

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 ??

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 of 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-conservative media influence consumers’ racial attitudes outside of an experimental setting? To answer this question, I use the expansion of Sinclair Broadcasting Group, a conservative media conglomerate, 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 Conservative Coverage, and What Does It Mean for Racial Attitudes?

I borrow the term-racially conservative from (Engelhardt, 2019) to denote a particular framing of issues popular among American 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” (*ibid.*, 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). 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).

2.2 The Sinclair Group and Its Advantages for Causal Inference

In this section, I make the argument for studying the effects of racially-conservative media messaging using the variation in station ownership provided by Sinclair Broadcasting Group’s expansion from 2004-2021. I discuss the history of Sinclair, give evidence for a racial bias in its coverage, and make the case that its expansion can be used to surmount several of the challenges associated with documenting media persuasion.

I use the four major hurdles to identifying the effects of media framing on public opinion documented by Ladd and Lenz (2009): 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 strategy overcomes (or struggles to overcome) each obstacle.

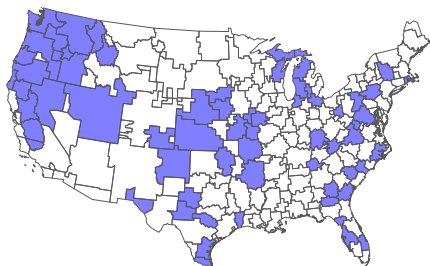
2.2.1 Variation in Messaging

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.

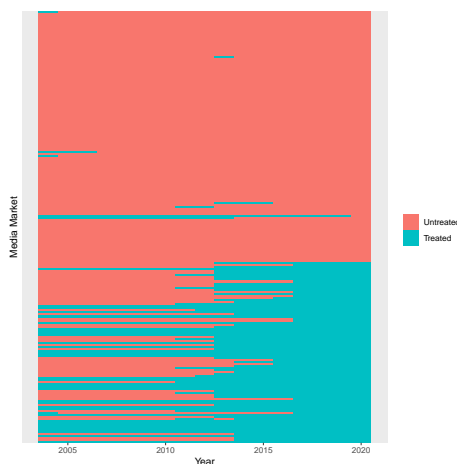
Sinclair Broadcasting Group is the largest telecommunications providers in the U.S, and has grown to serve the maximum 39% of households allowable under U.S. law since its founding in 1971 (Scherer, 2018, p. 1). A map of Sinclair’s expansion can be in Figure 1a each highlighted region is an area Sinclair bought or sold a station in 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 - when Sinclair buys a station, it shifts the coverage of racial issues sharply towards the right, and

(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



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-conservative 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. [Figure 2](#) shows images from one of these scripts being read on 30 stations and an accompanying transcript (ironically, a segment about elite control of media institutions). I offer examples of must-run segments with below which showcase racially-conservative 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](#)).

These segments do not represent the entire spectrum of political programming broadcast over

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



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

(A): But we’re concerned about the troubling trend of irresponsible, one sided news stories plaguing our country. The sharing of biased and false news has become all too common on social media.

(B): More alarming, some media outlets publish these same fake stories... stories that just aren’t true, without checking facts first.

(A): Unfortunately, some members of the media use their platforms to push their own personal bias and agenda to control ‘exactly what people think’...This is extremely dangerous to a democracy.

(b) Transcript of Segment (Cohen, 2018)

Sinclair stations, but the ease with which these segments can be found and the intense vitriol 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-conservative content than it would otherwise run.

Thus, the link between Sinclair ownership and racially-conservative 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 racially-conservative coverage on racial attitudes.

2.2.2 Primitive Measures of Media Exposure

Second, 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

First, the issue of audience selection. A widespread issue in individual-level studies of media effects on mass attitudes is that audiences select media outlets that cater to their predispositions. Audience-selection cannot function as an alternative causal explanation is primarily relevant to studies that link the media framings to opinions at an individual level, but a strong audience selection effect would leave no pathway by which Sinclair Ownership could influence racial animus (viewers would simply select away from their local station when the coverage shifted to must-run segments). I argue that audience selection is not an issue when considering Sinclair stations, 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 with regards 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 effects are not a major concern when evaluating this research.

2.2.5 Audience Pandering

Second, the issue of media institutions changing their coverage to pander to viewers. Sinclair’s structure of “must-run” content distribution means that this 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.

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

¹The 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 the exception rather than the rule.

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 of 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 as searches are 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 has 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).²

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.

