HIGH SCHOOL EDITION
Journal of Student Research

Volume 12 Issue 2 (2023)

Impact of Social/Traditional Media on Political Polarization

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ABSTRACT

There is a common perception that political polarization is increasing in American society and the blame is often assigned to highly partisan traditional media (e.g., TV news channels) and the emergence of social media *echo chambers* as the major influencers of political opinion. In this paper, we examine the impact of traditional and social media on political polarization in society via simulations. These simulations examine what happens when a population with normally-distributed unipolar political views is exposed to social/traditional media espousing very different types of political views. Our simulations reveal that the political polarization in a population is deeply affected by the political views espoused in the media. If the media is primarily unipolar in terms of political views, the population ultimately become politically unipolar as well. On the other hand, if the media is politically bipolar, the population ultimately becomes politically bipolar. Interestingly, the simulations reveal that social media *echo chambers* can undo the polarizing impact of partisan traditional media if the echo chambers strictly show content matching the current political views of the users. However, if social media echo chambers expose the users to extreme political views, a population that is initially unipolar in political views will ultimately look like two different populations with very different political centers.

Introduction

Political polarization is apparent in American society today. It is true that the American people have always had very diverse political views, and some experts in the recent past thought that political polarization in the US was no worse than before (Levendusky & Malhotra, 2016; Fiorina & Abrams, 2008). However, the perception that political polarization is increasing in American society is almost universal in mainstream media with some quantitative evidence (Dimock & Wike, 2020; Doherty, 2016; Dimock, 2014; Draca & Schwarz, 2019). Often the blame is assigned to the rise of social media as the major influencer of political opinion in the US (Hao, 2021; De Vynck, et al., 2021; Horwitz & Seetharaman, 2020; Netflix, 2020).

In today's world, social media plays a massive role in providing political commentary to the people (Mitchell, 2014). People no longer depend on traditional media (e.g., newspapers, magazines, TV/radio channels) to get opinions on political matters. Social media allows anyone to share their views with large sections of society. Both traditional and social media companies want to maximize their advertisement revenue and hence want to maximize the time people spend with their content. With this objective in mind, a traditional media company decides its target audience and tailors its content to appeal to that audience. Social media companies go one step further and use elaborate machine learning algorithms to customize the content an individual sees to appeal to their specific bias.

Machine learning helps a social media company estimate the political views of its users individually and identify the content liked by the users with specific views. The social media platform then presents each user with the content most likely to appeal to them. The machine learning algorithms are designed to maximize the user's engagement with the platform and often fail to prevent falsehoods or other content of extreme nature from being presented to a large number of users. Social media companies have no penalty to pay from a legal perspective for delivering such content to their users. Section 230 of the Communications Decency Act of 1996 protects social media companies from any legal liability for any content on their platforms not explicitly created by the company. In fact, some social media companies may knowingly present extreme content to the users because such content is known to grab the users' attention and hence increase their engagement with the platform. Many people use social media as their primary source for getting political news & opinions and are susceptible to adopting extreme political views because of their constant exposure to such views.

However, some experts push back against the narrative above. Several arguments have been presented to counter the notion that social media is responsible for the rise in political polarization in the US:

- Polarization in the US has been increasing since the 1990s, much before the advent of social media (Boxell, et al., 2020).
- The rise in polarization is most evident among older Americans, who are less likely to use social media (Boxell, et al., March 2017; Boxell, et al., October 2017).
- Rather than providing *echo chambers*, where people just hear views similar to their own, social media exposes people to politically diverse views, which may reduce mass political polarization (Barbera, 2015; Bakshy, 2015; Duggan & Smith, 2016).
- Exposure to opposing political views does not necessarily lead to moderation (Bail, et al., 2018; Primario, et al., 2017). Political views meant to "*rally the base*" may actually cause further alienation among people with opposing viewpoints.
- The number of *fake news* stories seen by an average American is not significant. It is unlikely to have a significant impression on the viewers' political thinking (Allcott & Gentzkow, 2017).

Also, research literature points to other possible causes of polarization, such as the emergence of highly partisan traditional media, increasing racial divisions & economic inequality in the US, and the impact of trade globalization (Boxell, et al., 2020; Autor, et al., 2020).

Materials and Methods

Clearly, social (and traditional) media has a complex relationship with political polarization in society, and we still need to understand this relationship better. This paper is an attempt to understand this relationship via simulations. Specifically, we aim to understand the conditions under which social and traditional media may cause a noticeable increase or decrease in political polarization. In particular, we want to understand the role of *echo chambers*, which by definition provides political views within a narrow range. For this purpose, we created a software simulation framework, where the political *shades* of the individuals in a population change as a result of their encounters (e.g., reading an article or watching a video) with social and traditional media.

