baseline definition is the ideological distance among parties. In a two party design democratic system, the political polarization incorporates all frictions of its binary ideologies and partisan status. Scholars have defined political polarization in various ways, using different settings and measurement techniques. DiMaggio et al. (1996) define the political polarization as both a state and a process, where party opinions on issues can be opposed due to ideological motivations or historical factors, while also evolving over time. In the United States, the polarization between Republicans and Democrats has today sharply increased reaching its highest level in history (Gentzkow, Shapiro, & Taddy (2019)).

When talking about political polarization it is also important to remember that it can be divided into two levels: elite (politicians) and mass (citizens) (Fiorina & Abrams (2008)) and how these two characters interact with each other (Baldassarri & Gelman (2008)). From the literature, the term "political elites" defines members of Parliament, and all the other influential players in the political process. While "mass polarization" refers to the polarization of the electorate or general public (McCarty et al. (2016)).

In this paper, I define the rhetorical polarization as a compelling proxy for measuring political polarization. This measure highlights the stark contrast in the way individuals from different political parties communicate about the same issue. When two individuals, each representing opposing parties, address a specific topic, their language, tone, and arguments tend to diverge significantly. This divergence may signify a deep-rooted ideological divide, ultimately shaping the political landscape. The strength of rhetorical polarization lies in its ability to capture the essence of the larger ideological conflict in a more disaggregated way, showcasing, at least in part, how partisanship and biases can influence the way individuals perceive and discuss issues. However, one of its weaknesses is that it mainly focuses on the surface level of communication and may not fully reflect the underlying reasons for political polarization. Nonetheless, examining rhetorical polarization remains valuable in shedding light on the divisive nature of contemporary politics and its implications for democratic discourse.

Causes. Various factors contribute to the rise of political polarization in the US. Congressional primaries play a role as candidates adopt extreme positions to appeal to voters ((Burden 2001)). Changes in US political geography, such as the dominance of Republicans in the South, contribute to increased conservatism (Mann & Ornstein (2006);Jacobson (2000); Fleisher & Bond (2004), Stonecash (2018)). Another possible motivation has to be found in a change in the socio-demographic characteristics of the country. For example, the increase in inequality parallels that of political polarization. The inequality and economic shocks facilitate the election of extreme candidates and polarization (McCarty et al. (2016), **?**). Fiorina et al. (2005) also propose religion as a possible element in favor of the political polarization. Another driver for the current rise in the political polarization has to be found in the media (Levendusky (2013), Mutz (2006)). Furthermore, the recent increase in partisanship could be also motivated by a new way of doing politics: to dislike and distrust those from the other party is currently becoming the normal way of expressing a political position (i.e. affective polarization, Iyengar et al. (2019)).

Consequences. Political polarization has wide-ranging effects on society, politics, and the democratic process, with both positive and negative consequences (Layman et al. (2006)). One of the possible positive consequence of the political polarization is the clarity of candidates. Polarized politicians offer divergent messages and use a language that citizens can easily understand. There is substantial evidence that public participation in American politics has increased with amplified polarization (Abramowitz & Stone (2006)). The polarization may help voters to elaborate on the substance of candidates (Layman et al. (2006)).

The political polarization phenomenon, on the other hand, has different negative consequences impacting both the political process and society. These studies show that Congress enacted more significant legislation pieces when it was less polarized. Political polarization may impact the quality of policies voted and passed (Binder (2000), Epstein & Graham (2007), N. Canen et al. (2020)). The data also shows how the partisan polarization is adversely affecting the federal judiciary's independence (Binder (2005)). Moreover, the polarization may also undermine the leadership of a country in foreign policy, damaging its image in the world (Beinart (2008)). Besides, polarized environments fundamentally change how citizens make decisions (Druckman et al. (2013)). The mentioned situation can influence individuals' civil behavior, creating a more and more divided society.

2.2 Guns Right as a divisive topic and MSE as a shock

The main objective of this paper is to study how a salient event affecting a divisive topic, influences not only polarization on that particular topic but spread polarization also to those not related to it. I am considering as a divisive topic the issue of gun rights. Guns Right is one of the most divisive topics today in the US (Conley (2019)). This fact is true both for politicians and citizens. The Democratic position on this topic is completely opposed to the Republican one. Gun rights supporters favor fewer government gun regulations, while those favoring gun control advocate for more (Jouet (2019)). Gun rights support is a function of non-social practical concerns as well as a reinforcement of political, social identity (Kohn (2004)). Support for gun control, however, has not been a marker for individual identity core values (Parker (2017)).

This paper uses mass shooting events as shocks on this divisive topic. Previous works which exploited mass shootings as a plausible exogenous variation (Duwe (2007); Krouse & Richardson (2015)) distinguished public mass shootings from private ones. I categorize shootings following the definition given by the FBI: *"Mass Shooting is an event that involved three victims (excluding shooter) in any public or private place. The event is not directly related to gangs, drugs, or organized crime"*. Following this definition, also terrorist attack or gang and drug related shootings are not defined as a mass shooting event. The literature previously used these shocks to study their economic, social and political impact on society with a particular focus on the voters (Yousaf (2021)). Mass shooting events have significant damaging effects on the victims and their families. Furthermore, such tragedies hit the communities where they occur, and they don't influence only those directly affected.

Indeed, these events hurt community well-being and emotional health outcomes that capture community satisfaction, sense of safety, and levels of stress and worry (Soni et al. (2020), Dursun (2019)). We know that mass shootings evoke significant policy responses, so study their effect on politicians ideology or position is a relevant research question in particular for its policy-making consequences. Indeed, these episodes may also affect the implementation of new gun policies at the state level (Luca et al. (2020)), but we still don't know if there any effects in the policy making at the national level. Demszky et al. (2019) studies how the mass shooting events impact the individuals' views on the topic by studying individual tweets after 21 shootings.

The literature in this area has considered how to extract information on gun violence from the news (Pavlick et al. (2016)) as well as quantify public opinion on Twitter (Benton et al. (2016)) and across the web (Ayers et al. (2016)). So, we should expect to see a reaction from politicians after such events, however is still not clear if this reaction may spread on other political topics and having also medium-long term effects on the policy-making and congressional composition.

3 Data

In this paper, I combine data from different sources which I describe in more detail in this section.

Political Speeches. I categorize politicians' positions on different topics by analyzing the speeches through text analysis techniques. From the "United States Congressional Record", and from Gentzkow, Kelly, & Taddy (2019), I collected all the political speeches (House of Representatives) from 1999 to 2016 (from the 106th Congress to the 114th one). The speeches follow a congressional meeting daily edition, and they present characteristics about the speaker: name, surname, party, state, district. I removed all non-Democrats or non-Republicans representatives' speeches, the Speakers' interventions, the President and Vice-President speeches. Finally, I exclude the Extensions of Remarks, which contains speeches, tributes, and other extraneous words that were not uttered during open proceedings of the full Senate or the full House of Representatives (this procedure was already suggested in Gentzkow, Kelly, & Taddy (2019)). For each remaining speech I apply different normalization procedure in the text. From these speeches I extract the main topics and sentiment and I compute my measure of rhetorical polarization (I explain in more details these steps and how I measure it in the next section).

Mass Shooting Events. The paper exploits mass shooting events as a quasi-natural experiment to study the impact of these facts on rhetorical political polarization. There are different definitions for mass shooting event. In this paper, I am considering the one of "active shooter" given by the FBI (which is also my main source). The agreed-upon definition of an active shooter by U.S. government agencies—including the White House, U.S. Department of Justice/FBI, U.S. Department of Education, and U.S. Department of Homeland Security/Federal Emergency Management Agency—is "an individual actively engaged in killing or attempting to kill people in a confined and populated area." Implicit in this definition is that the subject's criminal actions involve the use of firearms. Following this definition, it is possible to count 203 mass shooting events in the US territory from 1999 to 2016. Not all the states were treated, while some states were treated more than once.

I have collected data on mass shootings since 1999 from two different sources. The first one is the FBI supplementary homicide reports (SHR), which I complemented (Luca et al. (2020)) with data on mass shootings collected by the Mass Shootings in America (MSA) project at Stanford University (Stanford (2017)). With these two sources I am able to collect information on the shooter and on the victims. Moreover, they collect the precise location and time of the shooting and the number of victims and injuries of the event. Finally, from these sources, I also have an idea of the reason for the gun violence. For each shooting, I determine the location and date of the event, the characteristics of the shooter, the number of fatalities and injuries, and the possible motivation. The majority of these shootings is classified as "unknown" by the FBI

Other works also divide shootings between public or private depending on the locations where such events occurred (Duwe (2007); Krouse & Richardson (2015)). I use this information to run a heterogeneity test for understanding if shooting happening in a school generates a different reaction or not. Finally, in these sources are not reported all those shootings related to criminal organizations (gangs, terrorist attacks, drug cartels).

Twitter. Using the Twitter Developers Research Track I collect tweets of US politicians for the period 2009-2016.

I start from 2009 and not before because Twitter started to be widely used among US politicians in 2009. In the 111th Congress (2009-2010) almost 40% of the Congresspeople had an active Twitter account, while from 2011 this percentage increased to 60% (112th Congress) and became 85% in the 113th Congress. I use the tweets to study how politicians react to a divisive event on social media. More precisely, I use this data to proxy for affective polarization (Iyengar et al. (2019)). By using a regular expression, I then identify the tweets of each representative talking about another representative from the same state, but from the other party. I then compute the sentiment score of each tweet. I the mechanism section I explain in a more comprehensive way this measure and how I use it.

Roll Call Votes and Politicians ideological score. To study if and how policy implementation is affected by an MSE, I collected from Voteview (Lewis et al. (2019)) the roll call votes data. In particular, this data includes the result and ideological parameters of every poll taken in the selected congressional period (in my case, from 106th to 114th; 1999-2016). Ideological positions are calculated using the DW-NOMINATE (Dynamic Weighted NOMINA ONE Three-step Estimation developed in Poole & Rosenthal (1985)). In this database, it is possible to have information on the topic of the policy as well (Issue, Clausen and Peltzman codes). I supplemented this information by collecting from the Library of Congress data on bill characteristics, sponsorship and co-sponsorship and the text of the bill.

Finally, from the Congressional Bills Project I have further information on the topic of the policy (Adler & Wilkerson (2015)). From Voteview (Lewis et al. (2019))) I also have information about the ideological position of each US member of Congress over years. There, we can find two estimates of a legislator's ideology: NOMINATE and Nokken-Poole. NOMINATE estimates assume that members occupy a static ideological position across the course of their career. Nokken-Poole estimates assume that each congress is completely separate for the purposes of estimating a member's ideology. Moreover, this measure is time variant. In the last part of the paper I use this measure for understanding if after a salient event the probability to elect an extreme candidate increases.

Control Variables. This paper exploits different control variables depending on the specification.This data includes basic biographical information of each US congressperson (state, district, party, name). I also include demographic characteristics at the state level as part of these controls [5]. The main source for these variables is Census and the National Center for Education Statistics. I also add a dummy variable for capturing the period before a Democratic or Republican Primary Election.

4 Measuring Political Polarization

To find a measure of political polarization which varies across times and topics is not so straightforward for many reasons. In this work, I identify a new measure of polarization based on the sentiment of the words used by a politician to express a position about a precise argument. I call this measure rhetorical polarization. This measure quantify how differently members of the Congress, from different parties, talk about the same topic. Although the rhetorical polarization may not capture completely the change in the ideological position, it helps to show that politicians of different parties change their way of communicate after a shock. This measure is just a proxy for the real level of polarization on a topic in a precise moment, however it is still relevant for the purpose of this study and informative.

This paper uses as main outcome variable the rhetorical polarization between Republican and Democratic speakers on different topics. To extract a quantitative measure from the political speeches, I apply a sentiment analysis using a semi-supervised machine learning approach (or dictionary-based methods Fei et al. (2012)[6]).

To define what the speaker is talking about, I use a topic model technique. I identify

[5] Population at the Congressional District or at the State level, employment rate at the state level, education.

[6] Figure B.4 shows a word cloud as an example of negative and positive words in my corpus of speeches.

the most important discussed topics in my dataset running two different topic models: a Structural Topic Model (STM - Roberts et al. (2019)) to identify more specific topics (micro topics) and the more common Latent Dirichlet Allocation (LDA) model (Blei et al. (2003)) to identify the most general topics (macro topics[7]). In appendix I explain in more details the pre-processing applied to the specches and these procedures.

To determine the guns topic, I also follow a different approach as a robustness check. I recognize whether a speech is about guns using a pattern-based sequence-classification method. This method defines if a speech is about guns if it contains bigrams that are much more likely to appear in an external gun-related library (Mastrorocco & Ornaghi (2020)). The gun related training library is composed of articles from the Metropolitan Desk of the New York Times the day of or the day after each shooting with the tags gun violence, mass shooting events, or gun rights. I focus on bigrams because they convey more information than single words within a particular topic. Figure B.1 shows a word-cloud with the 50 bigrams that have the highest weight for the gun rights topic. The bigrams I identify to be about guns are quite general and make intuitive sense. In addition, they do not display an ideologically driven view of the gun, which lowers the concern of measurement error.

