Sinclair Broadcasting and Racial Resentment: Evidence from Google Trends and Project Implicit

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Abstract

Media framing describes how news outlets structure discussions on an issue, delinieate the bounds of acceptable discourse, and encourage interpretations of facts. Can framing influence racial resentment? Evidence from laboratory experiments suggests it can, but there has been little research about the effects of racially-biased media coverage on racial animus in the real world. I estimate the effect of racially-biased local T.V. news on racial attitudes using the expansion of Sinclair Broadcasting Group, a conservative media empire, from 2004-2020 as the basis for a difference-in-differences analysis. I draw from two internet-based measures of racial animus, data from Google Trends and Project Implicit (N=3,936,939), finding no link between Sinclair moving into a local area and changes in racial animus.

Contents

This paper uses Google search terms containing offensive language as a proxy measure for racial animus. Following the practice of similar works (Stephens-Davidowitz, 2014; Chae, Clouston, Hatzenbuehler, et al., 2015; Chae, Clouston, Martz, et al., 2018; Isoya and Yamada, 2021), I use coded language to refer to these terms. The words themselves can be found in Table 3

1 Introduction

Can media coverage influence racial resentment? Empirical studies suggest that when White Americans understand welfare policies to threaten their privileged status in the U.S. social hierarchy, they feel more hostile towards minorities, and their support for welfare decreases (Willer, Feinberg, and Wetts, 2016; Wetts and Willer, 2018). This tendency has historically been weaponized by conservative media institutions, who stoke racial hostility to erode support for social programs, as in the infamous example of the "Welfare Queen" narrative, a racial stereotype employed to undercut support for the Aid to Families with Dependent Children (AFDC). However, the link between media coverage and racial resentment has not been extensively studied outside experimental settings. Specifically, while we know from laboratory experiments that racially framings of news stories can increase racial animus (Wetts and Willer, 2018; Gilliam and Iyengar, 2000), there is little literature that documents this process in the real world, or helps understand the effects of *long-term* exposure to these framings (Schemer, 2013, p. 532).

Does racially-biased media influence consumers' racial attitudes outside an experimental setting? To answer this question, I use the expansion of Sinclair Broadcasting Group, a conservative media conglomerate known for its racially biased news, from the period of 2004-2020 as the basis for a preregistered difference-in-differences analysis.

Data on racial animus is scarce, and rife with social desirability biases, so I use an internet-based measure of racial animus: the number of Google searches containing the word "[Word 1] ." The Google trends data has high external validity as it is based on observational data from the real world, but its' variance is so high that it would likely be unable to detect small effects. Because of this, I incorporate data on scores from the Harvard Implicit Association Test, a massively popular online experiment (N=3,936,939), as a second measure of racial animus. This data provides significantly higher power at the cost of some external validity (it's less clear who takes the IAT).

Overall, I find no link between Sinclair moving into a county and changes of racial resentment. This result is robust to multiple measurement strategies and specifications.

2 Theoretical Framework

2.1 What Characterizes Racially biased Coverage, and What Does It Mean for Racial Attitudes?

Framing is the landscape or picture of a public debate that media institutions construct when discussing an issue (Nelson, Clawson, and Oxley, 1997). It showcases major positions, deliniates the boundaries of acceptable opinion, and provides vignettes thorough which to think about the issue. I use the terms racially-biased framing or racial coverage to denote a particular framing of issues popular among conservative news outlets characterized by its insistence that race does not shape modern-day Americans' life prospects and "that individual characteristics, not structural barriers, explain group-based disparities" (Engelhardt, 2019, p. 3). In its most extreme forms, this framing instructs consumers that "demands from minority groups for special attention and improvements to their station" (ibid., p. 3) are either without basis, attempts to defraud the welfare state, or calls to redress Black American cultural failings. These framings also disproportionately depict criminals and recipients of welfare spending as African-American, depictions that studies show increase anti-Black hostility among white viewers (M. Gilens, 2009; Gilliam and Iyengar, 2000).

Studies in the literature have focused on the effects of racial media coverage on racial attitudes in the short-term (respondents are typically asked questions on racial issues immediately after being shown a treatment), but there has been comparatively little investigation in to whether these effects are long-lasting, or persist outside of an experiment (Schemer, 2013, p. 532). We know from an extesive literature on the effects of partisan media framings (Ladd and Lenz, 2009; Barnes and Hicks, 2018; DellaVigna and Kaplan, 2007; Miho, 2018; Gentzkow, 2006; Gentzkow, Shapiro, and Sinkinson, 2011) that partisan media framings do translate into real-world changes in public opinon. Can the same be said for racial framings and racial attitudes?

I attempt to answer this question this area by investigating whether the Sincalir News, a conservative media empire in the US known for its racially-biased coverage, influenced implicit or explicit racial attitudes in the counties it moved in to in the period 2004-2020.

2.2 The Sinclair Group and Its Advantages for Causal Inference

Studying media effects on public opinion is notoriously difficult. Ladd and Lenz (2009) identify four major hurdles that stand in the way of identifying media persuasion effects: a lack of major variation in media coverage, poor measures of media exposure, and alternative explanations for media effects (consumer self-selection and media outlet pandering towards consumer). I use these hurdles to motivate using Sinclair's expansion to study racial attitudes. I discuss each of these hurdles in turn, and describe how my research strategecan be used to overcome each obstacle.

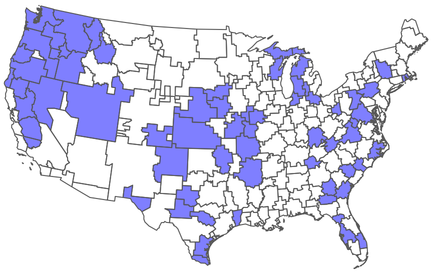
2.2.1 Variation in Messaging

One of the primary issues in studying the effects of media framing is there is little variation in media messaging; news outlets have a financial incentive to carve out a segment of the market (Mullainathan and Shleifer, 2005), and so generally endorse candidates / employ framings sympathetic to a single party (Ladd and Lenz, 2009, p. 395; Ansolabehere, 2006, p. 13). In this paper, I exploit Sinclair's expansion over the period 2004-2020 as the basis of a difference-in-differences model. Here, I describe Sinclair Broadcasting Group, and why its expansion can be used source of variation in media framing.

