Simple Data Visualization Techniques of Racial Demographic Change Sharply Increase Propensities Toward Violence

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ABSTRACT: Data visualization has direct political implications. Across four experiments which slightly vary the visualization of data about projected racial demographic change in the United States, we find that particular displays of racial demographic change strongly alter the inferences that Americans make about the future of the U.S. These inferences lead to threatened sentiments, which increase support for political violence. We conclude that more detail than less is needed when using data visualization because of the potential for misinterpretation that could unintentionally inflame anti-democratic political sentiments.

The current information environment of the United States is becoming increasingly politicized. Misinformation about a series of political issues is rife online and even in major mainstream media outlets. Understanding these complex, politically potent issues has developed into a problem for studying knowledge among Americans. Misinformation is proliferating throughout American society.

Scholars have given rightful attention to the rising spread of misinformation (Hameleers and van der Meer 2020; Hochschild and Einstein 2015; Jerit and Zhao 2020; Li 2020), but we argue that this focus has led to an undervaluing of misinterpretation. In this project, we focus on how misinterpretation can occur specifically in the realm of data. We argue that data interpretation is a crucial component of public attitude formation; specifically showing that misinterpretation of data can lead to increasingly violent attitudes. Through four experiments, we go about testing how visualizing projections about future racial demographic change in the United States affect Americans' interpretations of the political future. Then, we go to show that simple changes to data visualization can elicit threat which increases support for violence and anti-democratic ideas.

We arrive at three crucial takeaways for data visualization and misinterpretation. First, small changes to visualization can drastically shift Americans' political views. We show that simple visualizations generate grand inferences about the future of politics in the U.S. Second, extending from our first point, these future views of the country lead to shifting support for political violence and other anti-democratic ideas in robust ways. Third, as a takeaway for the effective, less-misinterpretable nature of data visualization, we argue that public facing data visuals about salient issues should be *more* detailed than less in order to avoid the downstream political effects. We assert that scholars and media who engage in frequent data visualization ought to be more attentive to detail, so as to not prompt unintended conclusions among viewers.

A New Fold to the Idea of Misinformation

The way that people process information in the current media environment has received significant attention and scrutiny, especially within the domain of misinformation. Misinformation occurs when people hold incorrect factual beliefs with confidence(Jerit and Zhao 2020). Political media and social media present pathways for the spread of misinformation in recent years. These closely-held, incorrect types of beliefs have been shown to lead to increased polarization, a greater likelihood in believing conspiracy theories, and even greater support for authoritarian leaders (Hochschild and Einstein 2015; Swire et al. 2017; Hameleers and van der Meer 2020). Adding more difficulty to the spread of misinformation, the attitudes that they establish are "sticky" or hard to correct, especially in the context of politics (Walter and Murphy 2018). So, once views are altered by the incorrect information, it is difficult to move them back. For all of the benefits of the focus on the spread, amount, and mechanisms of misinformation, the attention it has received in much of social science misses a very crucial fold to the establishment and processing of political ideas – this idea we argue and define as misinterpretation.

We argue that misinterpretation requires attention as a standalone idea in the development of political attitudes. Moreover, it can operate in similar ways to misinformation by leading attitudes that diverge from political reality. We argue that misinterpretation can sway political attitudes in *unintentional* ways. Specifically, we show that misinterpretation can elicit threat, shifting expectations about the future, and increased violent attitudes. Next, we briefly define information that we expect can be more easily misinterpreted.

Defining Misinterpretation-Prone Information

First, the political information provided concerns vague ideas. For example, a vague idea could constitute speculative discussion about the future of political parties. In this case, reports of the potential direction that political parties could go come from a place of speculation, yet, they could be misread predictions about the future of politics.

The second property is the lack of a tangible outcome for inference from the viewer. This property connects to the first property because it lacks context. If vague information is simply provided to add to a conversation about a larger issue, it leads viewers to rely on their own inferential abilities to deduce ideas from the information.[1] An example of this is a recent report on an ice sheet growing in Greenland (Popescu 2019). Coverage of the ice sheet growing in size, in and of itself, might mislead the viewer to presume that climate change is bunk as an idea because of expectations that climate change only concerns "global warming."

Last, the third property of misinterpretable information is that it is about a salient issue. This dimension adds urgency to answering the question while also opening up the potential for misinterpretation to shift related political opinions. This is especially so if viewers perceive a certain threat or danger to themselves.

We find that the framework we construct for misinterpretation aligns particularly well with the data visualization of politically relevant topics. Different forms of visualization can be used to represent salient political issues in vague ways, without the context of a concrete outcome for inference.

Data Visualization and Politics

The ways that data are visualized have received some attention in how they motivate changes in attitudes. Scholars have found that the framing of titles in graphs affects reactions to them (Kong, Liu, and Karahalios 2018). This work finds that the way that titles instruct readers' focus influences their interpretation of the graph, and ultimately affects what glean from the information. Extending from this, Kong et al. (2019) show the title to be more influential in its influence of interpretations of the data presented than the visualizations themselves. In related ways, similar studies have shown that small edits to visualizations can yield strong impacts on

[1] Work in psychology shows that human cognition struggles with attribution in general, so allowing for more open-ended inference from information that does not require it could have deleterious effects (Tetlock 1985; Sabini, Siepmann, and Stein 2001; Maruna and Mann 2006).

how viewers process the information; and the main conclusions of these works are that these impacts could lead to the intentional deception of people who are presented the visuals (Lisnic et al. 2022; Alves et al. 2022; Lauer and O'Brien 2020; Fan et al. 2022; McNutt, Kindlmann, and Correll 2020; Franconeri et al. 2021). This area of research strongly focuses on misinformation. On granular levels, these scholars have identified how changes to visuals can deceive viewers and users on social media, thereby facilitating the spread of misinformation. While misinformation through data visualization has proliferated in recent years, and deception is a very important point of focus, we argue that the overwhelming focus on these areas now requires an expanded view of how we consider visuals.