Having assigned the topic and applied the sentiment analysis approach, I compute polarization as the absolute distance between the Democratic and the Republican sentiment score[8].

$$Sentiment\ Score^{J}_{i,s,t} = [\sum_{j=1}^{n} Positive\ Words^{J}_{s,t} - \sum_{j=1}^{n} Negative\ Words^{J}_{s,t}] \times topic_i \tag{1}$$

$$Polarization_{i,s,t} = abs[Sentiment\ Score^{D}_{i,s,t} - Sentiment\ Score^{R}_{i,s,t}] \tag{2}$$

$Sentiment\ Score^{J}_{i,s,t}$ is the sentiment score of party J computed as the total positive words minus the negative ones spoken by speakers of the party J state s on topic i at the congressional meeting day t. I normalize the $Sentiment\ Score^{J}_{i,s,t}$ by the total number of positive

[7]Figure B.5 shows the 15 most spoken words for each topic.

[8]To make the interpretation of the results easier, I standardize the variables when I present the results for the different topic together

and negative words spoken by speakers of the party J state s on topic i at the congressional meeting day t. $Polarization_{i,s,t}$ is Polarization in topic i, in state s, at congressional meeting day t, computed as the absolute difference between Democratic position in topic i, in state s at day t and the Republican one.

4.1 Possible concerns about the measure

This measure is a proxy for rhetorical polarization. If on the one hand is a simple and useful method for the purpose of my paper, on the other hand may raise some concerns about its validity. There are three possible concerns: construction, measurement error and definition. The measure is constructed by assuming that the sentiment of a speaker is uniformally distributed across topics.

Another possible concerns relies on the error present in the measure. The measurement error in this case is likely to be as good as random (both in positive and negative words); it is affecting the Democrat and Republican speakers in the same way and my identification strategy (difference in differences design) should solve any problem of measurement error.

About the definition, this measure is impacting the language used to talk about a topic not the content. It is no a direct ideological measure, but it presents a change in the way of talking about the same arguments. In the results session, I will show that this measure may be helpful to show how two politicians from the same geographical area, but from different party, are distant in the their way of talking about the same topic using the A la Carte embedding method (Khodak et al. (2018)).

5 Empirical Strategy

Identification Strategy. The main objective of this paper is to study how a salient event affecting a divisive topic, influences not only polarization on that particular topic but spread polarization also to those not related to it. I am considering as a divisive topic the issue of gun rights. The significant challenge for answering my research question is finding a shock to the Gun Rights topic exogenous to my measure of polarization. I address the issue by exploiting mass shooting events (MSE).

The empirical strategy of this work is a difference-in-differences design that compares the rhetorical polarization of politicians in places with and without a mass shooting event, before and after the occurrence. Using panel data at the state-day of the congressional meeting level, I compared polarization in different periods among states directly and not directly affected by the shooting, both before and after their occurrence. The main identifying assumptions for my empirical strategy are that there are no pre-determined characteristics which may motivate a place to have an MSE compared to another, and that these events are exogenous with respect to my outcome variable. Figure 1 plots the mass shooting events from 1999 to 2016. This figure show that, unfortunately, it is not possible to predict when and where the next mass shooting will occur. MSEs are staggered across places and time. For this reason, one could exploit these variations in place and time to study their effects on the polarization of politicians. Figure B.2 and Figure B.3 show the variation over time of the shooting and the motivations given by the FBI for the shooting. This evidence suggests that MSEs are exogenous to polarization and to politics in general. Moreover, in a more rigorous specification I introduce state by month fixed effects in order to take into consideration any seasonality trends at the state level that may bias my results.

Specification. To study the influence of a divisive shock on the polarization in different topics, I first use the following dynamic difference-in-differences specification:

$$Polarization_{i,s,t} = \beta_0 + \beta_1 MSE_{s,t-1} + \gamma \mathbf{X}_{s,t} + \mu_s + \lambda_t + \epsilon_{s,t} \tag{3}$$

where $Polarization_{i,s,t}$ is my measure for rhetorical polarization on topic i, in state s at the congressional meeting day t; $MSE_{s,t-1}$ is an indicator variable equal to one if in state s at day $t-1$ there has been a mass shooting event. $\mathbf{X}_{s,t}$ is a battery of baseline controls at state level interacted with congressional period fixed effects[9]. μ_s and λ_t are respectively state and day of the congressional meeting fixed effects. Standard errors are clustered at the state level; however, I discuss the robustness of the results to alternative assumptions about standard errors. Finally, I weight observations by the number of speakers, in order to make the estimates representative at the national level.

Since some states in my dataset experienced multiple treatment during the period taken into consideration, I exploit different time windows to allow the treatment to switch on and off. My preferred time window considers a state treated for the rest of the Congressional period once the treatment is assigned. I use shorter time windows — 30 days, 1 semester and 1 year around the time of the shooting — to check that the results are stable and stronger immediately after such events as we would expect.

To verify if there are any pre-treatment characteristics which may select the treatment group, I exploit an event study specification. For the event study approach I transform my dataset at the month (or week) level to have more statistical power for the different topics and I follow this equation:

$$Polarization^i_{s,t} = \sum_{t=-q}^{-2} \gamma_\tau MSE_{s,\tau} + \sum_{\tau=0}^{m} \delta_\tau MSE_{s,\tau} + x_{s,t} + \mu_s + \lambda_t + \epsilon_{s,t} \tag{4}$$

where $Polarization_{i,s,t}$ is the rhetorical polarization on topic i in state s, at year-month t. I include q leads or anticipatory effects and m lags or post-treatment effects (excluding $t-1$ period). $x_{s,t}$ is a matrix including control variables[10]. μ_s and λ_t are state and year-month (or year-week) fixed effects. I omit the event time dummy at $t=-1$, implying that the event time coefficients measure the impact of MSE relative to the month (or week) just before the

[9]Time invariant controls: demographic characteristics, unemployment rate, education level at the state level which I interact with Congress FEs. Time variant controls: a dummy variable indicating 30 days around the Republican or Democrat primary elections for each state . A variable identifying the number of extreme speakers present in a precise state in each congressional period (varying every two years) and a variable with the mean value of the DM-nominate of the state in a precise congressional period.

[10]Time invariant controls: demographic characteristics, unemployment rate, education level at the state level, which I interact with Congress FEs. Time variant controls: a dummy variable indicating 30 days around the Republican or Democrat primary elections for each state. A variable identifying the number of extreme speakers present in a precise state in each congressional period (varying every two years) and a variable with the mean value of the DM-nominate of the state in a precise congressional period.

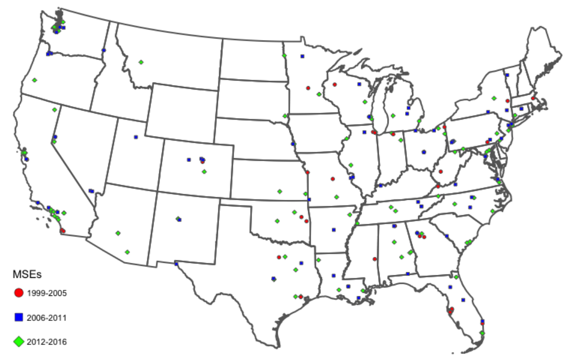


Figure 1: Variation across States and Years of mass shooting events

Notes: This figure shows the variation across states and years (6 years) of the mass shooting events present in my dataset.

occurrence.

I then run different robustness checks following the recent literature on DID (De Chaisemartin & d'Haultfoeuille (2020)), Goodman-Bacon et al. (2019) and Borusyak & Jaravel (2017)) to verify that my TWFE estimations are robust to the heterogeneity in time and unit in the treatment.

6 The effect of a salient shock on polarization

In this section I report the main results before discussing the heterogeneity and the robustness checks performed.

6.1 Divisive events and Polarization

Table 1 shows the results for the Equation 3 when i is the Guns Right topic. After an MSE, the distance in the way of speaking about gun rights between Republicans and Democrats from states directly affected by the shooting increases compared to the other states not affected by the shooting.

In particular, after a mass shooting, the treated states register an increase of almost 0.14 percentage point in the rhetorical polarization on guns compared to the control group. The results are statistically significant at 5% in my first specification which includes date of the

Table 1: Polarization on Gun Rights Topic after MSE

	Polarization on Gun Rights			
	(1)	(2)	(3)	(4)
MSE	0.0014**	0.0014**	0.0015**	0.0016**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Mean Outcome	0.0065	0.0065	0.0065	0.0065
Observations	20,997	20,997	20,932	20,932
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the guns' topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the guns topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by Congress period FE such as: log population, share male, share white, share black, share Hispanic, share unemployed and a time varying dummy variable representing the days aroung the Primary elections for each party at the state level. In column (3) I include seasonality trends. Finally, in column (4) I introduce state by year fixed effects. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

speech and state fixed effects (column (1)). In column (2), I show my main specification including my battery of control time invariant variables interacted by year fixed effects. In column (3), I also include seasonality trends to account for periodic fluctuations in the outcome that may occur at regular intervals (in this case month level). Finally, in column (4) I run a more rigorous specification controlling for state by year fixed for taking into account any state policies change or shocks. The standard errors are clustered at the state level. In appendix, I report the same results as robustness by (i) clustering standard errors by date of the congressional meeting (Table A.8), and by (ii) using two-way clustering by both state and congressional meeting day ((Table A.9)). From these results we can understand that after a salient shock on a divisive topic, the rhetorical polarization on that topic rises sharply by between 21 and 25% with respect the mean outcome depending the specification used.
To study if and how rhetorical polarization is contagious is important to focus on how a salient shock impacts the other political topics both directly and not directly related to the divisive one. In Figure 2, I show that also the level in polarization on other topics is impacted

by the MSE. Through the LDA topic model I identify the 5 most discussed topics: social policy, economy, environment, war and defense and justice and law[11].

Figure 2 shows how the polarization in all five topics is impacted positively, with the exception of the economy[12] topic which is not statistically impacted. The figure plots the coefficients of my baseline specification (column 2) including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.

In appendix, I present the tables showing the estimates for each of the 5 topics using the different specifications used in the guns topic table (Table A.1, Table A.2, Table A.3, Table A.4, Table A.5).

The rhetorical polarization is contagious, affecting positively and significantly different themes discussed in the House of Representatives. In particular, the polarization on the social policy topics, the environment, war and defense are more impacted after a shooting in all the studied specifications. The distance between democrats and republicans from the treated states is significantly higher in these topics than in the non-affected states at the 5% significance level, while the justice and law topic is as well positively impacted by at the 10% significant level. On the other hand, the rhetorical polarization on the economy topic does not seem to be affected after an MSE, the coefficients are never statistically significant, they are always close to zero and they become negative when introducing the state by year fixed effects. Thanks to the STM topic model, I am able to decompose the five Macro topics into the more specific political topics discussed in the congressional meetings (Micro topics).

In Figure B.7 I report the estimates for the Micro topics divided by the five Macro areas. The figure shows that the Micro topics of a Macro area move all in the same directions with different magnitude confirming the results presented in Figure 2. The estimates for these topics are noisier because not all congressional meetings present a discussion about so specific topics and because the weight assigned by the topic model is lower by construction

[11] In Figure B.5 I present the 10 most used words and their betas for each topic

[12] The justice and law topic is impacted at 10% is some of the specifications and robustness. See table Table A.5.

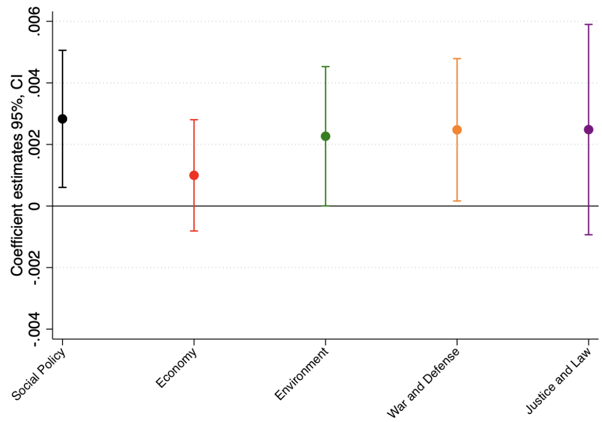


Figure 2: Polarization on the different Macro Topics and MSE

Notes: This figure shows the effect of mass shooting events on the 5 macro topics level of polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the 5 macro topics (social policy, economy, environment, war and defense, and justice and law), at time t. I show coefficients derive from my baseline specification including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period. Standard errors are clustered at state level.

for some of them because in general they are not highly discussed topics. More precisely, the rhetorical polarization on the so called "cultural identity" political topics increases, while the economic topic is not impacted. I will discuss the distinction between cultural and economic topics in the mechanism section, where I present a theoretical model based on this idea to support my finding and to show why some topics seem to be impacted more than others.