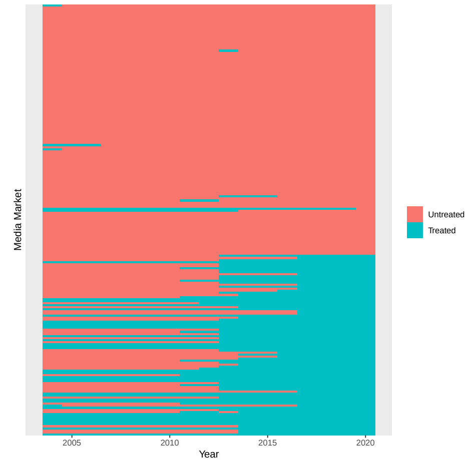
Sinclair Broadcasting Group is the largest telecommunications providers in the U.S., and has grown to serve the maximum 39% of houseolds allowable under U.S. law since its founding in 1971 (Scherer, 2018, p. 1). A map of Sinclair's expansion can be in Figure 1a each highlighted region is an area Sinclair bought or sold a station in the period 2004-2020. A chart showing when each station joined or left Sinclair can be seen in 1b. Rather than purchasing stations in large media markets across the country, Sinclair has expanded by buying up stations in small media markets, which means a large set of "treated" counties in the context of a difference-in-differences analysis - in the period I consider, Sinclair bought or sold stations in 68 markets.

Of course, using Sinclair's expansion as a source of variation in coverage presupposes that Sinclair stations differ from non-Sinclair stations on coverage of racial issues — if Sinclair stations deploy the same coverage on racial issues as other stations, then there is no causal pathway by which Sinclair acquisition can change levels of racial resentment in a market. I argue this is the case. While Sinclair's coverage of racial issues has not been extensively studied, quantitative research does show that Sinclair buying a station leads to a sharp rightwards shift in its coverage (Martin and McCrain, 2019). I argue that this effect extends to the coverage of racial issues -

(a) Media Markets Sinclair Bought or Sold a Station in between 2004-2020. DMA Boundaries From Hill, 2015



(b) Media Markets by Sinclair Ownership Status, Time



when Sinclair buys a station, it shifts the coverage of racial issues sharply towards the right, and provide anecdotal evidence to support this assertion.

Sinclair frequently pushes “must run” segments which are mandatory for owned stations to run and often push racially-biased framings of issues. Must-run segments often take the form of scripts local anchors are mandated to read, or pre-filmed segments that are broadcast over all Sinclair stations. As an illustration, Figure 3 shows images from one of these scripts being read on 30 stations. To document a pattern of racially-biased messaging, I offer examples of must-run segments with below which showcase racial framings.

This year, the Sinclair broadcasting has drawn ire for a series of “must-run” segments on police violence following the murder of George Floyd pushing the “Black-on-Black violence” canard and advocating for a military response to the protests (Pleat and Savillo, 2020; Pleat, 2020b). After Kyle Rittenhouse, a seventeen-year-old from Antioch, Illinois drove to Kenosha and allegedly murdered two protesters, Sinclair broadcast a segment to 93 stations warning that American cities were “ on the edge of a race war not seen since the sixties,” and promoted the idea of neighborhood blockades and patrols to defend neighborhoods from threat (Pleat, 2020a)

In 2010, Sinclair stations approved for broadcast and ran “Breaking Point,” an almost cartoonishly racist, 25-minute campaign advertisement which, among other things, cast aspersions that Obama’s 2008 presidential campaign was financed by Hamas and implied Obama was a Muslim by juxtaposing clips of him saying “As-salamu alaykum” (peace be with you) in a speech in Cairo against audio of Islamic prayers (2:08-2:50,4:36-5:15 GOP Trust PAC, 2010).

Figure 2: Sinclair News Anchors Reading a "Must-Run" Script (May 2018)

Figure 3: Images of 30 of 210 Sinclair Station Hosts Reading a Must-Run Script (Burke, 2018)

While these segments do not represent the entire spectrum of political programming on Sinclair stations, they contain point to a network that is extremely racially conservative. Thus, it is reasonable to suppose that Sinclair acquisition pushes a station to run more racially-biased content then it would otherwise run.

Thus, the link between Sinclair ownership and racially-biased coverage and the large variation in station ownership resulting from Sinclair's expansion in the period of 2004-2020 makes Sinclair's expansion an ideal source of variation to study the effects of racial coverage on racial attitudes.

2.2.2 Primitive Measures of Media Exposure

Measures of media exposure are often primitive and error-prone (Ladd and Lenz, 2009, p. 395), relying on proxies such as general political awareness (Zaller, 1992, p. 51). I contribute to a large body of research that uses expansion of media outlets in the USA as the basis of measures of exposure (DellaVigna and Kaplan, 2007; Miho, 2018; Gentzkow, Shapiro, and Sinkinson, 2011; Gentzkow, 2006). Admittedly, this measure could be made more robust by incorporating viewership information about the stations Sinclair owns (i.e. a small station would have less of an effect than a large station), but I make the choice to use data that is non-proprietary and freely accessible. I argue that the measure as it stands provides a good compromise between accessibility and specificity.

2.2.3 Alternate Explanations

Where a link between media framing and persuasion is found, it is difficult to tell whether this comes as a result of news consumers genuinely being convinced by the coverage, consumers shifting their news consumption to align with their existing views, or media institutions shifting their coverage to better align with the interests of their readers (Ladd and Lenz, 2009, p. 395). I argue that these alternate explanations are not a significant concern when discussing the persuasive effects of Sinclair news. Sinclair broadcasts and must-run segments are presented by the same local anchors that present the rest of the news, so viewers lack the contextual information needed to understand that their coverage is inconsistent with their predispositions, and will be less likely to select away from it. Further, Sinclair's coverage is dictated from the top down and as such, is less-sensitive to the opinions of its viewers. I discuss both points in turn.

2.2.4 Audience Selection / Motivated Reasoning

First, the issues of audience selection and motivated reasoning. Audiences select media outlets that cater to their predispositions, and tend to dismiss or ingore arguments that challenge their predispositions. Strong audience selection effect or motivated reasoning effects would leave no pathway by which Sinclair Ownership could influence racial animus (viewers would simply select away from their local station or stop paying attention when the coverage shifted to must-run segments). I argue that using Sinclair Media expansion is a way to sidestep these effects, as audiences exposed to Sinclair's must-run segments lack the contextual information needed to understand that the messages they are receiving are inconsistent with their predispositions and mentally resist or actively select away from them.