In terms of content, deception and misinformation through data visualization likely pales in comparison to the number of times viewers are unintentionally misled through misinterpretations they infer from how data are presented (Watson 2022). In this circumstance, neither the person doing the visualizing nor the viewer is to blame for the outcome, though, we assert that it is incumbent upon the visualizer to exercise careful attention in how they are visualizing an idea in order to minimize unintended consequences.

Next, using a set of preregistered experiments, we use a highly salient, politically charged issue to demonstrate how less specific yet still accurate data visualizations lead to distinct, unfounded inferences. We show that these visualizations lead to increased support for political violence attitudes.

Data, Racial Threat, and Misinterpretation

We specifically alter visual frames of future projected racial demographic changes of the United States. These projections have been previously shown to generate senses of racial threat, with visuals and text, but the visualizations alone have never been isolated (Craig and Richeson 2014b; 2014a; Major, Blodorn, and Major Blascovich 2018; Stewart and Willer 2022; Sohoni 2022).

We argue that the visualization of racial demographic change in the U.S. fits the first part of our criteria for misinterpretation because the idea of demographic change is vague; racial demographic change is a vague idea. It allows the viewer to project their own concerns of the world onto these changes, especially if they are already threatened by them. We assert that the way we visualize these changes satisfies our second property of misinformation, which is the lack of a tangible outcome. In the following study, we intentionally do not include any additional explanation of how to interpret the visualizations that we provide. This framing in addition to our intentional vague display of racial demographic change sets the stage for misinterpretation. As a final component of this issue that meets the third property of misinterpretation, in contemporary politics, racial demographic change, in the form of the coming majority-minority flip, has become a rallying call for the far right in U.S., a motivator of supporting anti-democratic ideas, and has been used as justification for racially targeted domestic terrorism (Mutz 2018; Bump 2022; Carlson 2022; Miller 2020). These factors make the discussion very salient, satisfying our third condition for misinterpretation.

Data Visuals, Demographic Change, and the Political Future

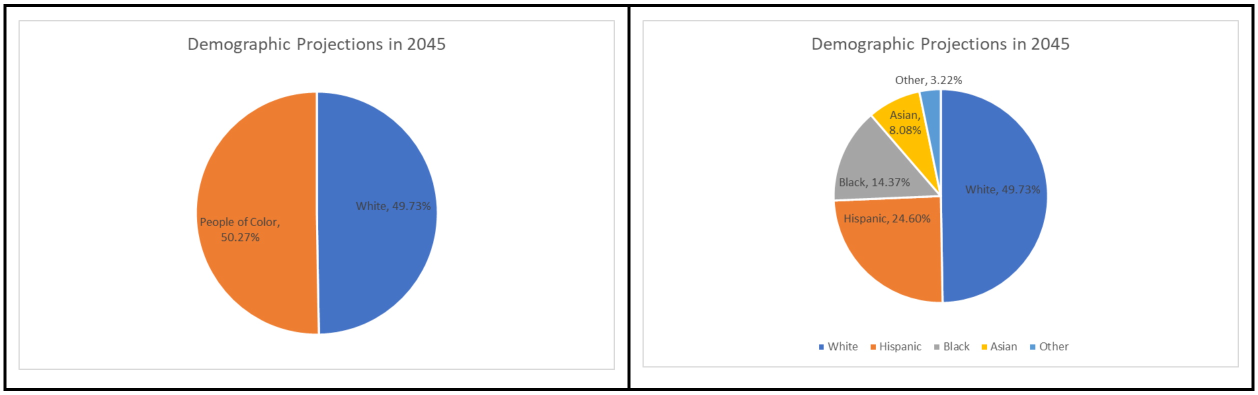
We manipulate the visualization of Census data using different types of data visuals across four studies. We expect that simple graphs, which describe people of color or racial minorities increasing in size will generate more threat, which will lead to more support for anti-democratic ideas. Specifically, we examine support for political violence.

Our central expectation behind increased threat is that the simplistic graphs will lead to widely different inferences about the future of the United States. There are two aspects to this threat which are related. The first is about racial groups, the second is about the future of politics in the U.S.

First, due to the prominence of the racial binary in American racial politics, we expect that Black Americans are strongly associated with both the terms “people of color” and “racial minorities.” So, when we prime that people of color or racial minorities are increasing in size, Americans will expect that many of those increasing in size will be Black Americans (H1). Second, branching from the expectation about Black Americans increasing in size, we also expect that the simple graphs will lead to inferences that the country will increasingly become liberal and Democratic (H2). This concept we define as *demographic determinism*, and has been intimated toward in media coverage of racial demographic change in the U.S. (Kercheval 2022). Conventional discussion of these changes often explicitly or implicitly asserts that racial minorities increasing in size will lead to a greater advantage for the Democratic Party. This expectation will be accentuated by the inference that Black Americans are mostly increasing because of their storied connection to the Democratic Party (Schickler 2016; White and Laird 2020). These two political outgrowths of data misinterpretation will prompt threat, which we expect will prompt anti-democratic attitudes (H3). Some Americans will feel racially threatened by Black Americans because of stereotypes, others will be threatened by the political future and Black Americans. We untether these dynamics in a discussion of heterogeneous treatment effects which conclude this paper.