Political Shade of an Individual

In our simulation framework, the entire spectrum of views on political issues is modeled as a range of values between 0 and 10. The political *shade* of an individual is a value in this range. Shade values 0 and 10 represent most extreme political views in opposite directions (e.g. *Far-Left* and *Far-Right*) and a shade of 5 represents moderate/centrist political views.

In our simulations, we interpret the political shade as representing an individual's position on the entirety of issues, although it is possible to interpret the shade value as political views on a specific issue (e.g., gun control) only. The political shade of an individual (*individualShade*) is modeled as the weighted average of a core immutable component (*coreShade*) and a second component (*acquiredShade*) that changes in accordance with the social and traditional media encounters the individual has:

$$individualShade = \alpha \times coreShade + (1 - \alpha) \times acquiredShade, \text{ where } 0 \leq \alpha \leq 1.$$

Encounters with Social/Traditional Media

Like individuals, the social/traditional media encounters are also characterized by political shades in accordance with the political views they represent. In a simulation, each individual in the population goes through a specified number of media encounters, which is an input parameter to the simulation (see Table 1 for a list of all input parameters). In our simulation framework, the probability that a media encounter involves an *echo chamber* is a configurable parameter. Based on the value of this probability, a media encounter is either an echo chamber encounter or a *non* echo chamber encounter. In an echo chamber encounter, an individual comes across shades very similar to their own with a possible tilt towards the extreme. Other encounters may expose the individual to a diversity of political shades (e.g., normally distributed around the center to represent moderate unipolar media, bi-normal distribution to represent partisan media with two poles).

Depending on an input parameter to the simulation, an echo chamber encounter has a shade that either is within a tight range around the individual's shade (normally distributed with the individual's shade as mean and 1.25/3 as standard deviation)[1] or more extreme than the individual's shade. Depending on another input parameter, a media encounter that is not an echo chamber encounter is either a unipolar media encounter (political shade normally distributed with mean 5.0 and standard deviation 5/3)[2] or a bi-polar media encounter (political shade drawn from one of two normal distributions with equal probability: Normal(mean 2.5, std dev 2.5/3) or Normal(mean 7.5, std dev 2.5/3)). Figure 1 shows the distribution of political shades for encounters with unipolar and bipolar media.

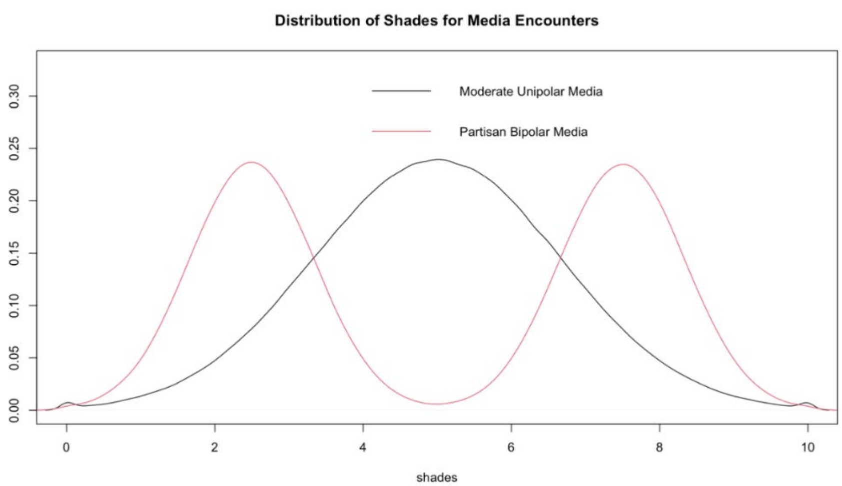

Figure 1 Distribution of shades for encounters with unipolar and bipolar media

In addition to their shade, the social/traditional media encounters are further characterized by their nature - whether they are meant to *Rally the Base* or *Build Bridges* across the political divide. In our simulation model, an individual's *acquiredShade* changes differently based on the nature of a media encounter. A media

[1] For a normally distributed random variable, 99.7% of the sample values will be within three standard deviations of the mean.

[2] Note that this distribution will have 99.7% of the values within the range 0 to 10.0.

encounter with a persuasive *Build Bridges* message attracts an individual towards its shade by adding/subtracting a small value (ß) to/from the individual's *acquiredShade*. On the other hand, an encounter with a *Rally the Base* message will only impact individuals in the same *base* as this message. In our simulation framework, the *base* associated with a message is the set of individuals with shades in a small range (±2.0) around the shade of the message. Individuals outside this base are not impacted at all by such a message.