Zaller, 1992 articulates the principle that viewers will resist arguments they understand as inconsistent with their predispositions in his model of public opinion as the resistance axiom:

> "RESISTANCE AXIOM: People tend to resist arguments inconsistent with their political predispositions, but they do so only to the extent that they possess the contextual information necessary to perceive a relationship between the message and their

predispositions." (Zaller, 1992, p. 44)

Here, Zaller is primarily concerned with "resistance" in the sense of mental resistance or skepticism to an argument, but I argue that logic also applies in reguards to consumers' choice of media outlets. Audiences will select away from outlets which run coverage that clashes with their predispositions, but only to the extent that they understand from contextual information that these outlets do challenge their predispositions. As Sinclair's must-run segments are read by the anchors and run under the chyron of the local station, news viewers lack the information needed to understand that they are watching coverage ideologically different from their normal broadcasts, they are unlikely to select away from this messaging. Indeed, Martin and McCrain, 2019 find that Sinclair coming to own a station has only a very small impact on its viewership - Sinclair coming to own a station is associated with a 3% drop in viewership over the following months (ibid., p. 17). This leaves a very large space for Sinclair to persuade its viewers. Accordingly, I argue that audience-selection and motivated reasoning-effects are not a major concern when evaluating this research.

2.2.5 Audience Pandering

Finally, the issue of media institutions changing their coverage to pander to viewers. If Sinclair statiosn began to pander to local preferences, then there would also be no pathway for coverage to influence racial attitudes. However, Sinclair's structure of "must-run" content distribution means that this is issue is not a concern. Coverage is dictated from the top-down, meaning that local audiences and news crews have no ability to change their coverage to suit the views of their viewers. [1]

2.3 Measuring Racial Animus

Measuring racial resentment is difficult. Overt expressions of racism are severely socially sanctioned in the U.S., so respondents who do harbor racial resentment often understate it when they are interviewed for traditional surveys (Krumpal, 2011; Kuklinski, Cobb, and Martin Gilens, 1997). These social-desirability biases confound traditional survey measures, and lead to underestimates of the levels of racial hostility in the states.

[1] The Seattle Sinclair station KOMO 4 is famous for running its must-run segments in the small hours of the morning so as to screen them to the fewest viewers (Rosenberg, 2018). However, as far as I can tell, this practice represents an extreme exception rather than the rule.

I sidestep social desirability biases by using two unconventional measures of racial animus: the number of Google searches for racial slurs in an area, and test scores from Harvard University's Project Implicit, an internet-based project to collect data on implicit biases. Both measures estimate racial animus from observed behavior (Google searches or the ability to associate Black and White faces with positive words) rather than asking respondents questions, so sidestep issues of self-reporting.

The Google search results provide higher external validity (almost all the population is represented in Google search data) at the cost of low power (the data is variable, so small effects would be difficult or impossible to detect). I compliment this with data from Project Implicit which trades on external validity (IAT takers do not represent the general population) but the large sample size offers extremely high power, so the chance of not finding a small effect is low.

In the next sections, I offer a summary of the literature surrounding each measurement, and make the case for its use as a measure of racial hostility in this context.

2.3.1 Google Trends Data

I use the concentration of Google searches containing racial epithets as a proxy measurement of the level of racial animus in an area. Originally developed by Stephens-Davidowitz (2014) to understand the link between racial animus and the under-performance of Black candidates in national elections, this measure has also been used to measure the contributions of racial hostility towards African-American mortality (Chae, Clouston, Martz, et al., 2018; Chae, Clouston, Hatzenbuehler, et al., 2015), election outcomes (Stephens-Davidowitz, 2014), and economic inequality (Connor et al., 2019), Data from Google searches are ideal are searches not subject to the social-desirability biases that confound traditional, survey-based measures of racial resentment, and provide a large, regularly-sampled source of data which represents a great deal of the population (at present, Google as an over 85% market share in the US).

Overt expressions of racism are socially sanctioned in the U.S., so mean that survey respondents often understate the extent of their racial hostility when asked by interviewers (Bonilla-Silva, 2006). Indeed, research has repeatedly demonstrated that respondents will understate or disguise their opposition to measures such as residential integration when directly asked by surveyors (Kuklinski, Cobb, and Martin Gilens, 1997). The underlying logic is that survey respondents do not want to disclose sentiments that cast them in a negative light or that could expose them to social sanction, so they will alter their responses to reflect social consensus (Krumpal, 2011).

First, Google searches do not suffer from the same social censoring as traditional measures of public opinion that rely on face-to-face or over-the-phone interviews. This measurement approach has an advantage over traditional survey-based measures of racial animus in that it is less subject to a social desirability bias: "Google searchers are online and likely alone, both of which make it easier to express socially taboo thoughts (Kreuter et al., 2009)" (Stephens-Davidowitz, 2014, p. 26). Further, it provides a high-resolution set of data that would be prohibitively expensive to collect from a traditional survey, especially given that the difference-in-differences approach requires a repeated survey comparable across multiple time periods.

The core assumption of this strategy is that Google searches for the word [Word 1] are a good proxy underlying racial animus in an area. I give several reasons to motivate this assumption by reporting the searches most associated with these words, and reporting robust correlations between this measure and other measures traditionally used to study racial animus.

Following the practice of Stephens-Davidowitz (ibid., p. 29), I report the queries most related to the word "[Word 1] ," as reported by Google Trends. These queries reflect what users search for the most while using the terms. As one might expect, some of the most related searches for the word "[Word 1] " express users learnign about the term: "definition of [Word 1] " and "what does [Word 1] mean" are both among the top 5 search queries related to term. However, almost all the remaining top searches clearly express racial animus: among the top 10 most related queries are [Word 1]'s are "I don't like [Word 1]'s ," "fuck the [Word 1]'s ," and "ship those [Word 1]'s back." These searches indicate that at least some portion of the searches for the word express genuine racial hostility or animus.

How well does this measure correspond to other traditional measures of racial animus? Stephens-Davidowitz (ibid.) reports strong correlations between opposition to interracial marriage as reported in the GSS and Google searches for [Word 1] at the state level. I provide further support for this also reporting correlations between searches for [Word 1] and the scores of respondents in a state on the IAT, and their responses to the question "how warmly do you feel about this group: Black Americans?" (lower scores indicating less warmth). Robust correlations between these two measures (.6,.45) suggest that these measures encode the same information.

Because searches related to the word "[Word 1] " clearly express racial animus, and estimates from this measure well correlate to other accepted measures of racial animus, I suggest that there is good evidence to motivate the assertion that Google searches can be used to capture racial animus in an area.