In each of our studies, we compare simplistic framings of racial demographic change to more complex framings with the same information. Studies 1-3 describe the forthcoming majority-minority flip with the labels that White Americans are decreasing and people of color are increasing. In study 4, we additionally use the term “racial minority” as a point of comparison to people of color. We display the pie graph visualization below (Figures 1a, 1b). In terms of sample demographics, race, gender, age, and region are benchmarked to the Census in Study 3. Across our other 3 studies, these same characteristics are mirrored (Appendix 1.1).

Figure 1a, Simple Graph	**Figure 1b, Complex Graph**



Respondents were randomly assigned to read over the graphs above or similar trend line visualizations (See Appendix 1.3). We use the same data in all figures, which come from the 2020 Census Report. The only difference between conditions is how the data are visualized. Our priming has an advantage over previous studies on interpretations of racial demographic change because we can isolate the effect of the visuals on attitudes. Crucially, we find that slight changes to data visuals have direct political implications, going as far as causing Americans to become more violent. This effect of the simple visualization is due to a set of inferences that Americans make about the graphs. This leads us to conclude that fewer points of detail lead to a greater likelihood of misinterpretation.

Visualization and Violence

Simple visualizations lead to misinterpretations. These misinterpretations lead to violent attitudes. In Figures 2.1 and 2.2 below we show across multiple studies that when the changing demographics of the U.S. are visually framed in simple ways, this directly leads to increasing support for the idea that "It is reasonable to use violence against people who are politically opposed to me." The simple POC graph increases support for violence by roughly 3 percentage points (using difference in means tests, Study 1, p-value = 0.03; Study 3, p-value = 0.07). This is a consequential shift that mirrors the effect size of recent research on the way that other political threats increase support for violence among Americans (Kalmoe and Mason 2022). This finding is especially important because we do not prime violence or any overt type of threat in our treatments. We simply vary data visualizations.

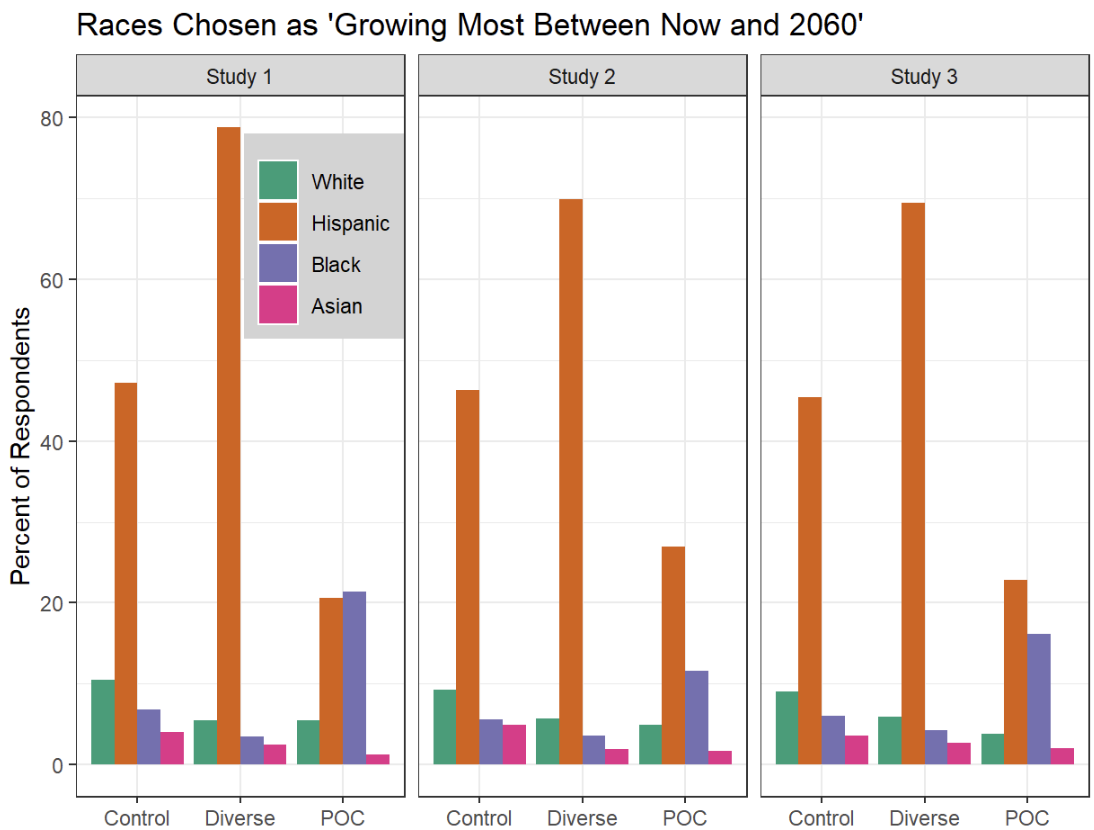
Figure 2

Data visualizations of people of color on the whole increasing, as opposed to displays of particular racial minorities increasing, consistently cause Americans to be more supportive of political violence. The relationship needs further elaboration in order to better understand the mechanism behind the misinterpretation, which we describe next.