The political polarization may be contagious, as a matter of fact an increase in the polarization on a divisive topic may propagate into other political themes generating higher division than before in the way of talking. Moreover, the political polarization is a multidimensional concept, indeed, not all the levels of polarization are impacted in the same way.

6.2 Event Study Specification - Congress Speeches

To study how long this effect lasts and if it satisfies the parallel trends assumption, I exploit an event study specification following Equation 4.

Figure 3 shows how the parallel trends assumption is satisfied for the gun rights topic. Indeed, there is no statistical difference between level of rhetorical polarization on this topics in the

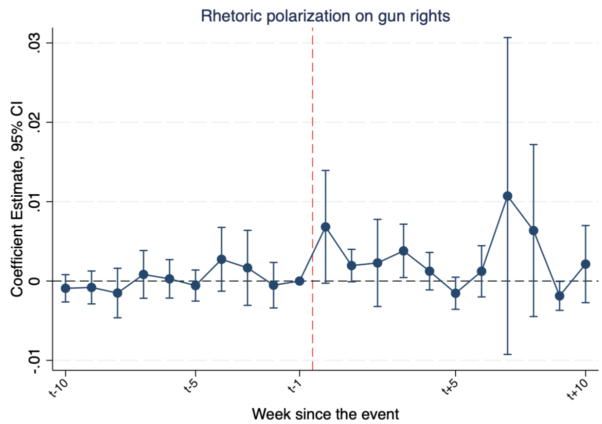


Figure 3: Polarization on Gun Right Topic after MSE, Event Study Week level (TWFE)

Notes: This figure reports the event study estimates for the gun righst topic at the week level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the week leading up to the shock. Standard errors are clustered at the state level.

treated and control groups in the weeks (and months from Figure B.6) leading up to the mass shooting. This means that the republican and democrat speakers in these states don't use different terms in talking about this topic before the event compared to the others democrat and republican speakers of the House of Representatives. While, after the treatment, they start to change their way of communication compared to their colleagues going more distant than before. More interestingly, the effect lasts for at least one month after the shooting. The effect for the gun rights topic lasts for at least 5 weeks, and it then shades away.

In appendix, I report the event study plots for the five different Macro Topics at the month level. As in the previous case, there is no statistical difference between treated and control groups in the months leading up to the mass shooting. The effect in the different topics lasts differently. These graphs are less informative than the one on the gun rights topic, but they still present a clear pattern. First of all, not statistical difference between the treated and control group before the shock and then an immediate and short lasting jump after the event.

Recent work in the econometrics literature has highlighted that two-way fixed effects (TWFE) regressions (i.e., regressions that control for unit and time fixed effects) recover a weighted average of the average treatment effect in each group and time period ((De Chaisemartin & d'Haultfoeuille 2020)). This may be problematic because weights can be negative ((Goodman-Bacon 2021)), which means that if treatment effects are heterogeneous, the TWFE estimates might be biased. I provide evidence that the impact of MSEs on the rhetorical polarization is robust to concerns related to heterogeneous treatment effects. In particular, I apply the machinery introduced by (Borusyak et al. 2021) to the difference-in-differences specifications that underlie my DiD estimates.

In Figure B.11 I present event study results using the robust estimator proposed in their paper aggregating the outcome variables at the month level to gain more power. The outcome variable in each one corresponds to a level of polarization in the different topics (Gun rights, social policy, environment, war and defense, economy and justice and law). Reassuringly, the robust estimation shows treatment effects that are very similar to the baseline estimates from the difference-in-differences specifications. Given that the estimates that underlie my main effects are robust to allowing for treatment effects to be heterogeneous, I am confident in my DiD estimates as well. To further verify this, in Table A.7 I report the DiD estimates using the Borusyak et al. (2021) estimator. Again, the TWFE estimates are robust to the different timing in treatment .

6.3 Does the saliency of the event matter?

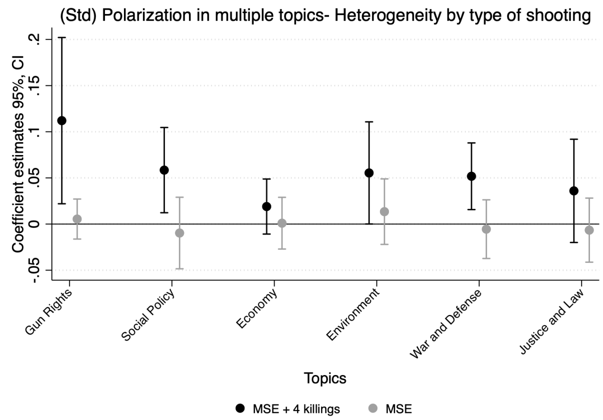
Are all the divisive events impacting polarization in the same way? I answer this question by studying different heterogeneity based on the salience of the event. I focus on two main different definitions of salience: number of fatalities of the MSE and the closeness of the MSE to the next congressional elections. The first heterogeneity should increase the importance and the public relevance of such an event. The second one should increase the attention that a politicians would invest on commenting such events. Indeed, if such an event happens close to the election, a politician may have more interest in talking about it to exploit the MSE as trigger for attracting more voters.

I defined two different dummy variables which I interact with my treatment variable: one for defining mass shooting events with more than 4 fatalities; and the second dummy is taking value 1 for those MSEs having occurred at least 6 months before the Congressional election (from May to October of each even year). These are characteristics that may generate more attention around the events, consequently attract more public attention, and/or, then, being more important for a politician. In Figure 5a, I report results for the heterogeneity based on the number of fatalities. In Figure 5b I present evidence for the heterogeneity based on the timing of the MSE. The outcome variable is the standardized level of rhetorical polarization for the gun rights topic and for the different macro topics I showed in the previous subsection. From the plots it is clear that the two definitions of salience matter in increasing the level of rhetorical polarization in different way. Indeed, an MSE involving more than 5 fatalities has a higher and statistically significant effect on polarization on the gun rights topic and on the other topics, compared to have involved less fatalities. The salience drives the majority of the findings. This evidence suggests that to activate the trigger-down effect of the political polarization the salience, in terms of how big is the event, matters. On the other hand, as concerning the timing the results are less clear. Indeed, we can't see a clear statistical difference between MSE happened close or far to election.

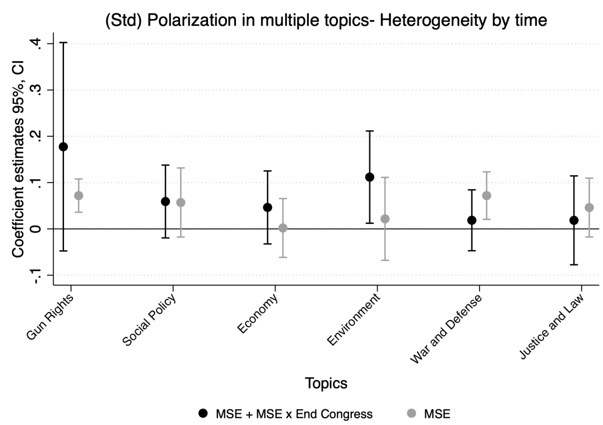
In appendix, I show a further heterogeneity for the salience by distinguishing between MSE school or not school related to understand if the location matters. For these particular MSEs the impact is not statistically difference with each other. In Figure B.13 I report these results.

7 Possible Mechanisms

This section aims to explore the underlying mechanisms behind the main findings of this study. Specifically, it addresses several key questions: How are extreme or moderate speakers influencing polarization? Is affective polarization a contributing factor? And why does polarization vary across different topics?



(a) Heterogeneity by saliency - More than 4 Killings



(b) Heterogeneity by timing - Close election events

Figure 4: Heterogeneity by salience

Notes: These figures report heterogeneity by saliecy. The outcome variables are respictively the standard level of rhetorical polarization on the gun rights, social policy, economy, environment, war and defense, and justice and law topics. In figure a, I interact the treatment with a dummy identifying thos mass shooting events with more than 5 victims; while in figure b, with a dummy identifying the last 6 months of a congressional period (May-October of each even year). The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.

7.1 Who is talking after a salient event?

In studying how the political polarization reacts after a salient shock on a divisive topic, it is relevant to understand who is talking after such an event. It is possible that after such a salient event, more extreme politicians from both parties are more inclined to speak out compared to their moderate counterparts. If this hypothesis holds true, it would justify the observed increase in polarization as a result of the heightened involvement of more extreme representatives, ultimately driving polarization across different topics.[13]. I verify this by constructing a dummy comparing extremist candidates with moderate ones as an outcome variable. Using the DW-Nominate score for each congressperson, I create a dummy variable that takes value 1 for very extreme candidates[14] and 0 otherwise.

Table 2 shows that after a salient topic, the probability that a more extremist candidate talks is not different from a moderate one. This is true in all the specifications studied. My results are not driven by the fact that after such divisive events the extremist Congresspeople speak more, or intervene, more than a normal day.

7.2 Affective Polarization

In the paper I report that after a divisive event, the level of polarization in different topics rises. However, from the literature we know that when talking about this phenomenon we should distinguish between ideological polarization and affective polarization. Affective polarization refers to the increasing negativity and animosity among individuals with differing political beliefs harbor. It is defined as *the tendency for partisans to dislike and distrust those from the other party* (Finkel et al. (2020), Iyengar et al. (2019)). In the extreme cases this may result in the dehumanization and demonization of opponents (Hopkins (2018)). This polarization can create a lack of empathy towards those with opposing viewpoints. It may also make it difficult for people to engage in civil discourse or find common ground on important issues (Flynn et al. (2017)). It is, then, important, to understand if there is a link

[13] Assuming that, more extreme politicians use a more polarized language in expressing their views.

[14] I define more extreme candidates the one with $-1 <= DWscore <= -0.5$ or $0.5 <= DWscore <= 1$. **??** uses similar bins for studying more conservative and more liberal candidates.

Table 2: Probability that an extremist representative talk after a salient shock

	DW-Nominate		
	(1)	(2)	(3)
MSE	-0.0310	-0.0040	-0.0276
	(0.0205)	(0.0592)	(0.0360)
Observations	505,056	505,056	505,056
Date FE	Yes	Yes	Yes
State FE	Yes	Yes	No
State Time Trends	No	Yes	No
State x Year-month FE	No	No	Yes

Notes: This table shows the effect of a mass shooting events on the probability that an extreme candidate talk compare to a moderate. The outcome variable is a dummy equal one if the speaker talking in the day t is an extreme one (DW-nominate at the extreme) and 0 otherwise. I control for state characteristics: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (1) I include date, and state fixed effects. In column (2) I control for State-Time trends and in column (3) I include also state times Year-month FE. Standard errors are clustered at state level. The dataset is at state-date of the speech level. Treatment is defined at the date level.

between my findings and this level of polarization.

To explore this connection, I study US Representatives Twitter feeds to see how the politicians interact with each other on the social network after a salient event[15]. Specifically, the focus is on how treated politicians communicate about their opponents compared to politicians unaffected by the event. I measure this by studying how each US Congressperson active on Twitter from 2009 to 2016 tweets about his/her counterpart after an MSE. First of all, I collect all the available tweets from US politicians active on the social network during this period. By using a regular expression, I then identify the tweets of each representative talking about another representative from the same state, but from the other party. I am able to select these tweets by searching for the account of the opponents or some specific words referring to him/her[16]. I then compute the sentiment score of each tweet by computing the number of negative words that are present in a tweet compared to the positive ones following the same procedure used before for computing my measure of rhetorical polarization.

[15]To study how the candidates of the different parties interact outside the House of Representatives with each other after a divisive shock it is crucial to understand what moves polarization (D'Amico & Tabellini (2022)).

[16]i.e., "Congressman + surname"; "Congresswoman + surname", "Rep + surname".

Table 3: Tweet about opponents after a salient event

	Sentiment on Tweets about Opponents		
	(1)	(2)	(3)
MSE	-0.1463**	-0.1457**	-0.1497**
	(0.0618)	(0.0580)	(0.0573)
Observations	12,458	12,458	12,458
Mean Outcome	0.5279	0.5279	0.5279
Week FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State x Year FE	No	Yes	Yes
Controls	No	No	Yes

Notes: This table shows the effect of a mass shooting event on the sentiment score of a tweet. The outcome variable is score computed as total positive words minus negative ones normalized by the total number of words. I am using a subsample of all the tweets: the tweets that are referring to a member of the opposite parties. The main regressor is my treatment, mass shooting event. In column (1) I control for week and Congressional District FE, in column (2) I introduce State by year fixed effects and in column (3) I control for district and individual characteristics at baseline interact by year. Standard errors are clustered at congression district level.