As mentioned before, the shade associated with an echo chamber encounter is close to the individual's current shade with a possible tilt toward the extreme. The simulation framework uses an input parameter to determine if the echo chambers have a tilt toward the extreme. If they do, the shade of an echo chamber encounter is influenced by the shade of the individual (*individualShade*). If the *individualShade* is less than 5.0, the shade of the echo chamber encounter is picked from a normal distribution with mean 0.5 × *individualShade* and standard deviation 1.25/3. On the other hand, if the *individualShade* is more than 5.0, the shade of the echo chamber encounter is picked from a normal distribution with mean 0.5 × (*individualShade* + 10.0) and standard deviation 1.25/3. Persistent encounters with such echo chambers will move the individuals towards extreme shades. Further, the simulation framework allows the echo chambers to be addictive (via another input parameter). This means that an encounter with an echo chamber will increase the probability of another echo chamber encounter by a value (another input parameter). Finally, by their very nature, all echo chamber encounters offer only *Rally the Base* messages. The complete list of all input parameters to a simulation can be seen in Table 1.

A simulation involves each individual in the population going through a specified number of media encounters under the conditions set by the input parameters. These encounters will modify the shade of each individual. We visually compare the shade distribution of the population at the end of the simulation with that at the beginning. We repeat each simulation with multiple seeds for random number generation to ensure that the results do not depend on a particular sequence of generated random numbers.

Table 1. Input Parameters to a Simulation

Nature of Echo Chamber Encounters 1: Show content with shades in a tight range around the individual's shade 2: Show contents that are more extreme than the individual's shade
Shades of *non* Echo Chamber Encounters 1: Normally distributed with mean 5.0 and std dev 5.0/3.0 2: Either Normal(mean 2.5, stddev 2.5/3.0) or Normal(mean 7.5, stddev 2.5/3.0) with equal probability
Probability that a Media Encounter is an Echo Chamber Encounter
Is Echo Chamber Addictive?
Increase in the Probability that a future Media Encounter is an Echo Chamber Encounter (when an individual has an encounter with an addictive Echo Chamber)
Probability that a *non* Echo Chamber Encounter is a *Build Bridges* Encounter
Number of Media Encounters for Each Individual in the Population
Weight associated with the *coreShade* of an individual (α)
Change in the *acquiredShade* when an individual has a media encounter (β)
Seed for Random Number Generation

Results

In this section, we report representative results from our simulations. These simulations were done on a population of 10000 individuals with initial core/acquired shades picked from a normal distribution with mean 5.0

and standard deviation 5.0/3 with values less than 0 or more than 10.0 changed to 0 and 10.0 respectively. Figure 2 shows the distribution of initial core/acquired shades of 10000 individuals.

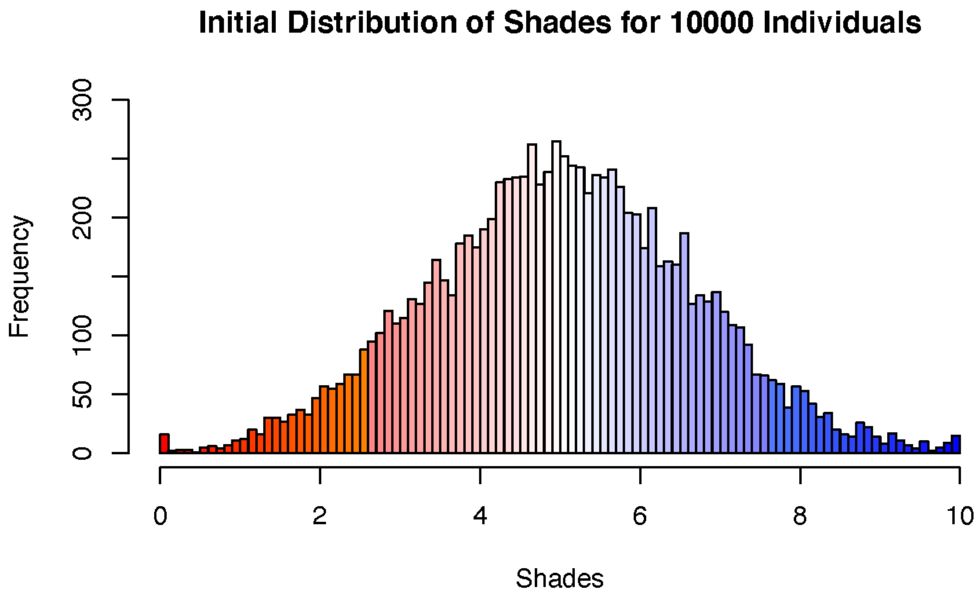

Figure 2. Distribution of initial core/acquired shades of 10000 individuals at the beginning of each simulation

We used 0.5 as the value of α in these simulations. In other words, the *individualShade* of each individual is calculated in the following manner:

$$individualShade = 0.5 \times coreShade + 0.5 \times acquiredShade$$

As mentioned before, the *coreShade* of an individual does not change, whereas the *acquiredShade* changes as per the media encounter the individual has.