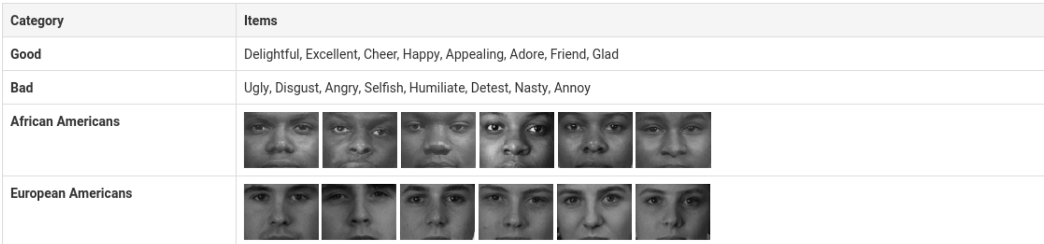
2.3.2 IAT Scores

To provide a second measure of racial animus, I use data from the Harvard race IAT (Xu et al., 2021). The Harvard IAT is an internet-based quiz founded in 1998 that seeks to measure implicit associations between "concepts (e.g., Black people, gay people) and evaluations (e.g., good, bad)" (Xu et al., 2020). Data from this test has previously used to estimate the effects of ingroup biases on health outcomes (Leitner et al., 2016b), anti-black racism on Black Americans' health (Leitner et al., 2016a), and anti-black implicit-biases on student outcomes (Chin et al., 2020).

The race IAT asks participants are sort good and bad words, and African-American and European-American into two categories. Examples of these faces and words can be seen in Figure 4. The IAT records the difference in the speed with which respondents can sort European-American faces with good words / African-American faces with bad words, and European-American faces with bad words / African-American faces with good words.

The IAT records the differences in the speed with which respondents can sort European-American + Good / African-American + Bad together and European-American + Bad / African-American + Good together. The IAT would record a positive score (an implicit preference for European-Americans) if a respondent was quicker to code European-American + Good / African-American + Bad together than they were to code European-American + Bad / African-American + Good together. The underlying logic behind using the differences in speeds is that "making a response is easier when closely related items share the same response key [category]" (Xu et al., 2021), so, on average, respondents who have a strong implicit association between African-American and Bad will find it more difficult to code European-American and Good together.[2]

[2] A popular misconception is that IAT scores can be used as a diagnostic of individual bias. This is not the case - IAT results are only useful predictors of behavior or bias when aggregated to a larger level (Xu et al., 2020)



Category	Items
Good	Delightful, Excellent, Cheer, Happy, Appealing, Adore, Friend, Glad
Bad	Ugly, Disgust, Angry, Selfish, Humiliate, Detest, Nasty, Annoy
African Americans	
European Americans	

Figure 4: Slides From an IAT test (Xu et al., 2021)

The IAT responses are not subject to social-desirability biases as they are determined by implicit associations that respondents cannot control. In fact, methodological studies have shown that even when asked to create a certain results, participants are unable to devise or enact a strategy to get their desired results unless given specific instructions on how to do so by a researcher (Kim, 2003, pp. 88–91).

Incorporating IAT scores does introduce one issue in that the concepts of racial animus and implicit racial bias or hostility are similar, yet distinct. Individuals may be explicitly committed to racial equality, yet still have implicit racial biases (Xu et al., 2020). Further, the link between IAT scores and behavior (e.g. self-reported explicit bias, discrimination) is contested (Forscher et al., 2019), so I also attempt an analysis using data from a more traditional IAT question, the question: "Please rate how warm or cold you feel toward the following group - Black people".

3 Measurement Strategy

Having provided a rationale for the measures I use, I now describe the process of constructing these measures, and the data sources used. I briefly describe how I track Sinclair's Expansion before discussing my two measures of racial animus, Google searches for "[Word 1] " and race IAT scores.

3.1 Measuring Sinclair Expansion

Traditionally, researchers track a network's expansion using datasets maintained by the Nielsen Corporation, the U.S. company responsible for tracking the boundaries of media markets. I create a record of Sinclair's station ownership over time from the company's yearly 10-K filings with the Securities and Exchange Commission. This dataset has an advantage over this dataset as it is open-access, and can be published freely alongside the research.

In each of their yearly SEC filings, Sinclair enumerates all the stations owned by the company at the end of the financial year, and the name of the media market they are in. I extract the unique media market names in each yearly filing to understand which markets Sinclair is present in. Because the media market names are inconsistent between years, I translate the media market names into their DMA codes manually, and use DMA codes for the rest of the analysis.

3.2 Measuring Google Trends Data

I use the frequency of searches for the word "[Word 1] " as a proxy for racial animus in an area. However, data from Google Trends is returned on an idiosyncratic scale. In this section I describe a novel approach data from the Google Trends interface into a measurement that is comparable both between times and between regions, a previous limitation when using Google search data at the market-area level.[3]

Google trends data measures the popularity of a search on an idiosyncratic scale: a term's "Google search score" in a given time is given as the volume of searches over that time divided by the volume of searches when the term was most popular. However, the difference-in-difference analysis I perform requires that the search volume is measured on the same scale. In this section, I describe the scaling process used to back out an interval-level measure of search popularity from these search scores.

Search popularity can be obtained from Google in two flavors: a measure that compares the popularity of a search across all regions at a given time, and a measure that gives the popularity of a search in a given region across all times.

The search score that can be used to make comparisons between regions at a given time is defined as the following:

$$\text{Between Regions Search Score} = \frac{\text{Popularity in Region } i}{\text{Popurality in the Most Popular Region}}$$

The search score that can be used to compare the popularity across different times in a given region is defined as the following.

$$\text{Between Times Search Score} = \frac{\text{Popularity at Time } i}{\text{Popurality at the Most Popular Time}}$$

[3]Connor et al. (2019) details a strategy for scaling at the state-level, but this requires an assumption of little or no missing data, and introduces larger errors by rounding

The first measure allows for comparisons between regions but not between times, while the second permits comparisons between times but only within one region. When combined, these measures can be used to compare the volume of searches across both time periods and regions.

As an example, we might want to compare searches for the word apple in Washington D.C. in 2017 to searches in Pensacola in 2018. Washington D.C. had twice the number of searches for the word apple as Pensacola in 2017. As Pensacola had three times the amount of searches for the word apple in 2017 as 2018, we know that Pensacola had just $1/6th$ the searches for the word apple in 2018 as Washington D.C. in the year 2017.