In Table 3 I show how after an MSE the sentiment score of tweets of a treated representative referring to the opponent decreases compared to politicians not affected by a shooting. In particular, controlling for specific characteristics of the representatives, and adding week, district and state by year fixed effects the estimates are stable and statistically significant at 5%. After an MSE, Representatives directly affected by the shock talk about their opposite members using more negative terms compared to not treated politicians. I interpret these results as an increase in the level of affective polarization which may motivate my previous results at least in part. Indeed, after such an event the conflict among politicians increases. This evidence suggests that after a trigger in a divisive topic there is a behavioral response from the politicians. They start to talk more in negative terms about their counterpart, and they attack the members of the opposite party more than before.

7.3 Politicians' strategic behavior - Theoretical Framework

Why does polarization on a divisive topic contaminate the other topics in different ways? To find an empirical answer to these questions is not easy. For this reason in this subsection I present a theoretical model which help to better understand and support my results. The idea of the model is based on the fact that politicians maximize their utility function by being re-elected. In order to be re-elected, politicians need consensus, and to do so, they need to know and follow, when possible, their electorate's positions on the different political topics. This model starts from the fact if, after these events, the electorate becomes more extreme than before it could be in the interest of a politician to follow the electorate ideological position not just as regarding the gun rights topic but also on other political issues. Specifically, my aim is to demonstrate that politicians become more polarized on topics where their electorate demonstrates a clear alignment. The underlying assumption is that politicians prefer to adopt a more polarized stance and express extreme positions on topics where their electorate is more homogeneously aligned. My theoretical framework derived by the idea of cultural and economic beliefs from Bonomi et al. (2021) and I interact it with a intra-party competition story (N. J. Canen et al. (2021)).

Political conflicts can today be divided into economic and cultural categories because these two factors often drive people's political beliefs and actions (Bonomi et al. (2021)). Economic conflicts typically arise from differences in wealth and power distribution. Cultural conflicts, on the other hand, stem from differences in values, beliefs, and attitudes towards issues such as immigration, race, and abortion. Economic and cultural values are often the underlying factors that shape political attitudes and behavior (Norris & Inglehart (2019)). From Bonomi et al. (2021) we know how individuals may respond to a salient shock on a particular topic. Indeed, following their model, a cultural shock (and mass shooting events may be considered as cultural shock) leads to increase the cultural conflict instead of the economic one. For this reason, since cultural identity gains more attention (and consequently importance) after such a divisive shock, the polarization on cultural topics increases, while the one on economic topics does not shift.

My theoretical framework leverages on this model, by adding the fact that in some topics voters assume binary positions in cultural topics, (e.g.: abortion, gun rights), while in others the discussion points are more. This model wants to show that when the topic presents a binary type of discussion after a cultural shock the probability to observe an increase in political polarization is higher because of intra-party competition. Politicians may strategically decide to polarize their opinion about cultural topic (following their own electorate), while on the economic topic they follow a median voter logic.

Following these works, I assume that the there are 2 different macro political identities: economical and cultural (Y_e and Y_c). There are three periods, $t \in \{0, 1, 2\}$. At time time $t = 0$ a cultural shock happens. Politicians then express their opinion on the topics Y_e and Y_c. There are two parties L and R. For each party $S \in \{L, R\}$ we have the following:

- Two politicians i_s and j_s who compete to become the leader of the party S
- A mass m_s of voters (we assume a continuum of total voters with mass 1) who are subscribed to the party and can select the leader of their party S (Primary election).
- There is also a mass of m_{sw} of voters who are not subscribed to any party.

The dynamic of the game is as follows:

t=0 Politicians express their opinion on the topics Y_e and Y_c.

t=1 m_L and m_R vote for the election of their party leader.

t=2 m_L, m_R and m_{sw} vote between the L leader and R leader to represent their state (or district)

Opinions are represented as points over a line $[0, 1]$ for each topic Y_k. For each Y_k, with $k \in \{e, c\}$, voters are distributed over the interval $[0, 1]$. We assume that the support of the marginal distribution over topic c is $X_c = \{0, 1\}$. Hence, voters can only adopt position 0 or 1 in terms of cultural topics. When expressing opinions, candidates try to maximize their expected utility to win both elections. When winning the first election, they get $u > \frac{1}{2}$. The utility of winning the first election is at least $1/2$ because winning the election is also useful in terms of visibility. When winning the second one, they get additional utility of 1. The probability of winning election 1 for candidate i of party S, is a function of

- her own opinion (i_s) on each topic k, denoted by $y_k^{i_s}$
- opponent opinion (j_s) on each topic k, denoted by $y_k^{j_s}$
- the distribution of S voters opinions on k, denoted by F^S[17]

We denote this probability by

$$P_1^{i_s}(y^{i_s}, y^{j_s}, F^S) \tag{5}$$

where $y^{i_s} = (y_e^{i_s}, y_c^{i_s})$, $y^{j_s} = (y_e^{j_s}, y_c^{j_s})$ and F^S is the joint distribution over the topics Y_r, Y_c of all the voters. In the same fashion, the probability of winning election 2 (conditioning on the event of winning election 1) for candidate i_s of party S, is a function of

- her own opinion (i_s) on each topic k, denoted by $y_k^{i_s}$
- other party leader opinion (i_z) on each topic k (where i_z is the leader of the party $Z \in \{L, R\} \backslash S$)
- The distribution of all the voters on each topic k, denoted by F_k

We assume m_L vote for L and m_R vote for R in the second election. We denote this probability with

$$P_{2|1}^{i_s}(y^{i_s}, y^{i_z}, F) \tag{6}$$

Observe that this probability is equal to $P_{1\cap 2}^{i_s}/P_1^{i_s}$ (whenever $P_1^{i_s} > 0$), where $P_{1\cap 2}^{i_s}$ is the probability of winning election 1 *and* election 2. Set it equal to zero when $P_1^{i_s} = 0$. F includes the mass of swing voters as well. We assume that each swing voter deterministically votes for the candidate with the closest opinion in terms of Euclidean distance. Therefore, the expected utility of politician i_s of party S is:

$$P_1^{i_s}(1 - P_{2|1}^{i_s})u + P_1^{i_s} \cdot P_{2|1}^{i_s}(u + 1) \tag{7}$$

[17] I assume that voters on cultural topics start in a more polarized position compared to economical ones, as suggested also in Bonomi et al. (2021).

which is equal to

$$P_1^{i_s} \cdot u + P_{1\cap 2}^{i_s}. \tag{8}$$

Definition 1. *We say that two politicians i and j have a polarized opinion about topic Y_k whenever*

$$y_k^i = 0 \qquad y_k^j = 1 \tag{9}$$

Definition 2. *We say that two parties S and Z have polarized opinions about Y_k whenever*

$$y_k^{is} = 0 \qquad y_k^{iz} = 1 \tag{10}$$

for any politician i_s of party S and any politician i_z of party Z.

Theorem 1. *There exists an equilibrium where parties L and R have polarized opinions on cultural topics.*

In appendix I present the proof for this theorem, and in Figure C.1 I present and discuss an example for better understand the theoretical model results. This example explains more concretely why the political polarization moves in some topics (cultural), while it does not in others (economic topics).

The theorem predicts polarization on cultural issues, meaning that opposing groups or individuals tend to take extreme positions on matters related to culture. More intuitevely, politicians anticipate polarization from their competitors within the party on cultural issues. Consequently, deviating from polarization would lead to their defeat in the first election. Since winning the initial election holds value for politicians, regardless of the outcome of the second election, they prefer to polarize in order to avoid losing votes. As a result, when we approach the second election, we observe politicians from different parties adopting extreme positions. However, this phenomenon may not occur in economic matters, as voters tend to hold less extreme positions on the subject, and politicians do not anticipate extreme stances from their competitors.

8 Policies and Congress composition

So far I show how a shock on a divisive topic impact the way politicians talk and interact with each other. I define this changes as an increase in the rhetorical polarization. Are there some consequences for the democratic process? In this last section, I study if and how a cultural shock, such as a mass shooting event, impact the democratic process. In particular, I focus on its influence on the discussion and implementation of policies in the House of Representatives. I shed some lights on this by showing how after a divisive event there is a decrease in the probability of passing a bill in the House of Representatives.

Table 4 shows how after an MSE, the probability of voting and passing a new law goes down by 4.6 percentage points. The result is significant at 1%. Controlling for the number of policies passed the previous week, and including also topic of the policy fixed effects, the result has unchanged. In column (2), with a more rigorous specification, we can see how after an MSE there is a reduction in the probability that a new law is passed in the House of Representatives by almost 4.7 percentage points compared to a normal day. It is relevant to note that divisive events make the democratic process weaker and slower by increasing the congressional gridlock. This result confirms the findings from the literature showing that polarization may generate division also in the policies proposed by the parties and impacting the congressional gridlock (Lee (2022), Gordon & Landa (2017)).

The reasons behind this result could be found in the number of speeches that characterized these highly polarized days. In Table A.12 I show that there is a positive correlation between the days following a shooting and the number of speeches and words used in the House of Representatives in the same period. These days are denoted by a higher number of speeches and words, meaning that the discussion is larger than in normal times.

Using the Voteview database, I can study the heterogeneity of the bills voted daily. Indeed, using the DW-nominate score, I can understand the leaning of a policy. The DW-nominate[18] give the score for the leaning of a policy going from -1 (ultra liberal policy) to 1 (ultra conservative policy). I generate different dummy variable depending on this score and I

[18] mid1 and mid2, see Lewis et al. (2019) for more details on how to compute these variables

Table 4: Probability to vote and pass a new policy the week after a MSE

	Probability to vote and pass a new law (1)	(2)
MSE	-0.0463***	-0.0465**
	(0.0164)	(0.0225)
Observations	4,550	4,550
Year-month FE	Yes	Yes
Topic FE	Yes	Yes

Notes: This table shows the effect of mass shooting events on the probability to vote and pass a new policy.The outcome variable is a dummy equal to one if at time t a new policy is voted and it has been passed, 0 if it is voted, but not passed. In both specification I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level.

identify three different categories of policies[19]: liberal ($-1 <= DWscore <= -0.25$), , moderate ($-0.25 < DWscore < 0.25$) and conservative ($0.25 <= DWscore <= 1$). I interact these dummies with the MSE dummy to study if there is heterogeneity in my results. In Figure 6 I report the coefficients for the interaction of each dummy with the MSE. In the regression I include year-month, and topic of the policy fixed effects. Interestingly, it is possible to notice that the results of Table 4 is completely driven by the less extreme policies. In particular, by those policies with a DW-score between -0.25 and 0.25, meaning with a more moderate leaning.

To investigate how much this effect lasts, I run an event study comparing seven days before and ten days after an MSE (the highly polarized days). I study the evolution of the probability to vote and pass a policy on different topics as a function of the event time. Specifically, I run the following regression:

$$Passed_{d,t} = \sum_{j \neq -1} \alpha_j \mathbf{I}[j = t] + \sum_k \beta_k \mathbf{I}[k = yearweek] + \epsilon_{d,t} \tag{11}$$

Where $Passed^i_{d,t}$ is a dummy equal to 1 if a policy has been voted and passed the day d at event time t, while is 0 if the policy has been voted, but it has not passed. I include a

[19] I select these thresholds by following **?**.

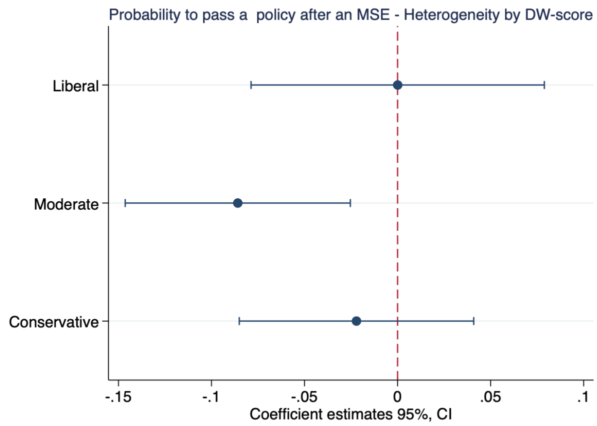


Figure 6: Probability to vote and pass a new policy after a MSE - Heterogeneity by Policy leaning

Notes: This figure shows heterogeneity in ideological by policy. The outcome variables is a dummy variable equal 1 if the policy voted has passed and 0 otherwise. Using DW-nominate score I identify three groups of policy: clearly liberal ($-1 <= DWscore <= -0.25$), clearly conservative ($0.25 <= DWscore <= 1$) and moderate ($-0.25 < DWscore < 0.25$). I interact the MSE dummy with these categorical variable controlling for year-month, and topic of the policy fixed effects. Standard errors are clustered at the congressional period level.

full set of event time $\sum_{j \neq -1} \alpha_j \mathbf{I}[j = t]$. I omit the event period just before the mass shooting event. By including a full set of specific month of the year dummies ($\sum_k \beta_k \mathbf{I}[k = yearweek]$), I control non-parametrically for underlying seasonality trends, while by including a full set of year, month and day dummies I control non-parametrically for time trends.