In these simulations, each individual had 400000 media encounters. We used 0.0001 as the value of ß in these simulations. This means that the *acquiredShade* of an individual changed by 0.0001 (towards the shade of the media encounter) when an individual has a media encounter. Further, the fraction of *Build Bridges* encounters in *non* echo chamber encounters was 0.5, i.e., half of the *non* echo chamber encounters had a *Build Bridges* message. All the simulations reported here used a particular value as the seed for random number generation[3].

Simulation 1: Encounters with Unipolar Media with No Echo Chambers

In the first simulation, each individual had 400000 encounters with unipolar media with political shades shown in Figure 1. As mentioned before, the distribution of initial core/acquired shades of these individuals can be seen in Figure 2. The media encounters changed the acquired shades of each individual. The distribution of final shades of 10000 individuals at the end of the simulation can be seen in Figure 3. Comparing the distributions in Figure 2 and Figure 3, we can see that encounters with a unipolar media alone cause the range of shades to shrink towards the pole. Since the encounters with a unipolar media are likely to have shades around 5, the

[3] All simulations were repeated for several different seeds for random number generation. We double-checked that the observations made here remain valid irrespective of the seed value used.

acquired shades of the individuals move towards 5 and, as a result, the overall range of political shades in the population shrinks.

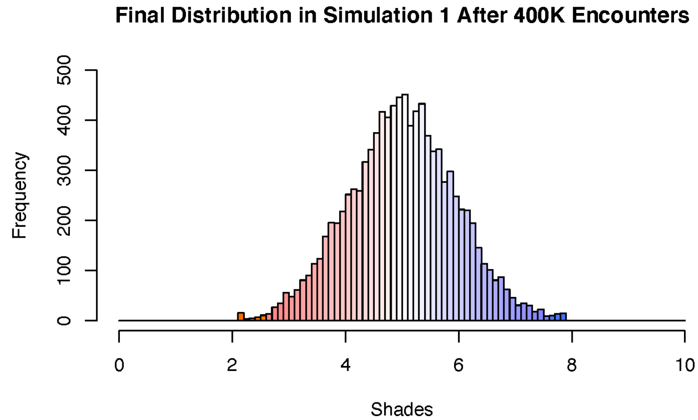

Figure 3. Final distribution of shades of 10000 individuals at the end of Simulation 1 (Unipolar Media, No Echo Chambers)

Simulation 2: Encounters with Bi-Polar Media with No Echo Chambers

In the second simulation, each individual had 400000 encounters with bipolar media with political shades shown in Figure 1. As in the first simulation, the distribution of initial core/acquired shades of these individuals can be seen in Figure 2. Encounters with the bi-polar media changed the shades of 10000 individuals in the population, as shown in Figure 4. Note the significant difference between the initial distribution (Figure 2) and the final distribution at the end of the simulation (Figure 4). While the initial distribution is unipolar, the final distribution is clearly bipolar and somewhat resembles the bipolar distribution of the media encounters. In Simulation 1, we saw that the final distribution shrinks towards the single pole of the distribution of media encounters. So, it seems that the distribution of shades in a population tends to assume the shape of the distribution of shades of encountered media. This behavior is, of course, a consequence of how we change the *acquiredShade* in our simulation framework. However, this behavior is consistent with what we have seen in the real world, where public opinions tend to align with those expressed in popular media. So, our simulation framework provides a simple explanation of the real-world observation that a high level of partisanship in popular media will directly impact polarization in society.

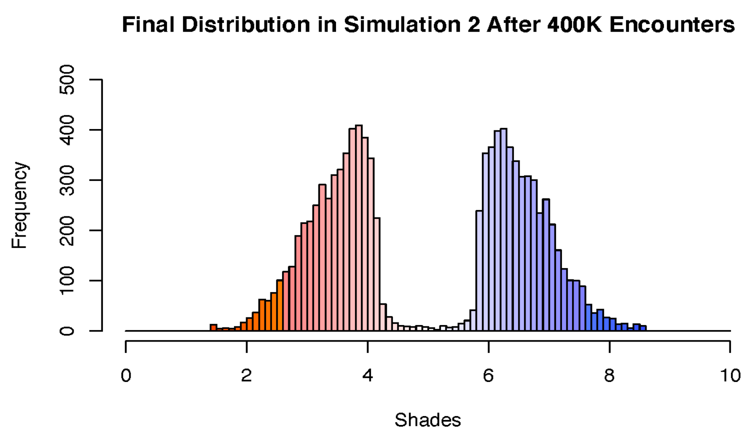

Figure 4. Final distribution of shades of 10000 individuals at the end of Simulation 2 (Bipolar Media, No Echo Chambers)