By comparing the volume of searches in each region at each time to each other region, I back out a measure, v that is comparable both between regions and between times. This measurement is on an arbitrary scale, so I standardize such that a value of 1 corresponds to the mean search popularity. Put formally, I derive search volume in region r at time t v_{jt} with the following formula:

$$v_{rt} = \frac{1}{J \times I} \sum_{i=1}^{I} \sum_{j=1}^{J}$$

- v_{rt} is proportional to the search volume in region r at time t (recall, the measure is on an arbitrary scale)
- Regions $j \in (1 \dots J)$
- Time periods $i \in (1 \dots I)$

Because we know the ratio of the search volume at each region / time to the search volume at each other / region time, by averaging the ratios of one region to every other, we can find the average ratio of the volume with respect to other volumes. [4]

3.3 Implicit Association Test Scores

Data from the IAT is recorded at the county level, I measure racial animus at the larger DMA level. To solve this issue, I aggregate IAT scores to the DMA level using a crosswalk of US

[4] Missing data means I actually compare the ratios of searches for the subset of data points between which all pairwise comparisons are possible (one cannot compare x and z through their ratios to y if y is zero). I use these data points to find the values for the larger set of observations for which all pairwise comparisons are not possible.

counties to DMA ID's from 2016 obtained from the Harvard Dataverse (Sood, 2016). In actual fact, DMA boundaries undulate slightly over time to include and exclude new counties, and a lack of publicly-accessible historical data means I cannot account for these movements. This is an issue shared by other research on media institutions that aggregate county-level data to the DMA level (Miho, 2018, p. 9), and might lead to a slight underestimation of the treatment effect, as a small fraction of units may be misclassified.

4 Methodology

4.1 Tools Used

I use Knitr (Xie, 2014) to integrate statistical calculations into the paper, eliminating the possibility of transcription errors. To ensure the findings are reproducible, I tested the analysis routines using the *testthat* package in R (Wickham, 2011) and the *unittest* module in Python (Van Rossum and Drake, 2009). But I won't make you take my word that my methods are properly implemented – I provide a Docker image and reproducibility materials to ensure others can replicate the calculations on their own systems (Merkel, 2014; Boettiger, 2015). The result is "one-click reproducibility" (Nüst et al., 2020); readers can reproduce this exact paper with the push of a button from the linked materials. [5]

4.2 Preregistration

To avoid the possibility of fitting hypotheses to the data after results are known, I preregistered my analysis using the Google trends data. Readers can find the preregistration plan in Appendix D. I wrote the original webscraping and scaling code using placebo data (searches for the words 'socks,' 'shoes,' and 'fish') before running the code on actual data.

I have made one deviation from the preregistration. In my preregistration, I describe a different strategy to scale the Google trends data than the one I actually employ. The original strategy was based on a misunderstanding of the format of Google trends data, and does not actually produce the desired measure. In the analysis I perform, I correct this mistake. I describe the correct scaling procedure in section 3.2.

[5] Replication materials available here. By default, the web-scraping does not run, as the data can take several days to collect.

4.3 Difference-In-Differences Analysis

Comparisons in levels of racial animus between markets and times when Sinclair owned a station and locations / periods where Sinclair did not would lead to a selection bias, as Sinclair regions/times differ systematically from non-Sinclair stations/times. Specifically, Sinclair has chosen to expand into media markets that have smaller, more local media markets than the average market (Miho, 2018, p. 3) undoubled, this also means that Sinclair stations differ from non-Sinclair stations in terms of other, unobserved covariates. In addition, Sinclair typically expanded into regions later on in the time period observed.

These differences mean that Sinclair stations / times and non-Sinclair stations / times are not plausible counterfactuals of each other, so cannot be directly compared. Accordingly, I estimate difference-in-differences models with the following structure:

$$\text{Racial Animus / Bias Measure}_{tr} = \beta \times \text{Sinclair Present}_{rt} + \lambda_r + \delta_t + \varepsilon_{tr}$$

Where $delta_t$ is a yearly fixed effect that absorbs all changes that affect all regions at a given time, and $lambda_r$ is a fixed-effect term that cancels out bias from unobserved region-specific factors that remain constant over time ε is the error term. The coefficient β recovers the effect of Sinclair moving into or out of a region - as all region-specific and time-specific unobserved factors are washed out, the remaining coefficient β captures the difference associated with Sinclair entering or leaving a region.

The assumption needed to identify the effect of Sinclair moving into or out of a region is that of one of parallel trends, meaning that absent treatment, we would observe the same trends in the media markets Sinclair moved into or out of as we can currently observe in the untreated groups. At each stage in this analysis, I estimate pre-treatment placebo effects which can be used to falsify this assumption - if there are large differences between treatment and control groups, then it is clear that Sinclair entry into a market also correlates with existing trends in racial animus, so the parallel trends assumption is not plausible. I further check that all findings are robust to specifications which include linear time trends, a more demanding specification which cancels out all linear trends in racial animus specific to each region.

5 Results

5.1 Sinclair Entry on Google Trends Measurement

In this section, I perform report the results of a difference-in-differences analysis estimating the effect of SBG entering or leaving a market on levels of racial animus in that area.

First, I test the parallel trends assumption by estimating treatment effects for using a set of treatment leads and lags. If there are treatment effects before Sinclair comes into a region then this is evidence that the parallel trends assumptions is not met, as Sinclair cannot plausibly cause a change in racial attitudes years before it has a presence in a market. I estimate and report the estimated lagged treatment effects in Figure 5

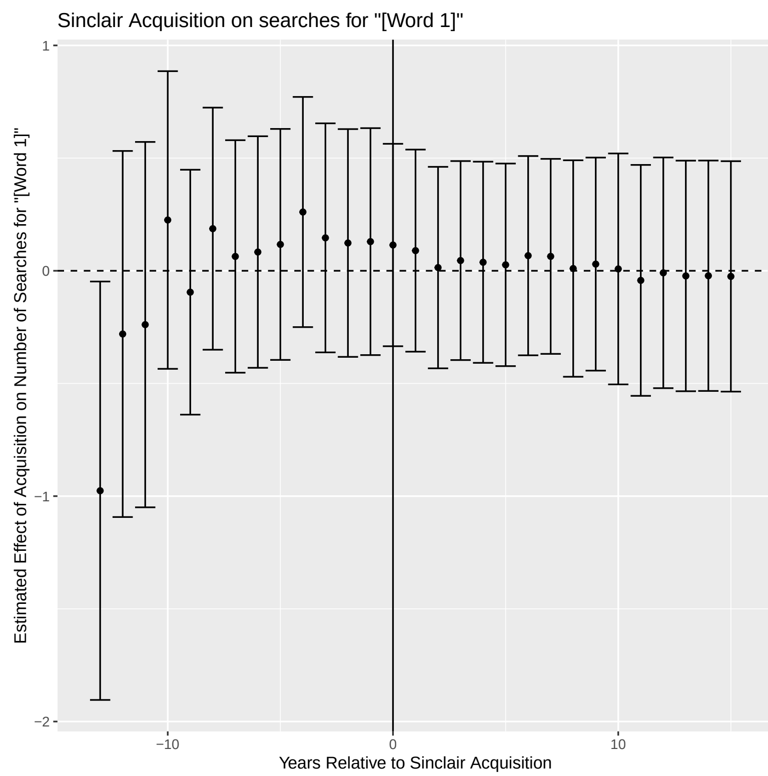


Figure 5: Fixed-Effects Estimates of the effect of Sinclair Acquisition on Searches for “[Word 1] ”

Across all years before the Sinclair enters a region, the estimated treatment effects are no different from zero. I find no pre-treatment effects, which suggests that there are no time-varying confounding variables in the time before Sinclair moves into a market. This gives us no reason to doubt the parallel trends assumption that absent treatment, the treated media markets would have progressed the same way as the untreated counties.