In Figure B.16, I report the event study for the probability to vote and pass a new policy. I study how this probability moves comparing seven days before and ten days after an MSE. Figure B.16 highlights how in the seven days before the shooting there is not statistical difference between passing and not a new policy, while, after the event, this probability goes down significantly. I include time and topic of the policy fixed effects in this specification, Furthermore, I am controlling for the ideological position of the policies voted (DW-nominate, mid). Interestingly, following the policies not passed after a mass shooting, so during a period of higher polarization, and comparing them to the other policies not passed in a normal time, the first has even less probability of being voted and passed in the future. Table 5 shows exactly this results. Using a score similarity approach, I follow the policies over time. I consider a policy to be the same if it has a score similarity greater or equal to 80% and if

Table 5: Probability to vote and pass a new policy not passed after a MSE

	Probability to pass in the future	
	(1)	(2)
MSE	-0.1796***	-0.1718***
	(0.0370)	(0.0278)
MSE X extreme		-0.0144
		(0.1077)
Observations	3,528	3,528
Mean Outcome	0.5890	0.5890
Year-Month FE	Yes	Yes
Topic FE	Yes	Yes

Notes: This table compare policies not passed in the 20 days after a mass shooting to the other policies that have not passed in normale time.The outcome variable is a dummy equal to one if at time t a policy is voted and it has been passed, 0 if it is voted, but not passed. The treatment is a dummy indicator equal 1 if the policy in consideration has been voted and not passed after an MSE, and 0 if the policy has not been passed in normal time. In column (2) I show that the effect is complitely driven by the moderate policies. In both specification I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level. Standard errors are clustered at the congressional period level.

the policy is voted again in the same congressional period of the first vote. Table 5 shows that these policies voted and not passed for the first time in a highly polarized period have 18 percentage point less probability of passing in the future compared to other policies not passed for the first time in normal times. Again, the results are completely driven by the moderate policies, while there is no effect for the ultra liberal or ultra conservative ones (column (2)). These results, with the previous ones, show that there is an impact of polarization also on policy-making, confirming in part the previous literature, but adding that the effects also have a long-lasting impact on the congressional gridlock. A policy voted and not passed for the first after a MSE needs to be modified more than another policy voted and not passed in normal times (far from a divisive event).

8.1 Congress Composition

In the previous subsection I show how after a divisive event, the probability to pass a new policy is negatively affected. This effect lasts not just in the short term, but also in the medium-long run. Indeed, those policies not passed after an MSE have a lower probability to be passed in the future compared to other policies that need more rounds to be approved by the House of Representatives. In this section I discuss whether contagious polarization affect also future congress composition. I study this by investigating how the composition of the House of Representatives changes after such a divisive shock.

Previous literature showed that after an MSE the probability to vote for the Republican party decreases (Yousaf (2021)) and that there is an impact in the policy preferences of individuals in the states affected by the shock (Luca et al. (2020)). Less is known about the composition of the politicians, and on the candidates characteristics. In particular, we don't know if after an MSE the probability to elect a Democrats or a Republicans is impacted and if there is an increase in the probability to have a more extremist candidate. For this analysis, I focus on a district-congressional period level dataset and I compare Congressional Districts (CDs) affected by an MSE to CDs not affected before and after the occurrence. In Table A.13, I show that after a divisive event the probability to have a Republican or Democratic candidate does not change. Indeed, there is no statistically significant effect in either of my specifications. This contributes to the literature, by showing that, even if it seems that the electorate starts to vote less for the republican party (Yousaf (2021)) this effect it is just marginal and it is not sufficient to change the composition of the House of Representatives.

On the other hand, running the same analysis using as outcome variable a dummy taking value 1 when the elected candidate is an extreme one and 0 otherwise, there is a statistically significant effect. In Table 6 I show exactly these results. Using the DW-Nominate score (Lewis et al. (2019)), I identify as extreme candidate (**?**) one with a score between 0.5 and 1 (ultra conservative) or -0.5 and -1 (ultra liberal). Using a difference-in-differences approach I compared candidate in CDs with and without a MSE before and after the event. In the congressional period after the shock the probability to have a more extreme representative increases by 7 percentage points in all my specification. In the most complete specification I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of

Table 6: Probability to have a more extreme candidate after a MSE

	Probability of electing extreme candidate			
	TWFE	TWFE	BJS	BJS
	(1)	(2)	(3)	(4)
MSE	0.0660**	0.0726**	0.0732**	0.0727**
	(0.0298)	(0.0287)		
Congress FE	Yes	Yes	Yes	Yes
Congressional district FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean Outcome	0.2954	0.2954	0.2954	0.2954
Observations	3,695	3,695	3,695	3,695

Notes: This table shows the effect of mass shooting events on the probability to have a more extreme US Representative in the future.The outcome variable is a dummy equal to one if the US Representative is an extreme candidate identified using DW Nominate. In the first two columns I present TWFE estimations controlling for Congressional peiod and Congressional District FEs and including control variables. In the last two columns I show the same results by using Borusyak & Jaravel (2017) estimator. The standard errors are clustered at the Congressional District level.

the incumbent candidate and I include congressional period and congressional district fixed effects. The results are robust to the new Borusyak et al. (2021) estimator (column (3) and (4)). Running an event study approach, I show in Figure 7 that the effects are statistically persistent for 4 congressional periods after the treatment. Using again the Borusyak & Jaravel (2017) estimator, I confirm my TWFE event study results in Figure B.17.

These evidences show that a divisive event such as an MSE, have long lasting effects on the candidates selection. Even if the effects on the rhetorical polarization seem to disappear in the short term, places affected by an MSE are electing more extreme candidates while the probability to elect a candidate from a party or the other does not change. This means that there is a change in the selection of the candidates running for the Primary elections (intra-party polarization N. J. Canen et al. (2021)). Further research should investigate this more by studying how a divisive shock impact the Primary election and if the election of more extreme candidates is supply or demand driven.

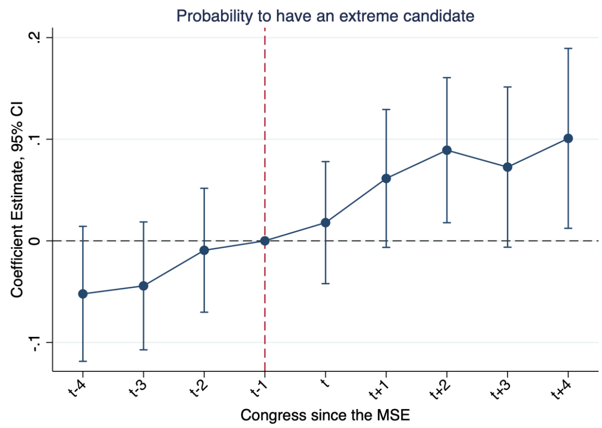


Figure 7: Probability to have a more extreme candidate after a MSE - Event Study

Notes: This figure shows event study estimates for the probability to elect an extreme candidate before and after a divisive shock (MSE). The outcome variables is a dummy variable equal 1 if the candidate is extremist and 0 otherwise identified using DW-nominate score. I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of the incumbent candidate and I include congressional period and congressional district fixed effect. Standard errors are clustered at the congressional district level.

9 Conclusion

Political polarization has reached unprecedented levels in Western democratic countries, especially in the United States. The existing literature attributes this phenomenon to various political, economic, and social factors, some of which have long-term effects, while others impact polarization temporarily. Previous research has primarily approached political polarization as a unified concept, focusing on its evolution over the medium to long term. However, it is evident that polarization varies across different political topics at any given moment. Furthermore, it is important to understand how different political issues intersect and shape polarization is essential. By exploring the interconnections of these topics, we can gain insights into how they collectively contribute to the overall level of polarization.

In this paper, I show that after a salient shock on a relevant and divisive political topic, such as gun rights for the US, there is a causal consequence of politicians' way of speaking, which I define as rhetorical polarization. The study measures political polarization by analyzing the official speeches of US Representatives, employing text analysis techniques. This measure captures the contrast in the way individuals from different political parties communicate about the same issue.

By examining the occurrence of mass shootings as a source of variation and trigger to the polarization on the gun rights topic. The paper employs a dynamic difference-in-differences design, comparing the rhetorical polarization of politicians from states directly affected by mass shootings with those not impacted before and after the occurrence.

The findings demonstrate that after a mass shooting event, politicians' rhetorical polarization increases not only on gun-related topics but also on other unrelated subjects, such as social policy, war and defense, environment, and justice. This suggests that polarization is contagious and should be understood as a multidimensional phenomenon, especially in the short term. Interestingly, the results are driven by those MSEs which involved more fatalities, meaning that the salience of the events matters for generating contagious effects. Using an event study approach, I show that there is no statistical difference between treated and control groups in the months (and weeks) leading up to the mass shooting. Furthermore, the effect lasts for at least one month of discussion after the shooting.

The paper investigates and discusses potential mechanisms underlying these findings, focusing on the communication patterns of politicians after these salient events. The study develops a theoretical framework to shed light on why cultural topics may elicit stronger reactions compared to economic issues.

After such events, the probability that an extreme candidate speaks is not statistically different from a moderate one.

Moreover, I proxy for affective polarization using the Twitter feed of the US Representatives. After an MSE, the treated politicians are referring to their opponents using more negative terms than before. This evidence suggests that, at least in part, my findings may be explained by an increase in the affective polarization among politicians. These findings contribute also to the sociology literature on the affective polarization, showing that this phenomenon may be present among the elites as well.

In addition to examining the immediate effects, the paper explores the consequences of divisive events on policy-making. It demonstrates that after such events, the probability of passing new policies decreases, confirming previous research that links polarization to congressional gridlock. Using a similarity score index, I follow these policies over time, showing that they have even less probability of passing in the future compared to other policies that did not pass in normal times. These findings indicate that divisive events may have enduring effects on policy-making.

Finally, the paper reveals that mass shooting events can impact the future composition of the House of Representatives. In the Congressional Districts affected by such events, there is a higher probability of electing an extreme candidate in the future, regardless of party affiliation. This suggests that the effect is not specific to Democrats or Republicans but rather leads to the election of more extreme candidates compared to the previous representatives of those districts.

In conclusion, this paper demonstrates that a salient shock on a divisive topic can contribute to shifts in political polarization. Furthermore, political polarization exhibits contagious properties across different topics, leading to a trickle-down effect on other political issues. The study highlights the multidimensional nature of political polarization, as not all topics experience an increase in partisanship. These findings are significant as they have long-lasting implications for policy-making and the future composition of Congress. Overall, the results emphasize that even random and infrequent events can play a crucial role in the polarization of politicians.

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Appendix

A Tables

Table A.1: Polarization on Social Policy Topic after MSE

	Polarization on Social Policy			
	(1)	(2)	(3)	(4)
MSE	0.0028***	0.0028***	0.0026**	0.0044
	(0.0010)	(0.0010)	(0.0010)	(0.0032)
Mean Outcome	0.0308	0.0308	0.0308	0.0308
Observations	20,997	20,997	20,974	20,979
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the social policy topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the social policy topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.2: Polarization on Economy Topic after MSE

	Polarization on Economy			
	(1)	(2)	(3)	(4)
MSE	0.0010	0.0011	0.0009	-0.0028*
	(0.0006)	(0.0007)	(0.0007)	(0.0015)
Mean Outcome	0.0330	0.0330	0.0330	0.0330
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the economy topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the economy topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.3: Polarization on Environment Topic after MSE

	Polarization on Environment			
	(1)	(2)	(3)	(4)
MSE	0.0020**	0.0021**	0.0018**	0.0026***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Mean Outcome	0.0219	0.0219	0.0219	0.0219
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the environment topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the environment topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.4: Polarization on War and Defense Topic after MSE

	Polarization on War and Defense			
	(1)	(2)	(3)	(4)
MSE	0.0025***	0.0025***	0.0025***	0.0034*
	(0.0009)	(0.0008)	(0.0009)	(0.0018)
Mean Outcome	0.0272	0.0272	0.0272	0.0272
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the war and defense topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the war and defense topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.5: Polarization on Justice and Law Topic after MSE

	Polarization on Justice and Law			
	(1)	(2)	(3)	(4)
MSE	0.0015*	0.0014*	0.0027	0.0031
	(0.0008)	(0.0007)	(0.0022)	(0.0035)
Mean Outcome	0.0477	0.0477	0.0477	0.0477
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the justice and law topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the justice and law topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

A.1 Different Time Windows

Before showing the event study and that the parallel trends assumption is satisfied, it is important to show the same results presented before using shorter time windows in order to understand if the levels in political polarization are mainly impacted immediately after an MSE and that the effect is stronger in the short term. To study this, I run the same specification discussed before, but using shorter time windows. This method allows me to exploit all the multiple treatments happening in the same Congressional period and see if the results remain the same in terms of magnitude and significance level. In Table A.6 I report the estimates for these different dynamic difference-in-differences. From these coefficients it is possible to state that the effect is stronger immediately after the shock and that it then decreases over time. In the month after an MSE, the polarization in the Gun Rights polarization increases by 0.36 percentage points at 1% confidence interval, while 1 semester and 1 year after it increases respectively by 0.4pp and 0.26pp respectively. I present the results using the most complete specification including date of the speech FE, state by year fixed effects, seasonality trends and my battery of controls.