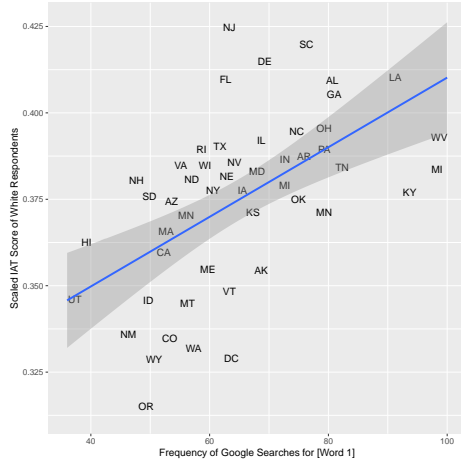
The core assumption of this strategy is that Google searches for the word [Word 1] are a good proxy underlying racial animus in an area. If readers find this assumption unconvincing, then they will have little reason to accept the conclusions of this analysis. Accordingly, I give reasons to suggest that Google searches can well proxy racial animus in an area 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]” might not actually express racial animus but, users learning 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, many of 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. A large portion of the related searches also include the words “jokes,” or “memes” (*ibid.*, p. 28) which, while they do not indicate the same sort of virulent prejudices as the previous searches, I argue they should also be considered as expressing some level of racial animus. Taken together, the related searches give reason to suggest that searches containing the word “[Word 1]” do express racial animus.

How well does this measure correspond to other traditional measures of racial animus?

²Stephens-Davidowitz, 2014 provides more evidence that Google searches are not subject to social censoring by providing search statistics for pornography and sensitive medical questions. Over the past 16 years, the number of searches for “porn” and “news” are commensurate, yet only 14% of GSS respondents tell the GSS they have visited a pornographic website in the past 30 days (Smith et al., 2020). By contrast, 73% of GSS respondents in 2004 told interviewers that they had visited a site for news in the past 30 days (*ibid.*).

(a) Searches for “[Word 1] ” Vs IAT Scores by State



(b) Searches for “[Word 1] ” vs Warmth Towards Black Americans by state

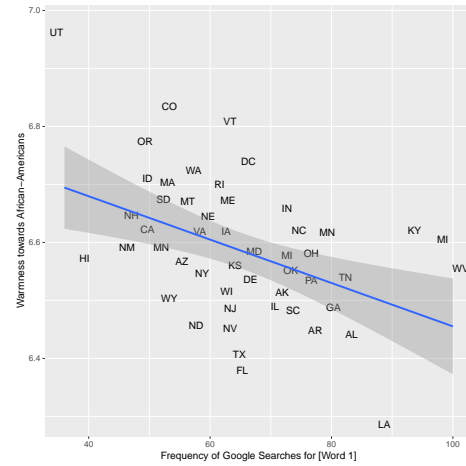


Figure 3: Correlations Between Google Searches and Other Measures of Racial Animus

Stephens-Davidowitz (2014) 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 claim by 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.

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.³



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 perform my analysis including data from a more traditional question on the IAT, the question: “Please rate how warm or cold you feel toward the following group - Black people”. This measure may be subject to some social desirability biases as it could ask subjects to admit to feeling coldly towards Black Americans, but the data is collected through an

³A 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)

anonymous online survey, which might diminish the social pressure respondents feel.

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.

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:

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

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

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

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 together, 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 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 leads to a slight underestimation of the treatment effect, as a small number 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

⁴Missing 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.

(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 ???. 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.

4.3 Difference-In-Differences Analysis

Comparisons in levels of racial animus between markets and times where Sinclair owned a station and locations / periods where Sinclair did not would lead to a selection bias, as Sinclair stations differ systematically from non-Sinclair stations. Specifically, Sinclair has chosen to expand into media markets that have smaller, more local media markets than the average market (Miho, 2018, p. 3).

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

$$\text{Racial Animus / Bias Measure}_{tr} = \beta \times \text{Sinclair Present}_{rt} + \lambda_{r0} + \delta_t + \lambda_{r1} + \varepsilon_{tr}$$

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

The identifying assumption is 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.

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, a precondition of the difference-in-differences approach I use is the parallel trends assumption that absent Sinclair’s presence, trends in the measure of racial animus I am using would progress in the same way as they do in the untreated markets. I test this assumption using a set of treatment leads and lags. Specifically, I estimate treatment effects for the years before and after Sinclair moves into a market. 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](#)