Mechanism Behind Misinterpretation and Violence

We find strong evidence that the potency behind the simple POC graph versus the diverse graph comes from a set of inferences that Americans make about the future of American society through their reading of the graphs. First, Americans infer that Black Americans are the racial group that is increasing in size. We have consistent evidence of this inference across all of our studies (Figure 3). Using a closed-ended question about which group Americans perceive to be growing, based upon the graph they read over, the simple graph leads significantly more Americans to infer that Black Americans are one of the main growing groups consistently.

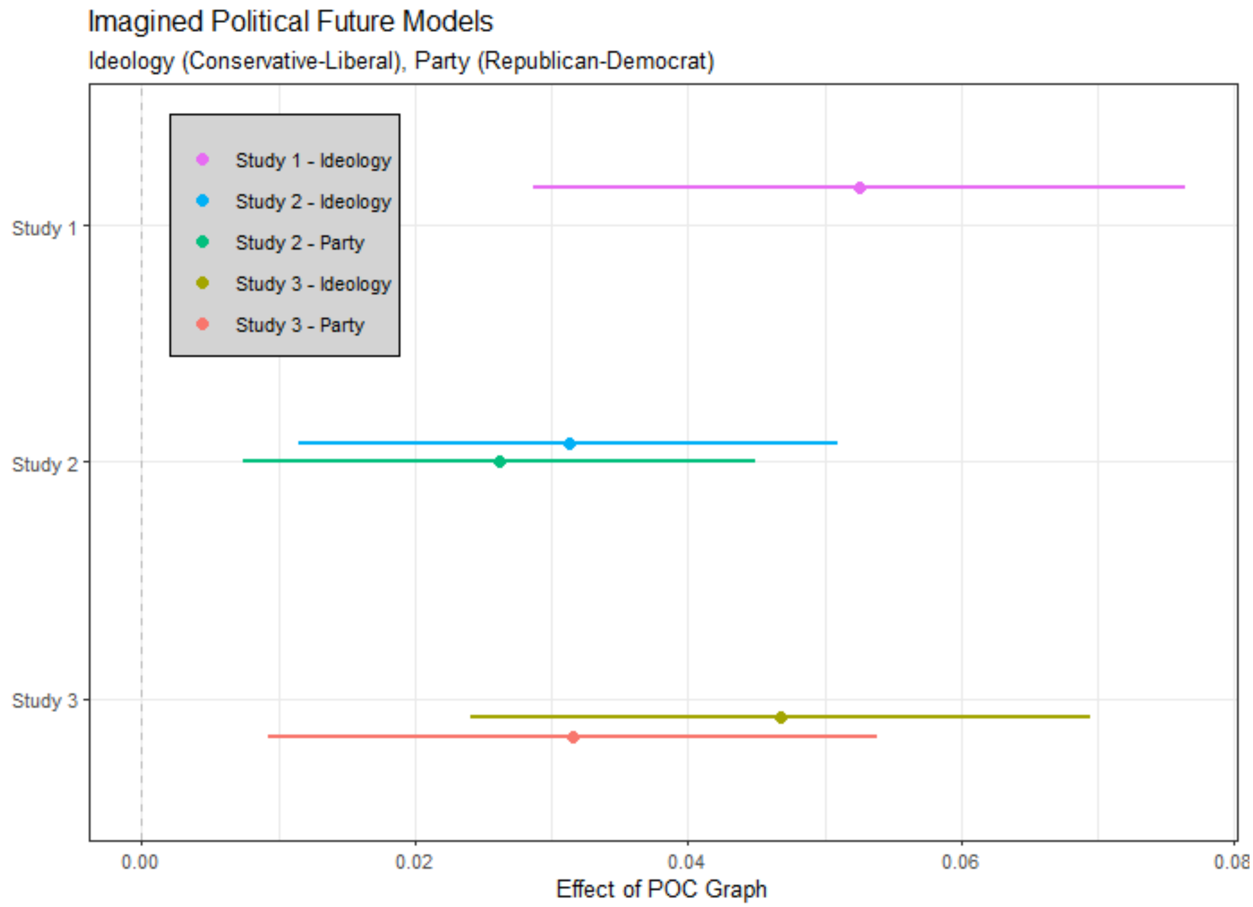
Figure 3



This inference about Black Americans, we also find, melds with stereotypes of Black Americans and their relationship to the Democratic Party (White and Laird 2020). This then connects to shifting Americans' views of the political future of the country in a liberal direction, which we find consistently across studies 1-3. This confirms H3. We use a set of measures which test the extent that when Americans are primed with these graphs, they think the future political landscape of the U.S. is likely to be more conservative or liberal (Figure 4 below).[2] In a second measure, we pose the same question, asking instead about the country becoming more Republican or Democratic (Appendix 1.4).

[2] To give even more support to this finding, we have strong evidence that Republicans are more threatened by the POC graph than the diverse graph, confirming that this inference is being made (See Appendix 1.5).