Next, I estimate the effect of Sinclair entry into a market on Google searches including the word [Word 1] . Table 1 shows the results of these analyses. Model 1 presents a "vanilla" difference-in-differences model including region and year fixed effects. In Model 2, I include region-specific linear time trends, a way to slightly relax the parallel trends assumption.

Table 1: Fixed Effects Models For Sinclair Aqusisition on Google Searches

	Dependent variable:	
	Standardized Frequency of Searches for [Word 1]	
	(1)	(2)
Sinclair Present	-0.049	-0.170^{*}
	$(-0.161, 0.062)$	$(-0.348, 0.008)$
Constant	1.141^{***}	134.264
	$(0.740, 1.541)$	$(-74.511, 343.040)$
Year Fixed Effects	Yes	Yes
Region Fixed Effects	Yes	Yes
Region Time Trends	No	Yes
Observations	3,570	3,570
R^2	0.234	0.349
Adjusted R^2	0.183	0.258
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The coefficient for Sinclair's presence recovers the average effect of SBG moving into / out of an area among the treated units. Across all models, this coefficient is not distinguishable from zero. However, the confidence intervals associated with these estimates do not rule out plausible effect sizes.

The confidence associated with the second model is (-.348, .008) which does suggest that Sinclair moving into a county is not meaningfully associated with the number of Google searches for the word [Word 1] in the region, but the confidence interval associated with the first model is (-..161, .062), which does not rule out as much 6% of the mean search volume.

Further, the width of these confidence intervals suggest that the analysis is severely underpowered - the fact that a -17% of the mean decrease in the volume of searches is only significant at the $\alpha = .1$ level suggests that the models would not be able to detect any small effects. The fact that a 17% is only significant at the $\alpha = .1$ level might cause some to question whether the models can detect any plausible effects at all. However, searches containing the word "[Word 1] " are likely driven by a small number of searchers, so a media effect which moved a few users to start completing searches with the word could plausibly result in a large percentage increase in the volume of searches including the word "[Word 1] ."

Undeniably however, the width of the confidence intervals mean that the results from the Google Trends analysis are unilluminating. Sinclair moving into a county could either have a negative effect, or no effect, or a small effect on searches for including the word "[Word 1] ." Only the presence of a large effect is ruled out. For this reason, I turn to evidence from the Project Implicit Implicit Association Tests.

5.2 Sinclair Entry on IAT Responses

As the analysis I perform using Google trends data is underpowered, I incorporate a second internet-based source of data on racial animus, data from the Harvard IAT. To investigate the possibility of Sinclair Broadcasting having a small effect on levels of racial animus in an area, I repeat the same difference-in-differences approach using two other measurements, scores on the Harvard Race IAT, and self-reported warmth towards Black Americans on the IAT. The IAT has a significant advantage over the Google trends data - a massive sample size. 3,936,939 Americans including 2,014,672 White Americans have taken the IAT between 2004 and 2021. I highlight the number of White respondents as the concept of racial animus is discussed in this paper is primarily relevant to the dominant racial group in the U.S. (Connor et al., 2019, p. 206). As such, I estimate the effect of Sinclair moving into a region among all respondents and, separately, among only White respondents. This approach is consistent with other works that use IAT data

(Connor et al., 2019; Leitner et al., 2016a)

I check the parallel trends assumption with respect to IAT scores. I present the results of this test in Figure 6 I test for pre-treatment differences between the treated and untreated markets *before the treatment occurs.* There are are two pre-treatment years when the pre-treatment effects are present. This makes it more difficult to sustain the parallel trends assumption that, there are no differences between the counterfactual trends of the treated groups and the observable trends of the untreated groups. However given the high power, it is worth noting that the largest estimated pre-treatment effect is less than 0.6% of the mean. Following the best practices for small pre-treatment effects described in Bilinski and Hatfield (2020, p. 9), I continue with my analysis, but also fit models with region-specific linear time trends.

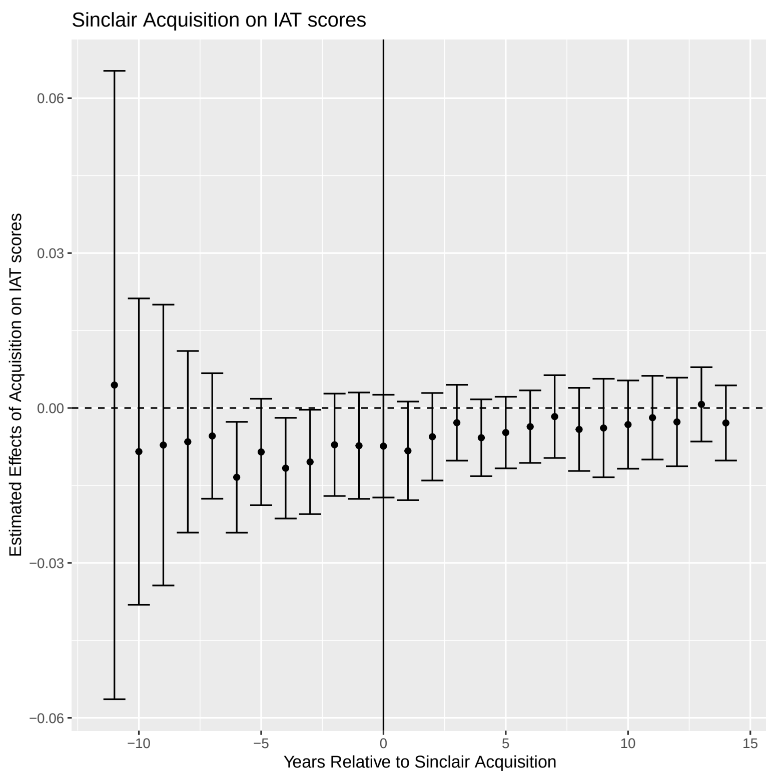


Figure 6: Fixed-Effects Estimates of the Effect of Sinclair Acquisition on IAT Scores (Among White Respondents)

I perform the same check with the measure of explicit bias, responses to the statement "I feel warm towards this group: Black Americans," and find that there are more sustained and substantively larger treatment effects. This suggests that Sinclair moving into a region correlates with other unobserved changes in explicit bias as measured by this approach. It may not be possible to disentangle these effects, so I do not pursue the analysis further.