Volume 12 Issue 2 (2023)

Simulation 3: 90% of Encounters with Bi-Polar Media, 10% Encounters with Non-Addictive Echo Chambers with No Tilt Towards Extreme

In the third simulation, 90% of each individual's media encounters are with bipolar media, and 10% of the encounters are with echo chambers that do not pull the users towards extreme views and are not addictive. The distribution of shades in the population at the end of this simulation is shown in Figure 5. The only difference between this simulation and the previous one is that each individual in this simulation has 10% of the encounters with echo chambers that do not pull the users towards extreme views and are not addictive. So, an individual will hear opinions very similar to their own in these echo chamber encounters, and hence these encounters will have little impact on the political shades of the individuals. Political shades will mostly change significantly only because of encounters with bipolar non-Echo Chamber media. Since individuals in this simulation have fewer bipolar media encounters than individuals in the previous simulation, the final distribution of shades in this simulation (Figure 5) is less bipolar than what it was in the previous simulation (Figure 4). Clearly, echo chambers with no tilt towards extremes helped alleviate the impact of bipolar media. This is an interesting result. So far, we have viewed echo chambers as the main culprit in causing polarization in society. It turns out that echo chambers can help alleviate the impact of polarizing content in other media if they do not show extreme content themselves.

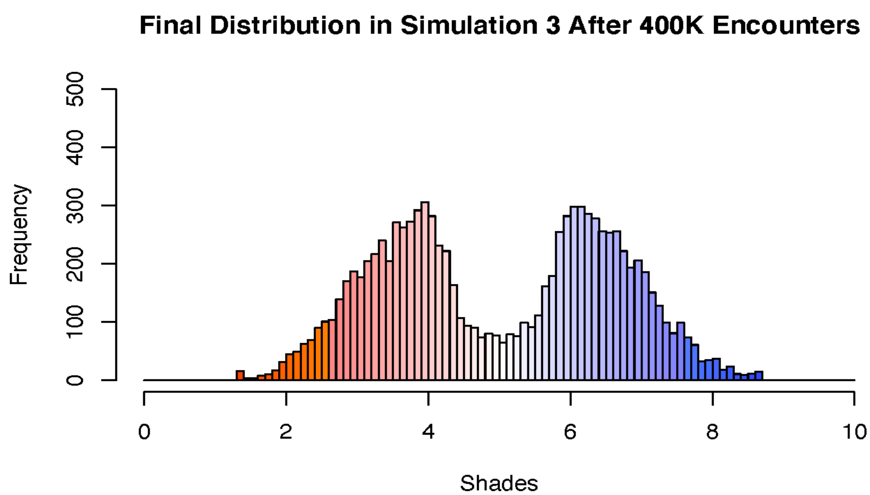

Figure 5. Final distribution of shades of 10000 individuals at the end of Simulation 3 (90% of Encounters with Bipolar Media, 10% with non-Addictive Echo Chambers that do not pull the users towards extreme views)

Simulation 4: Encounters with Addictive Echo Chambers with No Tilt towards Extreme

In the fourth simulation, the individuals encounter *addictive* echo chambers. This means that the probability of having another echo chamber encounter increases for an individual whenever they have an echo chamber encounter. In this simulation, the probability of having an echo chamber encounter gets multiplied by a factor (1.0001) whenever the individual has an echo chamber encounter. The initial probability for an echo chamber encounter is 10% for all individuals. All non-echo chamber encounters are with bipolar media, as before. The addictive nature of the echo chambers means that the probability of echo chamber encounters for an individual quickly approaches 1. However, since an echo chamber shows contents with roughly the same shade that the individual currently has, there is not much change in the shades of the individuals at the end of the simulation. This is clear in Figure 6, which shows the final distribution of the shades in the population at the end of Simulation 4. Note that the final distribution looks very similar to the initial distribution (Figure 2). The results of the third and fourth simulations imply that echo chambers that do not pull the users towards extreme views prevent partisan bipolar media from causing polarization in the society.