Figure 4



Conclusion

Ultimately, we confirm our expectations that data visualizations can lead to misinterpretations that have political implications. Simple graphs that display projections of racial demographic change led to increased support for political violence. We show there to be contextual reasons for this increase in support, the simple projections of U.S. racial demographics tap into political ideas that Americans maintain about people of color. As a main implication of findings on misinterpretation, we assert that simple data visuals can be politically harmful because of the way that they can lead the onlooker to make inferences based on misinterpretations. On the whole, we find data visuals about salient political issues that are consumed by the mass public, in the domains of media, government, academia, and beyond, ought to be more specific in order to avoid the pitfalls of misinterpretation.

References

Alves, Tomás, Carlota Dias, Daniel Gonçalves, and Sandra Gama. 2022. "Exploring How Temporal Framing Affects Trust with Time-Series Visualizations." In *2022 International Conference on Graphics and Interaction (ICGI)*, 1–8. https://doi.org/10.1109/ICGI57174.2022.9990428.

Bump, Philip. 2022. "Analysis | Why Tucker Carlson's Recent Embrace of 'Great Replacement' Is Different." *Washington Post*, 2022. https://www.washingtonpost.com/politics/2022/07/20/why-tucker-carlsons-recent-embrace-great-replacement-is-different/.

Carlson, Tucker. 2022. "Tucker Carlson: The Great Replacement Is an Electoral Strategy." Text.Article. Fox News. Fox News. July 19, 2022. https://www.foxnews.com/opinion/tucker-carlson-great-replacement-electoral-strategy.

Craig, Maureen, and Jennifer Richeson. 2014a. "More Diverse Yet Less Tolerant? How the Increasingly Diverse Racial Landscape Affects White Americans' Racial Attitudes." *Personality and Social Psychology Bulletin* 40 (6): 750–61. https://doi.org/10.1177/0146167214524993.

———. 2014b. "On the Precipice of a 'Majority-Minority' America: Perceived Status Threat From the Racial Demographic Shift Affects White Americans' Political Ideology." *Psychological Science* 25 (6): 1189–97. https://doi.org/10.1177/0956797614527113.

Fan, Arlen, Yuxin Ma, Michelle Mancenido, and Ross Maciejewski. 2022. "Annotating Line Charts for Addressing Deception." In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 1–12. CHI '22. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3491102.3502138.

Franconeri, Steven L., Lace M. Padilla, Priti Shah, Jeffrey M. Zacks, and Jessica Hullman. 2021. "The Science of Visual Data Communication: What Works." *Psychological Science in the Public Interest* 22 (3): 110–61. https://doi.org/10.1177/15291006211051956.

Hameleers, Michael, and Toni G. L. A. van der Meer. 2020. "Misinformation and Polarization in a High-Choice Media Environment: How Effective Are Political Fact-Checkers?" *Communication Research* 47 (2): 227–50. https://doi.org/10.1177/0093650218819671.

Hochschild, Jennifer L., and Katherine Levine Einstein. 2015. *Do Facts Matter?: Information and Misinformation in American Politics*. University of Oklahoma Press.

Jerit, Jennifer, and Yangzi Zhao. 2020. "Political Misinformation." SSRN Scholarly Paper. Rochester, NY. https://doi.org/10.1146/annurev-polisci-050718-032814.

Kalmoe, Nathan P., and Lilliana Mason. 2022. *Radical American Partisanship: Mapping Violent Hostility, Its Causes, and the Consequences for Democracy*. University of Chicago Press.

Kercheval, Hoppy. 2022. "Demography Is Destiny." *WV MetroNews* (blog). February 15, 2022. https://wvmetronews.com/2022/02/15/demography-is-destiny/.

Kong, Ha-Kyung, Zhicheng Liu, and Karrie Karahalios. 2018. "Frames and Slants in Titles of Visualizations on Controversial Topics." In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12. CHI '18. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3173574.3174012.

———. 2019. "Trust and Recall of Information across Varying Degrees of Title-Visualization Misalignment." In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13. CHI '19. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3290605.3300576.

Lauer, Claire, and Shaun O'Brien. 2020. "How People Are Influenced by Deceptive Tactics in Everyday Charts and Graphs." 2020. https://ieeexplore.ieee.org/abstract/document/9269159/?casa_token=es_tTpd6zyIAAAAA:Bmh0dtalQFWqmxBh3QQz7w4H2ZTtBpBQsP_XosMH_XbFMK9_giBXk-52X0_OomVAH1GZqVf8pg.

Li, Jianing. 2020. "Toward a Research Agenda on Political Misinformation and Corrective Information." *Political Communication* 37 (1): 125–35. https://doi.org/10.1080/10584609.2020.1716499.

Lisnic, Maxim, Cole Polychronis, Alexander Lex, and Marina Kogan. 2022. "Misleading Beyond Visual Tricks: How People Actually Lie with Charts." OSF Preprints. https://doi.org/10.31219/osf.io/ky6th.

Major, Brenda, Alison Blodorn, and Gregory Major Blascovich. 2018. "The Threat of Increasing Diversity: Why Many White Americans Support Trump in the 2016 Presidential Election." *Group Processes & Intergroup Relations* 21 (6): 931–40. https://doi.org/10.1177/1368430216677304.

Maruna, Shadd, and Ruth E. Mann. 2006. "A Fundamental Attribution Error? Rethinking Cognitive Distortions†." *Legal and Criminological Psychology* 11 (2): 155–77. https://doi.org/10.1348/135532506X114608.

McNutt, Andrew, Gordon Kindlmann, and Michael Correll. 2020. "Surfacing Visualization Mirages." In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. CHI '20. New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3313831.3376420.