I then estimate the effect of Sinclair entering or leaving a media market on IAT scores in the area among all respondents in Models 3 and 4, and among only white respondents in Models 1 and 2, I allow for linear time trends in Models 2 and 4. The model estimates can be seen in Table 2:

	Model 1	Model 2	Model 3	Model 4
Intercept	0.28*	0.29*	0.32*	0.32*
	[0.28; 0.29]	[0.28; 0.30]	[0.31; 0.33]	[0.31; 0.34]
Sinclair Present	0.00	−0.00	0.00	0.00
	[−0.00; 0.00]	[−0.01; 0.00]	[−0.00; 0.01]	[−0.00; 0.01]
Year Fixed Effects	Yes	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes	Yes
Linear Region Time Trends	No	Yes	No	Yes
White Respondents Only	No	No	Yes	Yes
Num. obs.	3936939	3936939	2014672	2014672
AIC	7746045.49	7746256.37	3467774.54	3468051.48

* Null hypothesis value outside the confidence interval.

Table 2: Statistical models

Across all four models, the coefficient estimates are always insignificant. Every confidence interval excludes effects larger than .006 (recall, IAT scores typically range from -2 to 2). The fact that the confidence intervals all exclude effects larger than .006 means that we can be confident that Sinclair Broadcasting Group moving into or out of a media market does not have any meaningful effect on the levels of implicit bias among IAT takers in the region.

6 Discussion

Taken together, the data from project implicit and Google tends give no reason to suggest that Sinclair broadcasting group moving into a has meaningful effect on levels of racial animus / implicit racial bias in an area.

This result is surprising in the face of many survey experiments which link exposure to racially biased coverage to increased levels of racial animus. This may suggest that the short-term media effects observed in laboratory experiments may be not translate well into real-world effects or are short-lived (Schemer, 2013). One reason may be that racial attitudes are typically, although not uncontroversially (Engelhardt, 2020), thought as foundations formed in early childhood (Sears and Brown, 2013, p. 65), and as stable of political foundations upon which other political attitudes are built (Martin Gilens, 1995). Existing estimates of partisan persuasion effects in the U.S. suggests that conservative media programming can sway the votes of between 0.13%, and 0.7% of a county (or between 2.6 to 28 percent of its audience) (Miho, 2018; DellaVigna and Kaplan, 2007), if racial attitudes are significantly harder to sway than partisan attitudes, then it could be that the entry of a news network has no meaningful effect on racial bias.

Racially-biased coverage could also be temporary if there is a "learning effect" in which consumers are initially uncertain of the bias of Sinclair news, and so are initially swayed by it, but pick up to its' slant over time, and are no longer receptive to the messaging (DellaVigna and Kaplan, 2007, p. 1990). If this learning effect happens in a short time period (say, over a few months), then it would be difficult or impossible to measure with year-based survey measures.

Alternatively, it could be that racially-biased coverage does influence racial attitudes, but that the effect is not observable here. If this is the case, it could be because IAT scores and Google trends are inappropriate to measure racial attitudes, or that while Sinclair does have a racial bias in its must-run segments, that the bias is not pervasive enough to create a shift in opinion.

All of this is speculative. Further research is needed to investigate whether a measurable effect of racially-biased news framing can be seen in other contexts, using other measurements, or with other stations.

7 Conclusion

In this paper I have investigated the link between Sinclair news entering a media market and racial attitudes in an area. I have made the case that Sinclair's news coverage is strongly racially biased, and for the use of Sinclair's expansion as the basis for a difference-in-difference analysis on the effects of racially-biased media coverage. Overall, I find no link between Sinclair moving into a region and racial attitudes in the area using this approach. This result is contrary to what we would expect from laboratory experiments, which almost universally suggest that exposure to racial messaging should increase racial hostility among viewers.

Further research is needed to better understand the discrepancy between these findings. Are racial attitudes insensitive to media persuasion effects in the long run? Or are the effects so small over the long run that they are not meaningful? Are media effects present when considering different networks, or more explicit levels of racial animus? All of these are promising avenues for further research.

I also make a methodological contribution to the emerging literature of researchers using Google Trends data to document social phenomena, and introduce a new method of scaling data from Google trends makes the measurements comparable between both times and places, a former limitation when working with DMA-level Google search data. This contribution allows for difference-in-difference analyses in the future at the DMA or city level, as data is available.

A Codings for Offensive Words

Table 3: Coding For Offensive Words

Code	Word
Word 1	Nigger

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C Code

I strongly recommend checking out the replication materials. To avoid any edits being made after submission, the sha hash of the last commit is .

D Preregistration Document

D.1 Pregistration

Pre-Registration for Undergrad Dissertation

Beniamino Green

March 15, 2021

This paper uses Google search terms containing offensive language as a proxy measure for racial animus. Following the practice of similar works (Stephens-Davidowitz 2014; Chae, Clouston, Hatzenbuehler, et al. 2015; Chae, Clouston, Martz, et al. 2018; Isoya and Yamada 2021), I use coded language to refer to these terms. The words themselves can be found in Table **??**

1 Introduction

Can media coverage influence racial resentment? Empirical studies suggest that when white Americans understand welfare policies to threaten their privileged status in the U.S. Social hierarchy, their resentment of minorities increases and their support for welfare decreases (Willer, Feinberg, and Wetts 2016; Wetts and Willer 2018). This tendency seems to be weaponed by conservative media institutions and politicians, who seem to encourage racial animus to erode support for social programs, as in the infamous example of the "Welfare Queen" narrative, a racial stereotype employed to undercut support for the Aid to Families with Dependent Children (AFDC). However, the link between traditional media coverage and racial resentment has not been extensively studied.

I propose a study exploiting the expansion of the Sinclair Media Network from 2004-2021 to understand how conservative media messaging impacts racial resentment in a media market. The expansion of Sinclair Media during this period provides the basis for a difference-in-differences analysis estimating the effect of Sinclair Media purchasing a station on racial animus in an area. I propose using data from Google search trends in an area as a proxy for racial resentment, a strategy that has already been used to measure racial resentment in the context of public health (Chae, Clouston, Martz, et al. 2018; Chae, Clouston, Hatzenbuehler, et al. 2015) and elections research (Stephens-Davidowitz 2014).