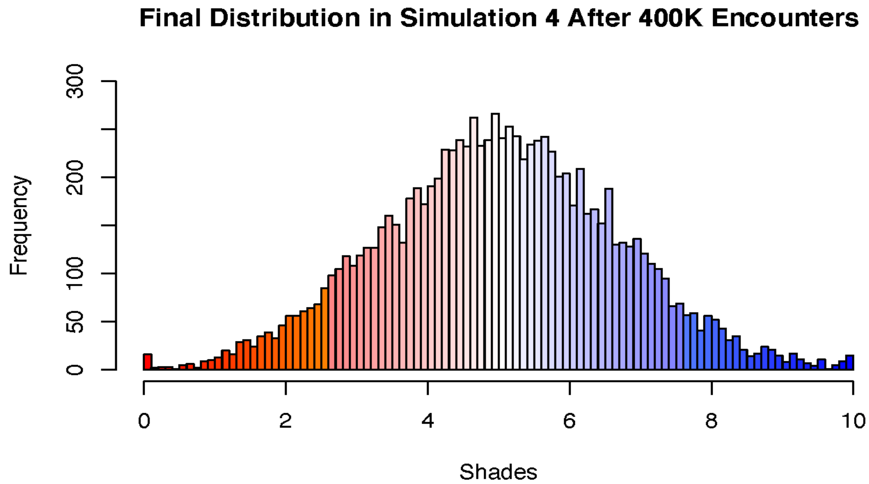

Figure 6. Final distribution of shades of 10000 individuals at the end of Simulation 4 (Addictive Echo Chambers that do not pull the users towards extreme views)

Simulation 5: 90% of Encounters with Bi-Polar Media, 10% Encounters with Non-Addictive Echo Chambers with a Tilt Towards Extreme

In the fifth simulation, we return to the configuration of the third simulation with one important difference: the echo chambers have a tilt toward showing extreme content. In this simulation, 90% of the media encounters that each individual has are with bipolar media, and 10% of the encounters are with echo chambers that are not addictive but do have a tilt towards showing extreme content. If the *individualShade* is less than 5.0, the shade of the echo chamber encounter is picked from a normal distribution with mean 0.5×*individualShade* and standard deviation 1.25/3. On the other hand, if the *individualShade* is more than 5.0, the shade of the echo chamber encounter is picked from a normal distribution with mean 0.5×(*individualShade*+10.0) and standard deviation 1.25/3. So, these echo chambers expose an individual to extreme views in the direction the individual tends to lean. The distribution of shades in the population at the end of this simulation is shown in Figure 7. This figure should be compared to Figure 4, which shows the distribution of shades in the population when the individuals have all their encounters with bipolar media. Clearly, having just 10% of the encounters with echo chambers showing extreme content causes the polarization in the population to become much worse. In fact, the final distribution of shades resembles two completely different populations with very different political centers. In the following subsection, we will see what happens when the echo chambers are not only showing extreme content but are addictive as well.

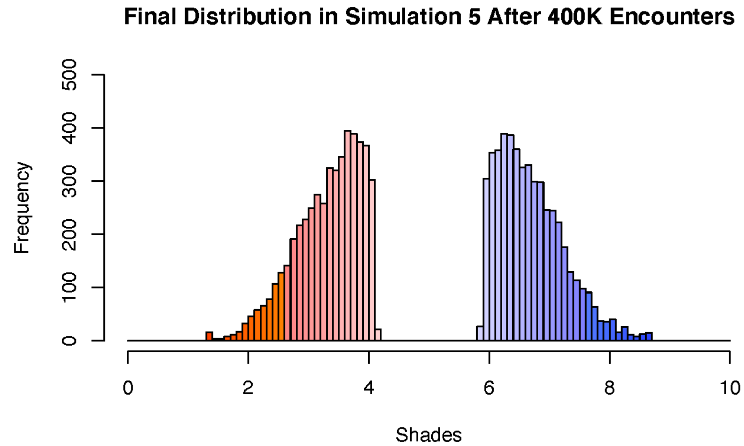

Figure 7. Final distribution of shades of 10000 individuals at the end of Simulation 5 (90% of Encounters with Bipolar Media, 10% with non-Addictive Echo Chambers with a tilt towards extreme)

Simulation 6: Encounters with Addictive Echo Chambers with a Tilt Towards Extreme

In the final simulation, the echo chambers show extreme content and are addictive as well. Initially, the probability of having an echo chamber encounter is 10% for each individual in the population. This probability gets multiplied by a factor (1.0001) whenever the individual encounters an echo chamber. This means that the probability of echo chamber encounters for an individual quickly approaches 1. These echo chambers show extreme content to the individual in the manner described previously. So, in this simulation, the individuals quickly get stuck in echo chambers that expose them to extreme views. The final distribution of the shades in the population at the end of this simulation is shown in Figure 8. As expected, this simulation ends in extreme polarization in the population, as was the case with the previous simulation. A detailed look at the partial simulation results reveals that extreme polarization happens much more quickly in this simulation than in the previous one. These results imply that addictive echo chambers that bombard their viewers with extreme content can quickly rip a society apart.