Miller, Cassie. 2020. "SPLC Poll Finds Substantial Support for 'Great Replacement' Theory and Other Hard-Right Ideas." Southern Poverty Law Center. 2020. https://www.splcenter.org/news/2022/06/01/poll-finds-support-great-replacement-hard-right-ideas.

Mutz, Diana C. 2018. "Status Threat, Not Economic Hardship, Explains the 2016 Presidential Vote." *Proceedings of the National Academy of Sciences* 115 (19): E4330–39. https://doi.org/10.1073/pnas.1718155115.

Popescu, Adam. 2019. "A Greenland Glacier Is Growing. That's Not Good News." Environment. March 25, 2019. https://www.nationalgeographic.com/environment/article/one-part-of-greenland-ice-growing.

Sabini, John, Michael Siepmann, and Julia Stein. 2001. "Target Article: 'The Really Fundamental Attribution Error in Social Psychological Research.'" *Psychological Inquiry* 12 (1): 1–15. https://doi.org/10.1207/S15327965PLI1201_01.

Schickler, Eric. 2016. *Racial Realignment: The Transformation of American Liberalism, 1932–1965*. Princeton, New Jersey: Princeton University Press.

Sohoni, Deenesh. 2022. "The Coming Majority-Minority State?: Media Coverage of U.S. Census Projections, Demographic Threat, and the Construction of Racial Boundaries." *The Sociological Quarterly* 63 (1): 94–113. https://doi.org/10.1080/00380253.2020.1792810.

Stewart, Sheridan, and Robb Willer. 2022. "The Effects of Racial Status Threat on White Americans' Support for Donald Trump: Results of Five Experimental Tests." *Group Processes & Intergroup Relations* 25 (3): 791–810. https://doi.org/10.1177/13684302211048893.

Swire, Briony, Adam J. Berinsky, Stephan Lewandowsky, and Ullrich K. H. Ecker. 2017. "Processing Political Misinformation: Comprehending the Trump Phenomenon." *Royal Society Open Science* 4 (3): 160802. https://doi.org/10.1098/rsos.160802.

Tetlock, Philip E. 1985. "Accountability: A Social Check on the Fundamental Attribution Error." *Social Psychology Quarterly* 48 (3): 227–36. https://doi.org/10.2307/3033683.

Walter, Nathan, and Sheila T. Murphy. 2018. "How to Unring the Bell: A Meta-Analytic Approach to Correction of Misinformation." *Communication Monographs* 85 (3): 423–41. https://doi.org/10.1080/03637751.2018.1467564.

Watson, Amy. 2022. "Journalists Seeing Fake Information U.S. 2022." Statista. 2022. https://www.statista.com/statistics/1319457/journalists-finding-false-information-us/.

White, Ismail K., and Chryl N. Laird. 2020. *Steadfast Democrats: How Social Forces Shape Black Political Behavior*. Princeton, New Jersey: Princeton University Press.

Appendix

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Appendix 1.1, Sample Demographics

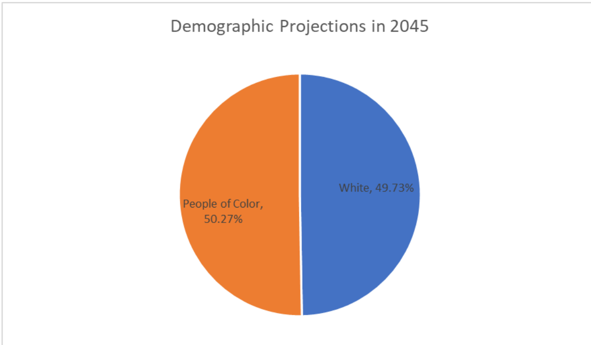
	Study 1	Study 2	Study 3	Study 4	U.S. Census	2020 ANES
Gender						
Female	52.5%	54.6%	50%	49.1%	50.5%	52%
Male	46.6%	43.8%	50%	49.2%	49.5%	47.9%
Party Identification						
Republican (includes leaners)	30.1%	26.7%	23%	22.7%	-	48.2%
Independent	17.5%	17.2%	21%	20%	-	13.0%
Democrat (includes leaners)	52.0%	56.1%	54%	57.1%	-	38.8%
Median Household Income	$60,000 - $69,999	$60,000 - $69,999	$60,000 - $69,999	$60,000 - $69,999	$71,992	$60,000 - 64,999
Average Age	N/A	N/A		35-44 years old	40.2	45-49
Race						
White	74%	75.7%	71%	70.1%	71%	65%
Black	9.7%	9.2%	9.4%	9.6%	14%	11%
Asian	6.8%	6.3%	8%	7.6%	6%	4%
Region						
Northeast	20.6%	20.4%	21%	20.4%	17.4%	-
Midwest	24.0%	22.8%	20%	20.6%	20.8%	-
South	33.5%	35.8%	37%	37.1%	38%	-
West	21.9%	21.1%	22%	21.9%	23.7%	-