2 Background

2.1 Sinclair Broadcast Group

In this paper, I suggest exploiting the expansion of Sinclair Network over the period of 2004-2021. During this, the Sinclair Broadcast Group sold or purchased stations in 67 media markets. I use the same strategy to track the expansion of Sinclair Media outlets employed by Miho 2018, namely, by extracting a record of the stations Sinclair Owns at the end of each financial year from their SEC form 10-K filings. These filings have an advantage over the typical sets data used to track network expansion maintained by the Nielsen Corporation as they are publicly available, so the findings can be easily reproduced.

Previous research has demonstrated that Sinclair acquisition of a network is associated with a sharp rightwards shift in its coverage (Martin and McCrain 2019). However, a quantitative analysis of the effect of Sinclair ownership on coverage of racial issues has not been conducted. There is significant evidence to suggest that Sinclair ownership does push stations to run more

D.2 Pregistration

racially conservative stories than they otherwise would. This year, the Sinclair corporation drew ire for a series of "must-run" segments on police violence following the murder of George Floyd pushing the "black-on-black violence" canard and advocating for a military response to the protests (Pleat and Savillo 2020; Pleat 2020).

In analyzing the effects of news coverage on racial animus, it might be natural to examine the expansion of Fox News, which occupies a position in the public consciousness as among the most conservative stations on racial issues, and is the most trusted media outlet among Republican and Republican-leaning respondents in many polls (Mark Jurkowitz and Walker 2020). However, I choose to use Sinclair over Fox News Stations for two reasons. First, Fox News' expansion strategy has involved purchasing a larger stations. As television companies in the US can only expand until they broadcast to 39% of U.S. households (Scherer 2018), Fox News has been able to buy fewer stations than Sinclair, which entails a smaller sample size of stations that changed ownership. Second, Fox News' expansion primarily happened before 2004, the first year for which Google Trends data is available, which further limits the sample size of stations which changed ownership for which there is data on racial animus.

2.2 Google Trends Data

Following Stephens-Davidowitz 2014, I use Google trends data as a proxy measure for racial animus. Specifically, I use trend data for the searches for the terms "[Word 1] " and "[Word 1]'s ".

This measurement approach has an advantage over traditional survey-based measures of racial animus in that it is less subject to a social desirability bias; "Google searchers are online and likely alone, both of which make it easier to express socially taboo thoughts (Kreuter et al., 2009)" (ibid., p. 26). Further, it provides a high-resolution set of data that would be prohibitively expensive to collect from a traditional survey, especially given that the difference-in-differences approach requires a repeated survey comparable across multiple time periods.

A pressing concern is that Google searches for "[Word 1](s) " may not actually capture the extent of racial bias in an area, but simply reflect users learning about the term. In fact, "definition of [Word 1] " and "what does [Word 1] mean" are both among the top 5 search queries related to the "[Word 1] ". These queries suggest that many who search for the term are searching out of curiosity to investigate the term.

This is not to suggest that searches for the term do not capture any variation in racial animus: among the top 10 most searched related queries to the term [Word 1]'s are "I don't like [Word 1]'s ," "fuck the [Word 1]'s ," and "ship those [Word 1]'s back."

The concern that Google Searches for racial slurs may largely reflect curiosity about the term is valid. Subject to data availability, I suggest controlling for the frequency of searches for the definitions of these terms in each area, to try and isolate the effect of Sinclair media entering a market on searches expressing "hardcore" racial animus rather than curiosity.

3 Methodology

3.1 Scaling Google Trends Data

3.1.1 Between Regions

Google trends data provide a sample of the searches made by Google users over a certain time frame in a region. The popularity of a search in a region at a certain time is expressed as a search score, calculated as the following:

$$\text{Search Score}_{ijk} = [\frac{\text{number of searches for } i \text{ during time } j \text{ in region } k}{\text{maximum number of searches for } i \text{ over any month in region } k}] \times 100$$

2

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Where

- i is the search term in question
- j is the time period analyzed (a given year)
- k is the region surveyed

This poses a problem for a difference-in-difference approach, as the maximum number of searches for a word in any time period changes between areas. As the maximum monthly searches for a term differs between regions, A score of 50 in one region might correspond to 500 searches per capita, while the same score might correspond to 5000 searches per capita in another area.

Accordingly, I scale searches between regions to make them directly comparable by multiplying the search score in a given area for a term by the average frequency with which that term is searched in that region when compared to other regions, a separate set of data also available from Google Trends. This has the effect of standardizing the search scores, so that any given score always corresponds to the same number of searches per capita.

$$\text{Scaled Search Score}_{ijk} = \text{Search Score}_{ijk} \times \text{average frequency of searches for } i \text{ in region } k$$

3.1.2 Between Search Terms

Past studies have only used search data for one or two searches (Stephens-Davidowitz 2014, p. 26), primarily "[Word 1](s) ". This approach makes for easily interpretable results, but leaves open the possibility that the findings simply reflect idiosyncratic changes in searches these terms rather than changes in racial animus as a whole. I suggest, subject to data availability, using a larger pool of search terms (registered before running tests) to try and understand whether findings are consistent across a larger set of searches that express racial animus.

Currently, Google Trends only allows for the direct comparison of up to five searches at once. When these queries are performed, the search score for each search is expressed as a percent of the frequency of searches in the most popular region. I solve this problem by using several linked sets of comparisons. By running several sets of 5 queries with a shared term (in this case, "smart"), I can scale the searches so they are directly comparable. In the example below, this entails multiplying the score of words 5-9 by 2, so that the scores are on the same scale - a percent of the frequency of searches for "fruit" in DMA 803 (the term / region combination searched most frequently). This makes the scores directly comparable.

Table 1: Example Raw Data From Google Trends

DMA Code	shoe	fruit	horse	cup	smart
803	23	100	5	10	27
616	26	86	3	15	45
617	32	94	6	24	31

Search trends data for words 1-5

DMA Code	smart	pen	waltz	gnome	boots
803	14	32	5	3	100
616	22	54	13	2	88
617	16	50	12	1	96

Search trends data for words 5-9

3.2 Difference in Differences Analysis

To estimate the difference-in-difference models, I will use the following model:

$$\text{Racially Charged Search Rate} = \beta_1(\text{ Sinclair Present }) + \beta_2(\text{ DMA fixed effects }) + \beta_3(\text{ year fixed effects }) +$$

3

D.4 Pregistration

I will also estimate the effect using a Poisson / negative binomial regression if the counts of searches for the terms used are over-dispersed, as performed in Chae, Clouston, Hatzenbuehler, et al. 2015.

$$\log(\text{Racially Charged Search Rate}) = \beta_1(\text{ Sinclair Present }) + \beta_2(\text{ DMA fixed effects }) + \beta_3(\text{ year fixed effects }) +$$

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A Codings for Offensive Words

Code	Word
Word 1	nigger

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