Table A.6: Polarization on Gun Right Topic after MSE - Different Time Windows

	Polarization on Gun Rights		
	(1)	(2)	(3)
MSE month window	0.0036***		
	(0.0011)		
MSE semester window		0.0040***	
		(0.0014)	
MSE year window			0.0026***
			(0.0009)
Mean Outcome	0.0065	0.0065	0.0065
Observations	20,997	20,997	20,997
Date of Speech FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Seasonality Trends	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Controls x Congress	Yes	Yes	Yes

Standard errors are clustered at the State level

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the effect of mass shooting events on the guns' Topic Polarization. The outcome variable is computed as the absolute difference between the Republican Position and the Democratic Position from state s, on the guns Topic, at time t. I control for date of the speech and state fixed effects. I include state linear trends and control at baseline interacted with year fixed effects as well. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting till the end of the time window (1 month, semester or year after the MSE, respectively column(1), column (2) and column (3)).

Table A.7: Polarization on Macro Topics after MSE - Borusyak et al. (2021) estimator

	(1)	(2)	(3)	(4)	(5)	(6)
	Gun Rights	Social Policies	Economy	Environment	War and Defense	Justice and Law
MSE	0.0004**	0.0048***	0.0021	0.0023**	0.0047**	0.0030*
	(0.0001)	(0.0009)	(0.0016)	(0.0004)	(0.0023)	(0.0016)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different macro topics. The outcome variable are respectively the standardized levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic . These coefficients are generated using the new machinery suggested by Borusyak & Jaravel (2017) for controlling for the fact that treatment varies across times (staggered time). I control for date of the speech and state fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.8: Polarization on Macro Topics after MSE - Standard errors clustered at date of the congressional meeting

	(1)	(2)	(3)	(4)	(5)	(6)
	Gun Rights	Social Policies	Economy	Environment	War and Defense	Justice and Law
MSE	0.0015**	0.0026*	0.0009	0.0021*	0.0025**	0.0024
	(0.0006)	(0.0016)	(0.0012)	(0.0013)	(0.0012)	(0.0020)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different topics. The outcome variable are respectively the levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic. These coefficients are generated using the prefferred specifications controlling for the date of the speech, and state fixed effects, and for the seasonality trends and including the battery of controls. Standard errors are clustered at day of the congressional meeting level. The dataset is a state by date of congressional meeting panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.9: Polarization on Macro Topics after MSE - Standard errors clustered at date of the congressional meeting and state level

	(1)	(2)	(3)	(4)	(5)	(6)
	Gun Rights	Social Policies	Economy	Environment	War and Defense	Justice and Law
MSE	0.0015***	0.0026**	0.0009	0.0021*	0.0025**	0.0024
	(0.0005)	(0.0012)	(0.0009)	(0.0012)	(0.0012)	(0.0019)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different topics. The outcome variable are respectively the levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic. These coefficients are generated using the prefferred specifications controlling for the date of the speech, and state fixed effects, and for the seasonality trends and including the battery of controls. Standard errors are clustered at day of the congressional meeting and state level. The dataset is a state by date of congressional meeting panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table A.10: Specific words used by Republicans and Democrats about guns

Control		Treated	
Dem	Rep	Dem	Rep
victims	illegal	suspected	stopped
silence	prohibited	buy	attack
commonsense	list	walk	shot
mass	sale	loophole	murdered
killed	law	purchase	violent
deadly	ban	weapon	prayers
tragedy	shows	prevent	thoughts
children	criminal	ban	happened
violent	dealers	legally	killing
innocent	used	crime	taken

Notes: This table shows the specific words used by treated and control republican and democrat speakers about the guns topic. Using the ALC embedding tool I identify the most common words used around the word: ”gun”.

Table A.11: Specific words used by Republicans and Democrats about second amendment

Control		Treated	
Dem	Rep	Dem	Rep
act	liberty	gun	constitution
legislation	freedom	legislation	protected
issue	exercise	firearms	fundamental
must	fundamental	issue	liberty
bill	protecting	reason	citizens
strongly	arms	case	protecting
provision	obligation	commonsense	obligation
colleagues	responsability	case	freedom
support	property	act	liberties
gun	bear	control	defend

Notes: This table shows the specific words used by treated and control republican and democrat speakers about the second amendment. Using the ALC embedding tool I identify the most common words used around the bigram: ”second amendment”.

Table A.12: Number of Words and Speeches the day after a MSE

	(1) Number of Words	(2) Number of Speeches
MSE	272.2040***	3.1618***
	(14.9592)	(0.0585)
Mean_outcome	50361.99	81.9430
Year-Month FE	Yes	Yes
Observations	4,550	4,550
Adjusted R^2	0.196	0.317

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the effect of mass shooting events on the number of speeches and words. I include year-month fixed effects. The dataset is a time series by date of the speech. Treatment is defined at the date level.

Table A.13: Probability to have a Representatives of one of the two parties after a MSE

	Probability of electing Democratic candidate			
	TWFE	TWFE	BJS	BJS
	(1)	(2)	(3)	(4)
MSE	-0.0005	0.0159	-0.0503	-0.0323
	(0.0306)	(0.0299)	(0.0342)	(0.0323)
Congress FE	Yes	Yes	Yes	Yes
Congressional district FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean Outcome	0.4858	0.4858	0.4858	0.4858
Observations	3,695	3,695	3,695	3,695

Notes: This table shows the effect of mass shooting events on the probability to have a Democratic US Representative in the future.The outcome variable is a dummy equal to one if the US Representative is from the Democratic party. In the first two columns I present TWFE estimations controlling for Congressional peiod and Congressional District FEs and including control variables. In the last two columns I show the same results by using Borusyak & Jaravel (2017) estimator. The standard errors are clustered at the Congressional District level.

B Figures

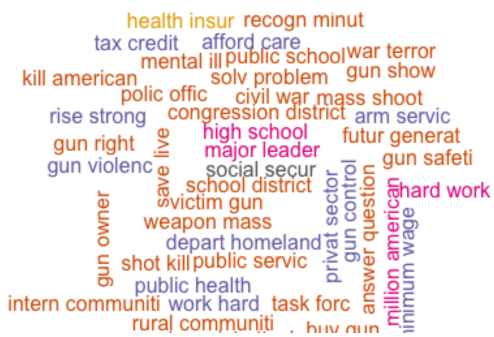


Figure B.1: Word Cloud - Gun Bigrams

Notes: This figure shows a word-cloud with the 50 bigrams that have the highest weight for the gun rights topic.

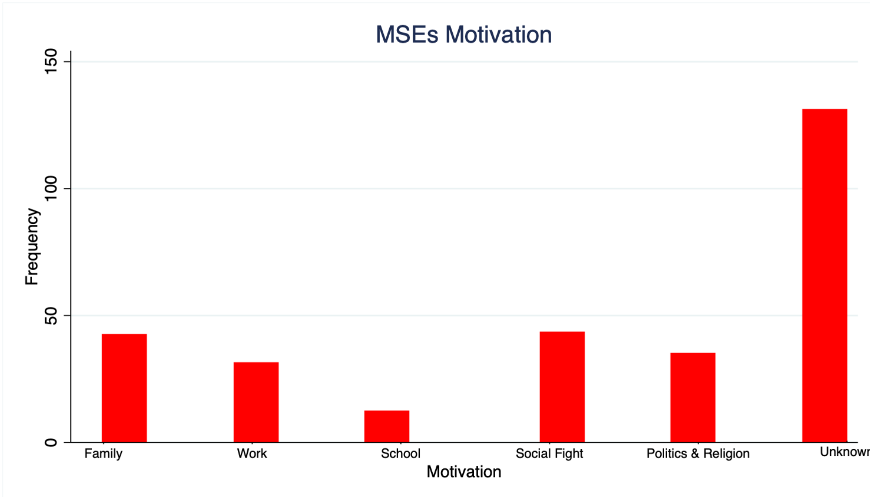


Figure B.2: Motivation of mass shooting events

Notes: This figure shows the frequency of the mass shooting events' motivations. The motivation are assigned by the FBI.

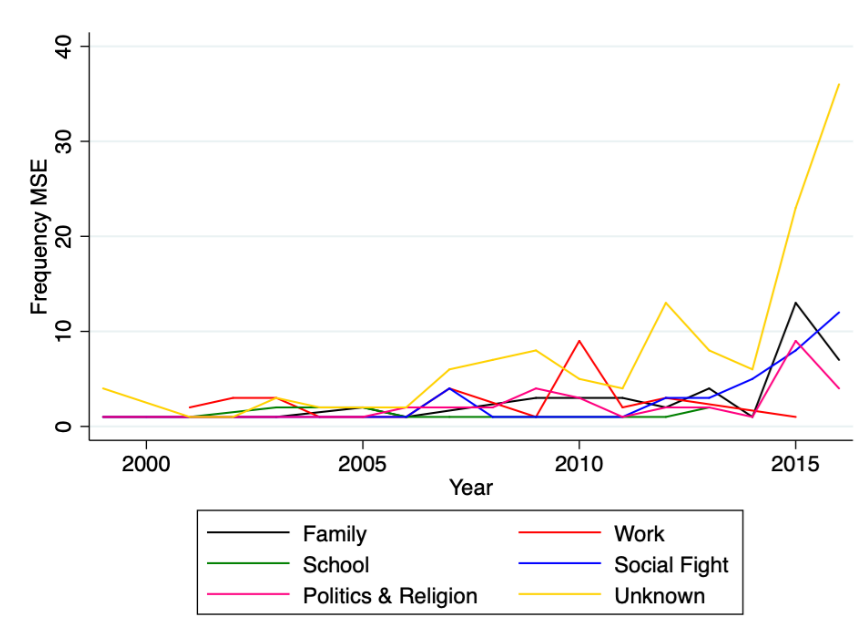


Figure B.3: Variation over years of mass shooting events

Notes: This figure shows the variation over years of the mass shooting events.I plot this variations by motivation.

B.1 Sentiment Analysis and Topic Model

Before applying the sentiment analysis and topic models to my corpus of speeches I apply the pre-processing tranformation to normalize the text (Ash & Hansen (2023)). I, first, remove punctuation, hyphens, apostrophes, numbers, "stop-words" (common words in English). At this point, after having severely reduced the number of words, I transform each word to their stems following the Porter algorithm (Porter et al. (2002)). Finally, I remove the rare and common words by applying a TF-IDF (term frequency-inverse document frequency). After these cleaning procedures I end up with a corpus composed by each cleaned speech presenting words that appear at least 100 times and in at least 10 documents. In the next section, I will explain more in details these procedures and the other tools I implement for constructing my measure of rhetorical polarization.

The paper uses a dictionary-based sentiment analysis to identify negative and positive words in a speech. The dictionary-based methods find the sentiment of a piece of text by adding up the individual sentiment scores for each word in the text. There are various ways and dictionaries for evaluating the opinion or emotion in texts. In this work, I use two different lexicons together: "NRC" (Mohammad & Turney (2013))) and "BING" (Liu & Zhang (2012)). These lexicons are based on unigrams, i.e., single words, and they contain many English words. A score for positive/negative sentiment is assigned to each word. Not all the words are in the lexicons because of the neutrality of some words. Following this procedure, I assign a quantitative measure to each speech based on the number of positive and negative words in the speech. I then correct for some specific language constructions[20]

To understand the topic of a speech I exploit two different topic models: LDA and STM. These two models are very similar to each other as regarding the technical procedure. Both these techniques are generative probabilistic model for collections of discrete data such as text corpora. They are three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In

[20]When some negative terms such as "not" appears in front of a negative or positive word, the sentiment is reverted.

the context of text modeling, the topic probabilities provide an explicit representation of a document (in this case, a document is a single speech). The intuition behind is that a distribution of topics can describe a distribution of words that can explain each speech and each topic. STM is particularly useful for this work because it employs metadata about documents (such as the name of the author, the date in which the document was produced or the party) to improve the assignment of words to latent topics in a corpus. STM is a mixture model, where each document can belong to a mixture of the designated k topics. In choosing the STM model or assessing the goodness of fit, two measures can be used: semantic cohesion and exclusivity (Roberts et al. (2014)). A topic is cohesive when high-probability terms for a topic occur together in documents. A topic is exclusive if the top words of the topic are not likely also to be top words in other topics. This model is also handy for the very high-quality R package available for implementing it. Moreover, this model does not need any predetermined decisions, but it can understand the number of topics presented in the documents. This allows me to identify the most discussed topics from all speeches.

Figure B.4: Word Clouds of Negative and Positive - Sample

Notes: This figure shows a word-cloud representing a sample of negative-positive words. In blue I show the negative words assigned by my algorithm and in red the positive ones.