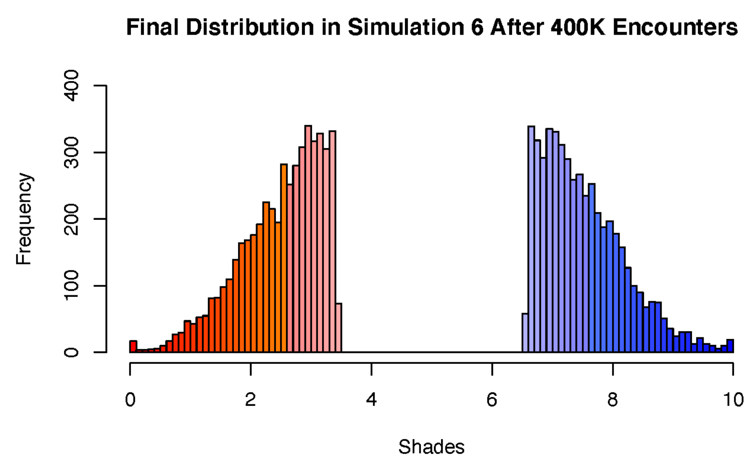

Figure 8. Final distribution of shades of 10000 individuals at the end of Simulation 6 (Addictive Echo Chambers with a tilt towards extreme)

Discussion and Conclusions

In this paper, we used simulations to study the impact of partisanship in traditional/social media on political polarization in society. In particular, we investigated the role machine-learning-powered echo chambers can play in improving or worsening this situation. Our simulations confirm that partisanship in traditional/social media directly impacts political polarization in society. If a society is only exposed to unipolar views in media (as it probably happens in countries where the government has strict control over the media), the society as a whole will slowly converge to a unipolar distribution of political views among its citizens. On the other hand, if the media is bipolar, society will also become bipolar over time. Traditional media like newspapers and TV channels show the same content to all users irrespective of their political views. However, social media platforms (e.g., Facebook, Twitter, and YouTube) have the ability to use machine learning to sense the political views of an individual user and show them customized content that aligns with these views. Machine learning allows the social media platforms to become *echo chambers*, where the users only get an *echo* of their own current views and never get exposed to other views that may possibly be closer to truth. Such echo chambers may exploit their deep knowledge of the user's online behavior to constantly offer them content that may be extreme/false but is likely to be watched by the user. Such addictive echo chambers may completely eliminate the user's interactions with other non-addictive sources of information. Our simulations indicate that echo chambers may help alleviate the impact of highly partisan traditional media IF they do not show extreme/false content to their users. However, if the social media echo chambers do show extreme content to the users even if it is mostly false, they can cause extreme polarization in society.

Our research is clearly important for American society. The political polarization of the kind we have seen in recent years possibly presents an existential threat to the United States. There is a growing realization of the dangers of extreme content reaching a large number of vulnerable people because of amplification by social media echo chambers. On the other hand, there have also been loud complaints about the *censorship* of specific political views by social media platforms. Many think that social media platforms unfairly filter out political views they disagree with. So, there have been suggestions that social media platforms should not be allowed to do any promotion or demotion of content their users have posted, and these platforms should not get the liability protection they currently enjoy under Section 230 of the Communications Decency Act of 1996. Section 230 was framed to protect Internet platforms from liability for content posted by their users on the platform. The idea was that an Internet platform was like a bulletin board, and a bulletin board cannot be blamed because someone posted something offensive there. Today's social media platforms are clearly not simple bulletin boards. These platforms use highly sophisticated machine learning algorithms to promote/demote content shown to a particular user to maximize their engagement with the platform (which allows the platform to maximize its revenue from advertisements). So, there have been calls to remove Section 230 or modify it significantly.

However, there are compelling arguments for not getting rid of Section 230 (Johnson & Castro, 2021). First, while big platforms like Facebook and Twitter can afford to protect themselves from frivolous litigation, smaller upcoming platforms may be unable to do so. Small platforms do need liability protection to survive. So, removing Section 230 would likely allow only big, well-funded social media platforms to survive, thereby harming competition and free speech. The second and perhaps more significant argument is about the First Amendment rights of social media platforms. The argument suggests that a social media company has the right to promote or demote the content on its platform in whatever way it wants under the Freedom of Speech guaranteed by the First Amendment to the US constitution. These concerns must be considered before removing Section 230 or modifying it significantly.

Irrespective of whether Section 230 is removed/modified or not, we think that there is a clear need for strong consumer protection laws that will force a social media platform to inform its users what information the platform has learned about the user's online behavior and how this information affects the content the user sees on the platform. The individual can then make an informed choice regarding whether to use that platform. The fear of losing the users and hence the advertisement revenue may force the social media platforms to respect the privacy of their users and not collect invasive information about their online behavior. Without this information, the social media platforms may not be able to operate manipulative echo chambers that have the potential to cause serious harm to our society.