Appendix 1.2, **Study Design**

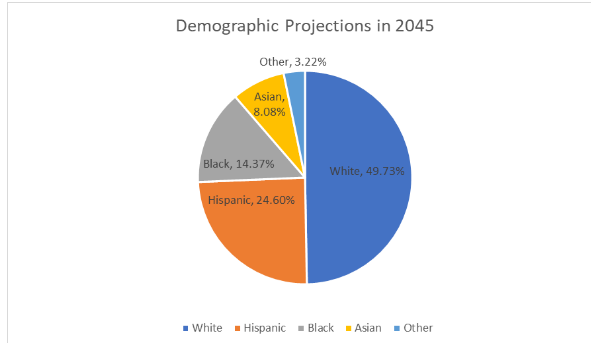
Studies	Data visualization	Intention behind study	N	Data Source
Study 1	Trend Lines	Frame majority-minority flip as either people of color or specific racial groups	1442	Cloud Research
Study 2	Pie Charts	Frame majority-minority flip as either people of color or specific racial groups	2079	Cloud Research
Study 3	Trend Lines and Pie Charts	Validate effects with an alternative sample	1945	Prolific
Study 4	Trend lines and Pie Charts	Test the effect of the label “racial minorities” against “people of color”	3448	Cloud Research

Appendix 1.3, Treatments

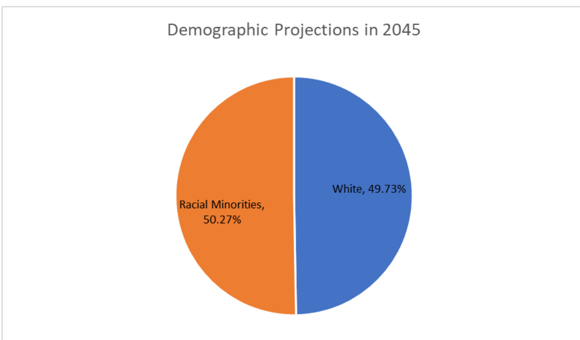
Simple Graph, POC



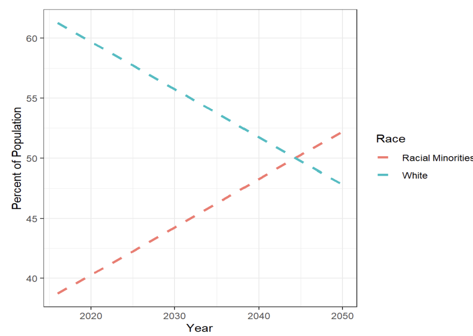
Complex Graph



Simple Graph, Racial minorities

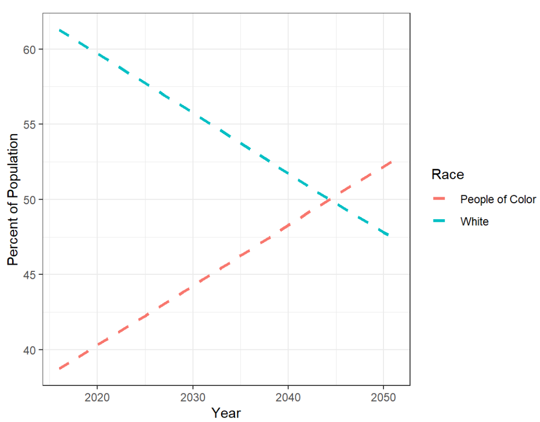


Simple trend lines, Racial minorities

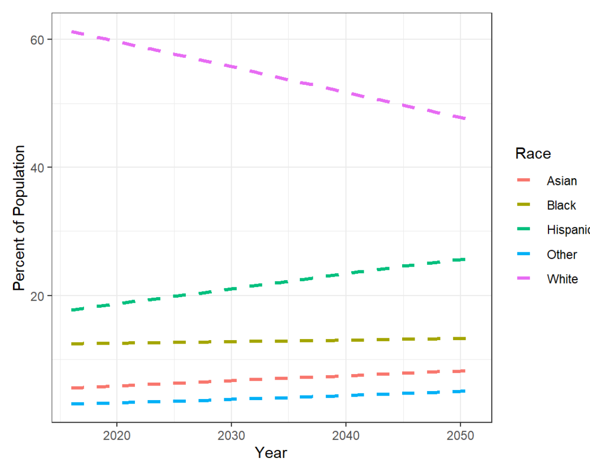


Trend lines

Simple trend lines, POC



Diverse trend lines



Appendix 1.4, Outcome variables

Support for violence

"It is reasonable to use violence against people who are politically opposed to me." (Strongly Disagree - Strongly Agree)

Groups growing in size

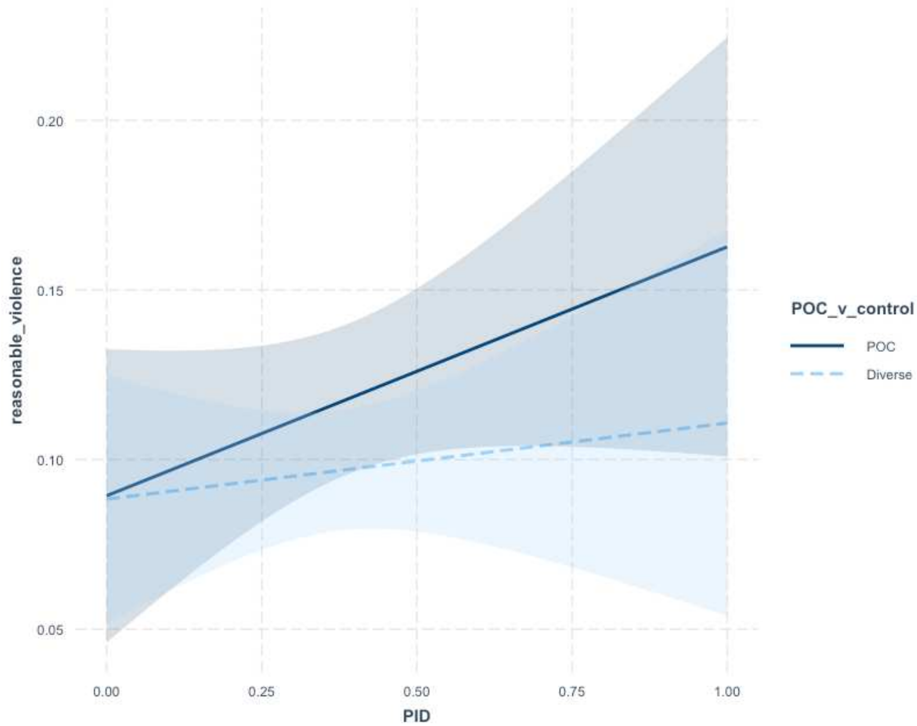
"Which demographic group will grow the most between now and 2060?" (You may select more than 1).
[Black Americans; White Americans; Asian Americans; Hispanic Americans; Other (please specify)]