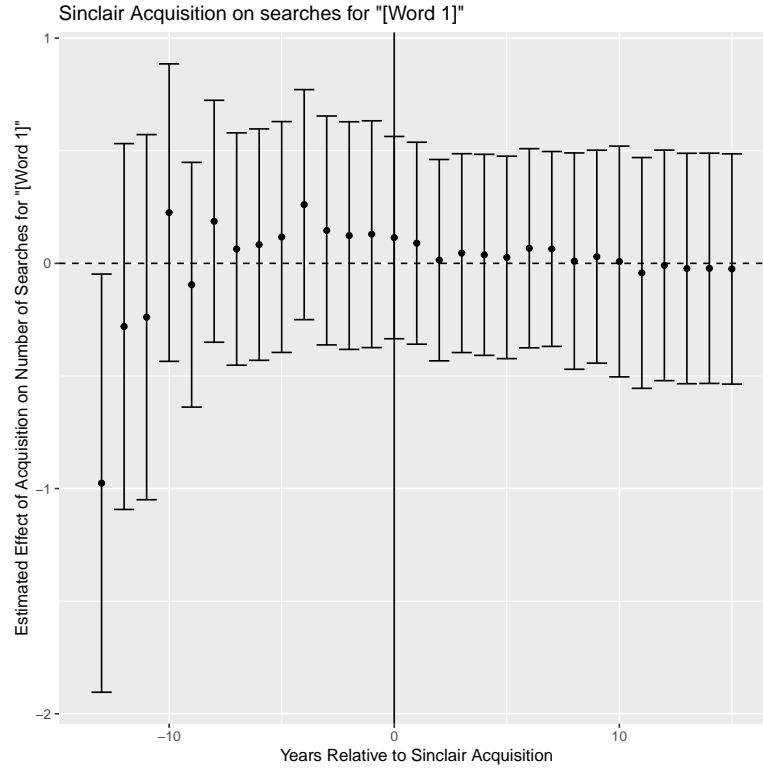


Figure 5: Fixed-Effects Estimates of the effect of Sinclair Acquisition on Searches for “[Word 1] ”

Across all years before the Sinclair enters a region, the estimated treatment effects are no different from zero. I find no pretreatment 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 levels of racial hostility in the area, as measured by 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 Aquisition on Google Searches

	<i>Dependent variable:</i>	
	Standardized Frequency of Searches for [Word 1]	
	(1)	(2)
Sinclair Present	-0.049 (-0.161, 0.062)	-0.170* (-0.348, 0.008)
Constant	1.141*** (0.740, 1.541)	134.264 (-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. This finding is robust to adding linear time trends within each county. However, the confidence intervals associated with these estimates do not rule out plausible effect sizes.

Recall that the original measure of search frequency I constructed was on an arbitrary scale, so I standardize the measurement. 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. I suggest there is no reason to prefer the results from model 1 over model 2, so the link between SBG moving into a market and racial hostility as measured by Google searches should be considered ambiguous.

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 small number of 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].” 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 appear to be two pretreatment years where the pretreatment 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 pretreatment effect is less than 0.6% of the mean. Following the best practices for small pretreatment effects described in Bilinski and Hatfield (2020, p. 9), I continue with my analysis, but also fit models with region-specific linear time trends.

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.

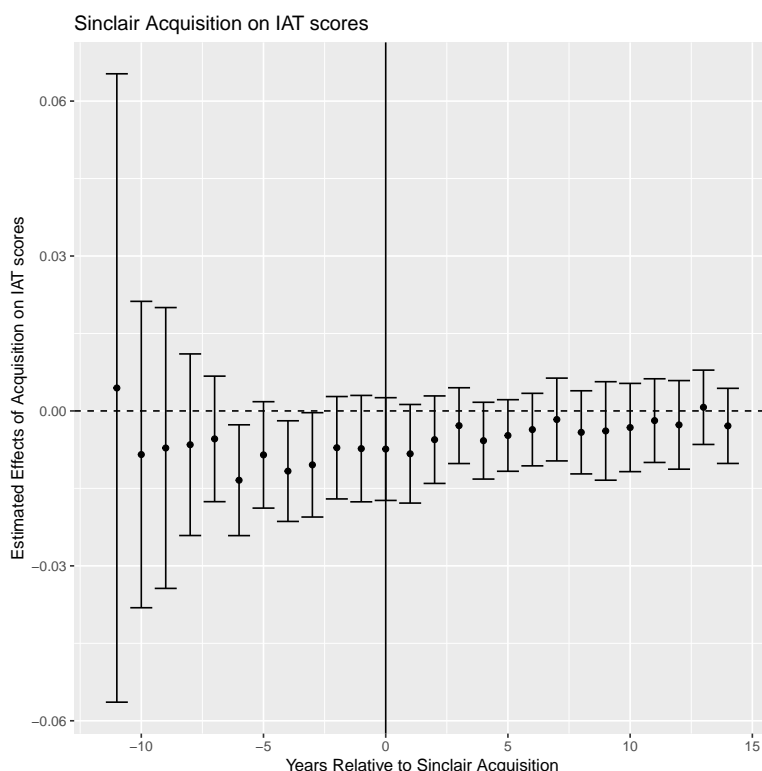


Figure 6: Fixed-Effects Estimates of the Effect of Sinclair Acquisition on IAT Scores (Among White Respondents)

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 relax the parallel trends assumption by allowing for linear time trends in Models 2 and 4. The model estimates can be seen below:

	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 IAT scores and

7 Conclusion

In this paper I have investigate 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 conservative.

Overall, I find no link between Sinclair moving into a region and racial attitudes in the area. This result is contrary to what we would expect from laboratory experiments, which almost universally suggest that exposure to racial or racially conservative messaging should increase racial hostility among viewers.

One reason this may be is that Racial attitudes are typically thought to emerge early in adolescence and stay relatively stable over time (Sears and Brown, [2013](#), pp. 65–70). Exposure to racially biased media may attenuate racial attitudes for a short time, but over the long run leave racial attitudes unaffected.