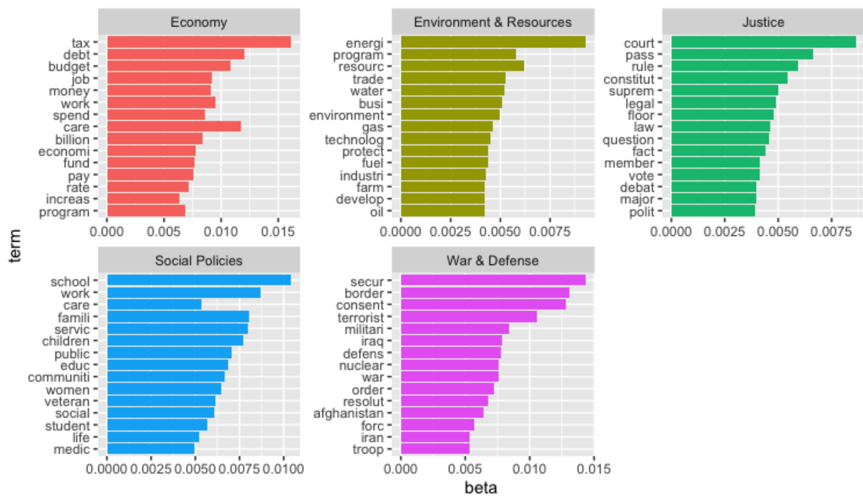


Figure B.5: Topic Model - LDA

Notes: This figure shows the results of an LDA topic model run on the congressional speeches. I identify the 5 Macro topics: Economy, Environment, Justice and Law, Social Policies and War and Defense.

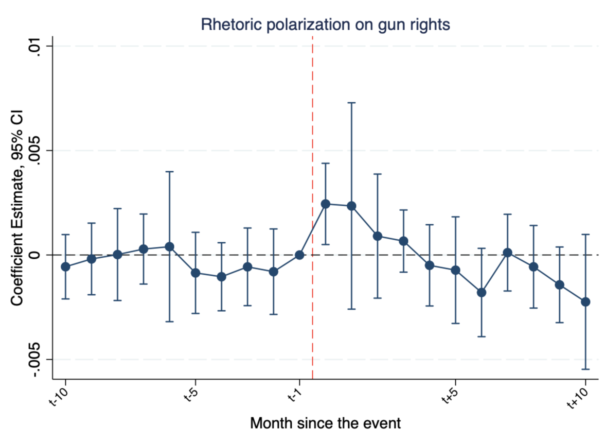
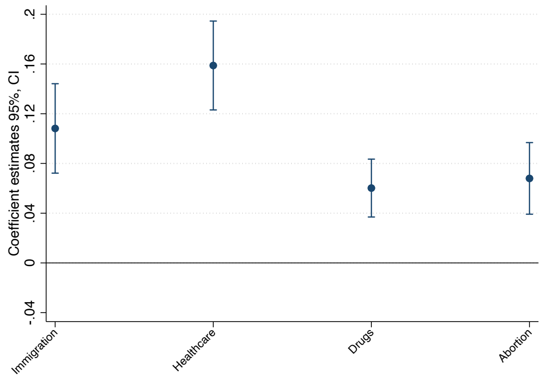
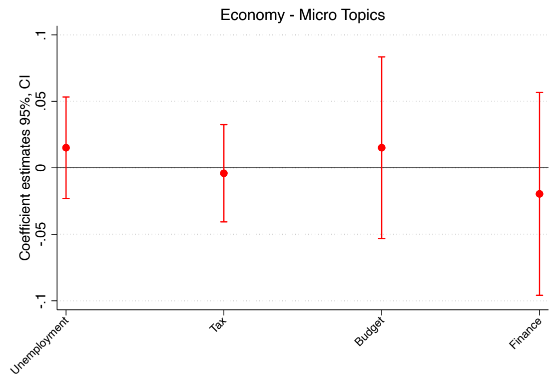


Figure B.6: Polarization on Gun Right Topic after MSE, Event Study Month level (TWFE)

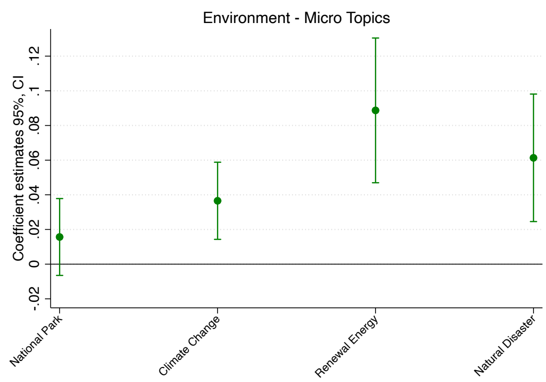
Notes: This figure reports the event study estimates for the gun righst topic at the month level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the month leading up to the shock. Standard errors are clustered at the state level.



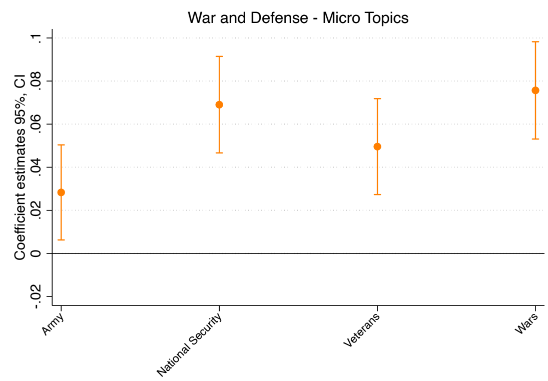
(a) *Social policy*



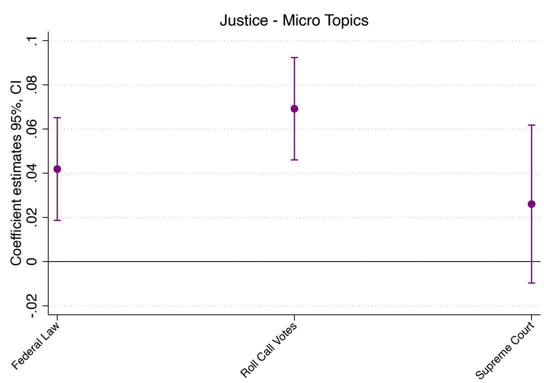
(b) *Economy*



(c) *Environment*



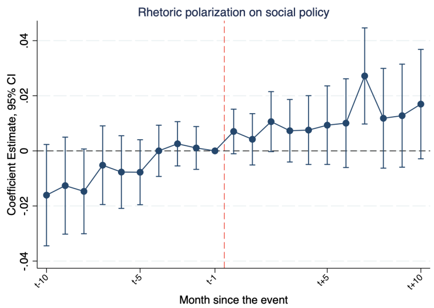
(d) *War and defense*



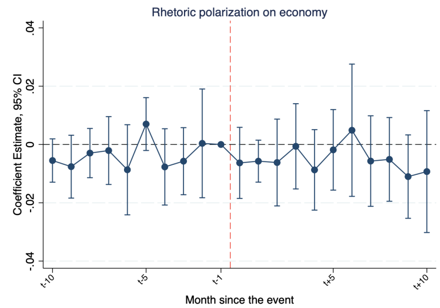
(e) *Justice and Law*

Figure B.7: (Std) Polarization on the different Micro Topics and MSE

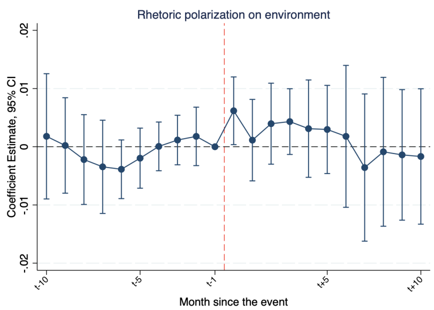
Notes: This figure shows the effect of mass shooting events on the micro topics level of polarization divided by the 5 macro topic. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the a topic identified using a Structural Topic Model, at time t. The outcome variables are standardized. I show coefficients derive from my baseline specification including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period. Standard errors are clustered at state level.



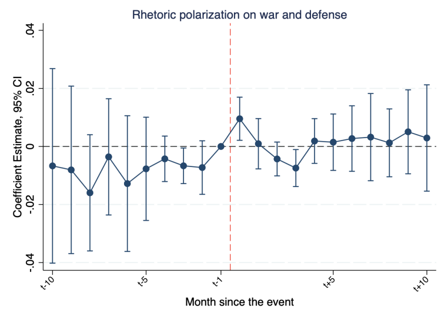
(a) *Social Policy*



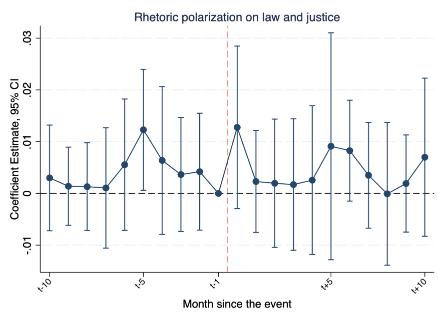
(b) *Economy*



(c) *Environment*



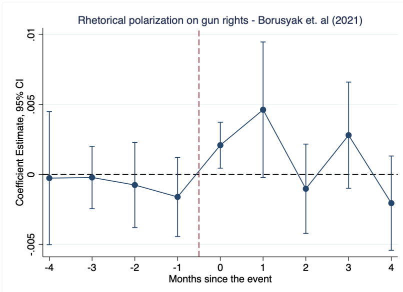
(d) *War and Defense*



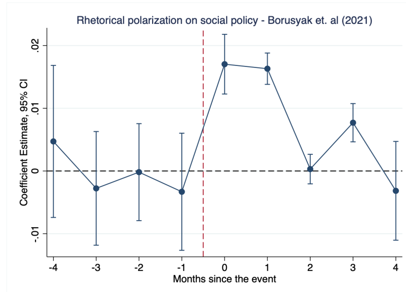
(e) *Justice and Law*

Figure B.9: Polarization on the different Macro Topics and MSE, Event Study

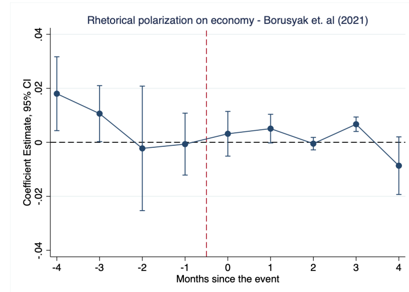
Notes: This figure reports the event study estimates for the 5 Macro topics at the month level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the month leading up to the shock. Standard errors are clustered at the state level.



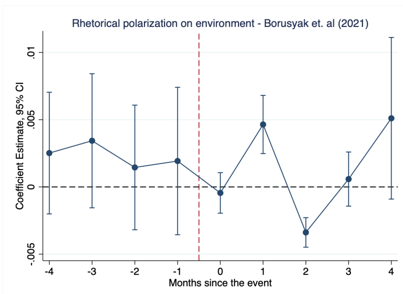
(a) *Gun rights*



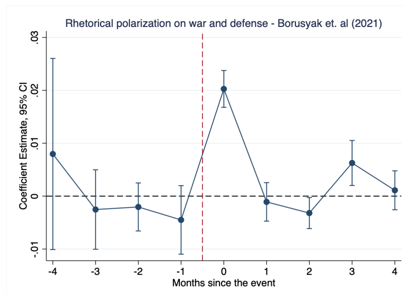
(b) *Social policy*



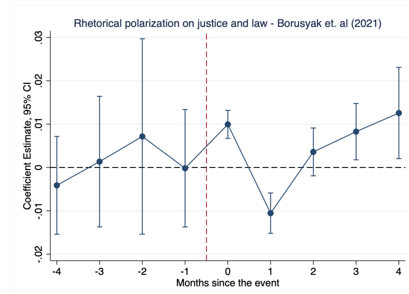
(c) *Economy*



(d) *Environment*



(e) *War and Defense*



(f) *Justice and Law*

Figure B.11: Event Study - Borusyak et. al. (2021)

Notes: This figure reports the event study estimates for the 5 Macro topics at the month level using the Borusyak et al. (2021) machinery for taking into account the time heterogeneity of the treatment. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. Standard errors are clustered at the state level.