Demographic Determinism

"How will the politics of the United States change between now and 2060? It will become…"
(Ideology: Much more conservative - Much more liberal; Party: Much more Republican - Much more Democratic)

Appendix 1.5, Heterogeneous treatment effects

Study 3, party ID interactions for Violence (Republicans are trending in the direction of being more violent in light of the POC graph)



	Dependent variable:
	reasonable_violence
POC_v_control	0.001
	(0.023)
PID	0.022
	(0.044)
MEDIA	-0.043
	(0.027)
GENDER	-0.042***
	(0.014)
IDEO	-0.021

	(0.042)
INCOME	-0.018
	(0.024)
EDU	-0.005
	(0.033)
POC_v_control:PID	0.051
	(0.048)
Constant	0.149***
	(0.026)
Observations	953
R2	0.018
Adjusted R2	0.009
Residual Std. Error	0.217 (df = 944)
F Statistic	2.126** (df = 8; 944)
Note:	*p<0.1; **p<0.05; ***p<0.01

Political Future interactions with EDU

Interactions - Political Future(Party, Ideology) with EDU

	Dependent variable:	
	Study 3-Ideology (1)	Study 3-Party (2)
POC Treatment	0.700***	0.626***
	(0.033)	(0.032)
Diverse Treatment	-0.0005	0.016
	(0.029)	(0.029)
EDU	0.051	0.061
	(0.038)	(0.037)
PID	0.034	-0.078**
	(0.032)	(0.032)
IDEO	-0.135***	-0.022
	(0.035)	(0.035)
INCOME	0.009	0.011
	(0.020)	(0.020)
GENDER	0.004	0.003
	(0.012)	(0.011)
MEDIA	0.024	0.054***
	(0.018)	(0.017)
POCboth_v_Diverseboth:EDU	-0.087*	-0.090*
	(0.051)	(0.050)
Observations	1,333	1,332
R2	0.049	0.048
Adjusted R2	0.039	0.039
Note:		*p<0.1; **p<0.05; ***p<0.01

Political Future interactions with PID

Interactions - Political Future(Party, Ideology) with PID

	Dependent variable:			
	Study 2-Ideology (1)	Study 2-Party (2)	Study 3-Ideology (3)	Study 3-Party (4)
POC Treatment	0.466**	0.596***	0.708***	0.638***
	(0.214)	(0.203)	(0.031)	(0.030)
Diverse Treatment	-0.059***	-0.048***	-0.015	-0.006
	(0.016)	(0.015)	(0.018)	(0.017)
PID	-0.011	-0.059*	0.079**	-0.041
	(0.033)	(0.032)	(0.037)	(0.036)
EDU	-0.064***	-0.054**	0.005	0.014
	(0.024)	(0.023)	(0.028)	(0.027)
IDEO	-0.125***	-0.064**	-0.137***	-0.025
	(0.032)	(0.031)	(0.035)	(0.035)
INCOME	0.016	0.023	0.007	0.010
	(0.018)	(0.017)	(0.020)	(0.020)
GENDER	0.022**	0.014	0.004	0.003
	(0.010)	(0.010)	(0.012)	(0.011)
MEDIA	0.005	0.007	0.025	0.055***
	(0.016)	(0.015)	(0.018)	(0.017)
POCboth_v_Diverseboth:PID	0.072**	0.057*	-0.087**	-0.070**
	(0.031)	(0.029)	(0.036)	(0.035)
Observations	1,808	1,805	1,333	1,332
R2	0.048	0.040	0.051	0.048
Adjusted R2	0.038	0.031	0.041	0.039
Note:				*p<0.1; **p<0.05; ***p<0.01

Violence interactions with Race (white, nonwhite binary)

Interactions - Violence with Race

	Dependent variable:
	Study 1
POC Treatment	0.272***
	(0.036)
Diverse Treatment	-0.062***
	(0.024)
white	-0.105***
	(0.029)
EDU	0.072**
	(0.028)
PID	0.041
	(0.031)
IDEO	-0.011
	(0.035)
INCOME	-0.043**
	(0.022)
GENDER	-0.054***
	(0.012)
MEDIA	-0.097***
	(0.019)
POC_v_diverse:white	0.045*
	(0.027)
Observations	1,343
R2	0.064
Adjusted R2	0.055
Note:	*p<0.1; **p<0.05; ***p<0.01