References

Levendusky, M. & Malhotra, N. (2016). (Mis)perceptions of Partisan Polarization in the American Public. Public Opinion Quarterly. 80: 378–391. https://doi.org/10.1093/poq/nfv045

Fiorina, M., & Abrams, S. (2008). Political Polarization in the American Public. Annual Review of Political Science. 11: 563-588. https://doi.org/10.1146/annurev.polisci.11.053106.153836

Dimock, M., & Wike, R. (November 2020). America is Exceptional in the Nature of its Political Divide. Pew Research Center. https://www.pewresearch.org/fact-tank/2020/11/13/america-is-exceptional-in-the-nature-of-its-political-divide/

Doherty, C., Kiley, J., & Jameson, B. (June 2016). Partisanship and Political Animosity in 2016. Pew Research Center. https://www.pewresearch.org/politics/2016/06/22/partisanship-and-political-animosity-in-2016/

Dimock, M., Doherty, C., Kiley, J., & Oates, R. (June 2014). Political Polarization in the American Public. Pew Research Center. https://www.pewresearch.org/politics/2014/06/12/political-polarization-in-the-american-public/

Draca, M., & Schwarz, C. (2019). How Polarized are Citizens? Measuring Ideology from the Ground-up. Econometric Modeling: Macroeconomics eJournal. https://dx.doi.org/10.2139/ssrn.3154431

Hao, K. (March 2021). How Facebook Got Addicted to Spreading Misinformation. MIT Technology Review. https://www.technologyreview.com/2021/03/11/1020600/facebook-responsible-ai-misinformation/

De Vynck, G., Zakrzewski, C., Dwoskin, E., & Lerman, R. (March 2021). Big Tech CEOs Face Lawmakers in House Hearing on Social Media's Role in Extremism, Misinformation. The Washington Post. https://www.washingtonpost.com/technology/2021/03/25/facebook-google-twitter-house-hearing-live-updates/

Horwitz, J., & Seetharaman, D. (May 2020). Facebook Executives Shut Down Efforts to Make the Site Less Divisive. The Wall Street Journal. https://www.wsj.com/articles/facebook-knows-it-encourages-division-top-executives-nixed-solutions-11590507499

Netflix (2020). The Social Media.

Mitchell, A., Blazina, C., Kiley, J., & Matsa, K. (October 2014). Political Polarization & Media Habits. Pew Research Center. https://www.pewresearch.org/journalism/2014/10/21/political-polarization-media-habits/

Boxell, L., Gentzkow, M., & Shapiro, J. (June 2020). Cross-country Trends in Affective Polarization. Working Paper, National Bureau of Economic Research. http://www.nber.org/papers/w23258

Boxell, L., Gentzkow, M., & Shapiro, J. (March 2017). Is the Internet Causing Political Polarization? Evidence from Demographics. Working Paper, National Bureau of Economic Research.

Boxell, L., Gentzkow, M., & Shapiro, J. (October 2017). Greater Internet Use is not Associated with Faster Growth in Political Polarization among US Demographic Groups. Proceedings of National Academy of Science USA. https://doi.org/10.1073/pnas.1706588114

Barbera, P. (2015). How Social Media Reduces Mass Political Polarization. Evidence from Germany, Spain, and the US. Job Market Paper, New York University. http://pablobarbera.com/static/barbera_polarization_APSA.pdf

Bakshy, E., Messing, S., & Adamic, L. (2015). Exposure to Ideologically Diverse News and Opinion on Facebook. Science. https://doi.org/10.1126/science.aaa1160

Duggan, M., & Smith, A. (October 2016). The Political Environment on Social Media. Pew Research Center. https://www.pewresearch.org/internet/2016/10/25/the-political-environment-on-social-media/

Bail, C., Argyle, L., Brown, T., Bumpus, J., Chen, H., Fallin Hunzaker, M., Lee, J., Mann, M., Merhout, F., & Volfovsky, A. (September 2018). Exposure to Opposing Views on Social Media can Increase Political Polarization. Proceedings of National Academy of Science USA. https://doi.org/10.1073/pnas.1804840115

Primario, S., Borrelli, D., Iandoli, L., Zollo, G., & Lipizzi, C. (2017). Measuring Polarization in Twitter Enabled in Online Political Conversation: The Case of 2016 US Presidential Election. IEEE International Conference on Information Reuse and Integration. doi: 10.1109/IRI.2017.73.

Allcott, H., & Gentzkow, M. (2017). Social Media and Fake News in the 2016 Election. Journal of Economic Perspectives. Journal of Economic Perspectives. https://www.aeaweb.org/articles?id=10.1257/jep.31.2.211

Autor, D., Dorn, D., Hanson, G., & Majlesi, K. (October 2020). Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. American Economic Review. https://www.aeaweb.org/articles?id=10.1257/aer.20170011

Johnson, A., & Castro, D. (February 2021). Fact-Checking the Critiques of Section 230: What Are the Real Problems?. Information Technology and Innovation Foundation. https://itif.org/publications/2021/02/22/fact-checking-critiques-section-230-what-are-real-problems/