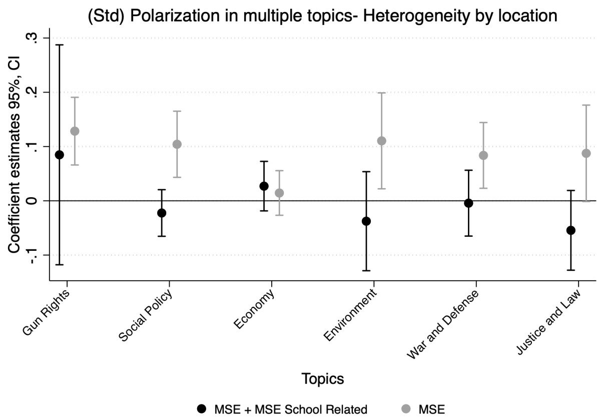
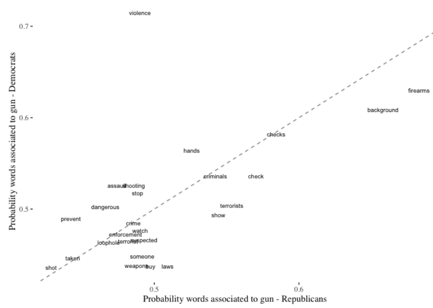
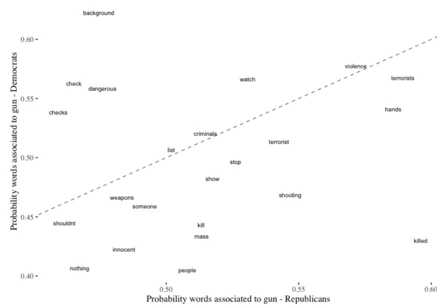


Figure B.13: Heterogeneity by saliency - School related

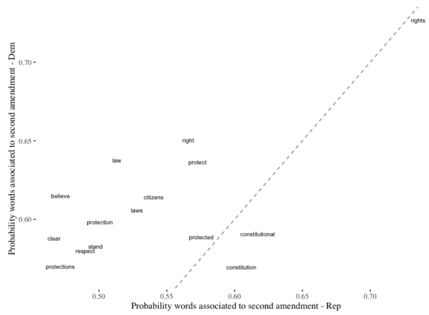
Notes: This figure reports heterogeneity by saliecy. The outcome variables are respictively the standard level of rhetorical polarization on the gun rights, social policy, economy, environment, war and defense, and justice topics. I interacted my treatment witha dummy identifiying those mass shooting events school related. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.



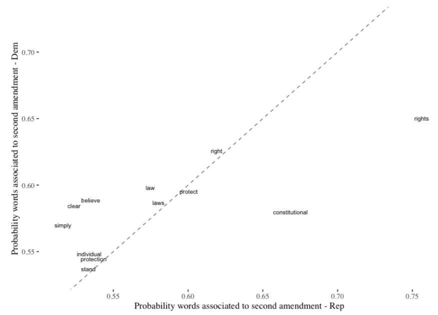
(a) *Gun Violence - Control Group*



(b) *Gun Violence - Treated Group*



(c) *Second Amendment - Control Group*



(d) *Second Amendment - Treated Group*

Figure B.14: Cosine similarity associated to Gun Violence and Second Amendment

Notes: These graphs show the words with the highest cosine similarity associated to the focal bigrams ”gun violence” and ”second amendment”. I plot on the y axis the probability assigned to the democratic candidates and in the x axis the one assigned to the republican party. The dashed grey line is a 45 degree line. For each focal bigrams I plot one graph for the control group and one for the treated group.

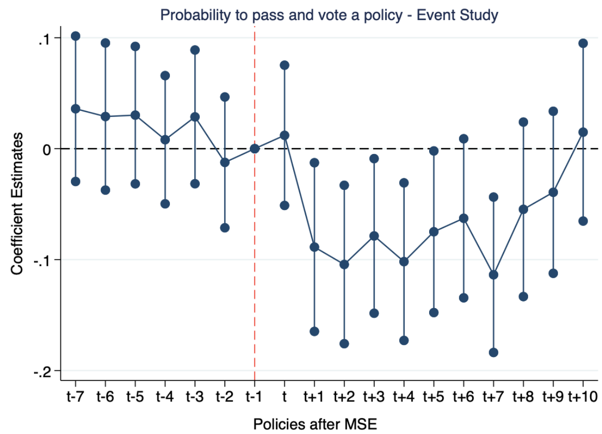


Figure B.16: Probability to vote and pass a new policy

Notes: This figure shows event study for the probability to vote and pass a new policy. I am comparing the probabiity to pass a new policy before and after a mass shooting event. I focusing on a 20 congressional meeting days window. The omitted category is the last congressional meeting before the shooting.The outcome variable is a dummy equal to one if at the congressional meeting day t a new policy is voted and it has been passed, 0 if it is voted, but not passed. I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level.

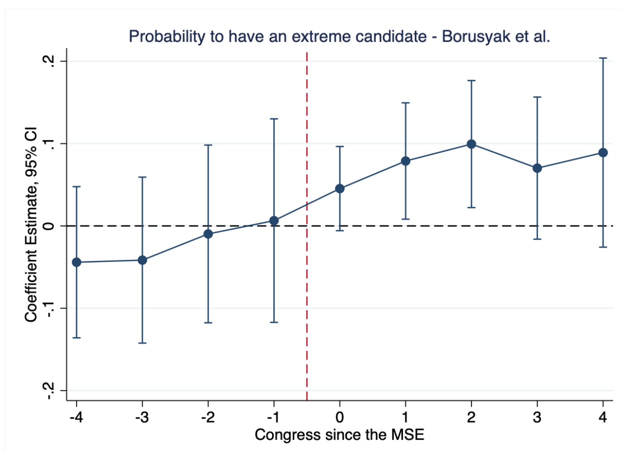


Figure B.17: Probability to have a more extreme candidate after a MSE - Event Study, Borusyak et. al

Notes: This figure shows event study estimates for the probability to elect an extreme candidate before and after a divisive shock (MSE). I use the Borusyak et al. (2021) command for accounting the heterogeneity in time of my treatment. The outcome variables is a dummy variable equal 1 if the candidate is extremist and 0 otherwise identified using DW-nominate score. I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of the incumbent candidate and I include congressional period and congressional district fixed effect. Standard errors are clustered at the congressional district level.

C Theoretical Model - Proof and Example

Proof. Consider party S such that $F_c^S(0) = 1$, where F_c^S is the marginal distribution of voters subscribed to party S over the topic c. Now, suppose two candidates s_1 and s_2 are competing for the leadership of party S while z_1 and z_2 are competing for the leadership of party $Z \in \{L, R\} \backslash S$. Assume $y_c^{s_2} = 0$ and $y_c^{z_1} = y_c^{z_2} = 1$. First, we prove that $y_c^{s_1} = 1$ cannot be optimal for player s_1. In fact, observe that the minimum distance between s_1 position (i.e., opinion) and any S voter's position is at least one. The maximum distance, instead, between s_2 position and any S voter's position is less than one. Therefore, $P_1^{s_1} = 0$, and since by definition $P_{1\cap 2}^{s_1} \leq P_1^{s_1}$, we have that s_1 utility is 0. A profitable deviation is $(y_c^{s_1}, y_e^{s_1}) = (y_c^{s_2}, y_e^{s_2})$. In fact, in this case, $P_1^{s_1} = \frac{1}{2}$ and the expected utility is $P_1^{s_1} \cdot u + P_{1\cap 2}^{s_1} > 0$. Therefore, we must have $y_c^{s_1} < 1$. Hence, assume $y_c^{s_1} \in (0, 1)$. Suppose we are in equilibrium. Then, $P_1^{s_1} = P_1^{s_2} = \frac{1}{2}$,[21] and clearly $y_e^{s_1} \neq y_e^{s_2}$ (otherwise $P_1^{s_2} = 1$). Moreover, $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2}$ (otherwise either s_1 wants to imitate s_2 or vice-versa). Observe that $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_s} \in \{0, 1/4, 1/2\}$ in equilibrium, as $P_{2|1}^{s_1} \in \{0, 1/2, 1\}$ and $P_1^{s_1} = \frac{1}{2}$. Therefore, first suppose $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = 0$. Then, s_2 can set $y_e^{s_2} = y_e^{s_1}$, so that s_2 is closer to any S voter than s_1, and hence $P_1^{s_2} = 1$. Since $P_{1\cap 2}^{s_2}$ is unchanged, this is a profitable deviation, a contradiction. Now, assume $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = \frac{1}{4}$. Again, change s_2 position on topic r, so that $y_e^{s_2} = y_e^{s_1}$. As before, $P_1^{s_2} = 1$. In the worst case scenario, this implies $P_{1\cap 2}^{s_2} = 0$. Yet,

$$1 \cdot u + 0 > \frac{1}{2} \cdot u + \frac{1}{4}$$

since $u > \frac{1}{2}$. Therefore, we still have a profitable deviation. Finally, assume $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = \frac{1}{2}$. In equilibrium, it is not a profitable deviation for s_2 to imitate s_1 on topic r. Since the expected utility that s_2 obtain when setting $y_e^{s_2} = y_e^{s_1}$ is $u + \tilde{P}_{1\cap 2}^{s_2}$ (where $\tilde{P}_{1\cap 2}^{s_2}$ is the new

[21] Since there are two candidates and voters' choice is deterministic, we must have $P_1^i \in \{0, 1/2, 1\}$. If $P_1^i = 1$, then $P_1^j = 0$ (where j is i's competitor), and j could increase this probability by assuming i's position, hence we would not be in equilibrium.

probability of winning both elections when imitating s_1 on topic r), we must have that

$$1 \cdot u + \tilde{P}^{s_2}_{1\cap 2} < \frac{1}{2} \cdot u + P^{s_2}_{1\cap 2},$$

which implies

$$u < 2 \cdot (P^{s_2}_{1\cap 2} - \tilde{P}^{s_2}_{1\cap 2}).$$

and therefore we must have $\tilde{P}^{s_2}_{1\cap 2} = 0$ and $P^{s_2}_{1\cap 2} = \frac{1}{2}$. Since the swing voters w such that $y^w_c = 1$ will vote for the leader of party Z in case s_2 win the first election, and $P^{s_2}_{2|1} = 1$, we must have that the mass of voters v such that $y^v_c = 0$ is strictly greater than $\frac{1}{2}$. But then, setting $y^{s_2}_e = y^{s_1}_e$ will increase $P^{s_2}_1$ to 1 and since the mass of voters v with $y^v_c = 0$ is more than $\frac{1}{2}$ and will not vote for the leader of party Z (the distance between them is at least 1 while it is less than one with s_2), we still have $P^{s_2}_{1\cap 2} = 1$. Hence, we have a profitable deviation, a contradiction. Therefore, we must have $y^{s_1}_c = 0$. ■

Figure C.1 shows an example explaining the intuition of the theoretical model. The different colored lines represent voters preferences, where m_L and$m_R$are positions of party's voters L and R respectively, while m_{sw0} and m_{sw1} are the swing voters positions. The main focus of this example is to elucidate why some political topics polarize more than others. According to the theoretical findings, politicians are expected to polarize along the horizontal axis (cultural topic), taking positions at the extremes of 0 and 1. However, when we consider the vertical axis, we observe that polarization is not conducive to optimal outcomes in elections. Remarkably, any deviation from extreme positions toward the median value on the vertical axis leads to an increase in the number of votes received. This trend applies to both political parties involved. Consequently, it is not possible that any party would position itself strictly at 0 or 1 on this axis. As a result, we can anticipate a relatively smaller disparity in economic stances (and thus opinions) compared to the broader spectrum of positions seen in the cultural domain. By highlighting this disparity, our analysis demonstrates that economic considerations tend to converge to a certain extent, limiting the range of differences in opinions between political parties. On the other hand, the cultural dimension exhibits a

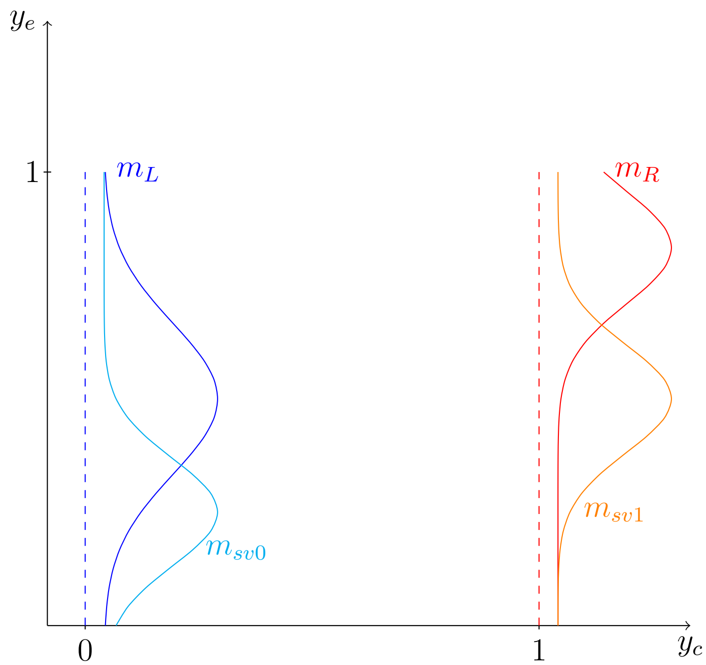


Figure C.1: Example

scriptsizeNotes: This figure shows an example useful for explaining the main results of theoretical model.

wider divergence in positions, indicating a greater scope for varying opinions. This example within our theoretical framework provides valuable insights into the dynamics of political polarization.