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

April 14, 2021

# Acknowledgments

## Abstract

# 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* **??**

# 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 use the expansion of the Sinclair Broadcasting Group from 2004-2021 to understand how conservative media messaging impacts racial resentment in a media market. The expansion of the Sinclair Broadcasting Group 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 use the number of Google searches containing racial epithets in an area as a proxy of the racial animus in an area. This measure has previously been used to measure the contributions of racial resentment 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), and does not suffer from the same social censoring issues that confound traditional measures.

Using two internet-based measures of racial animus, I show that Sinclair moving into a region has no effect on the level of racial bias in an area.

# 2 Theoretical Framework

# 3 Background

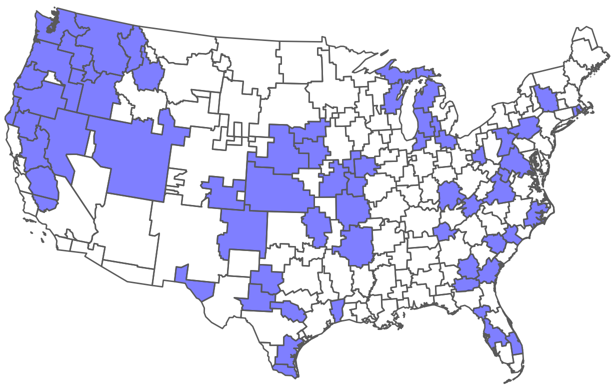
## 3.1 Sinclair Broadcast Group

Sinclair Broadcasting group is one of the largest telecommunications operators in the United States. Founded in 1971 as the Chesapeake Television Corporation, Sinclair Broadcasting group has since expanded to reach the maximum 39% of total houseolds any operator can service under U.S. law. In this paper, I use the variation in station ownership caused by Sinclair's expansion in the period of 2004-2021 as the basis of a difference-in-differences analysis.

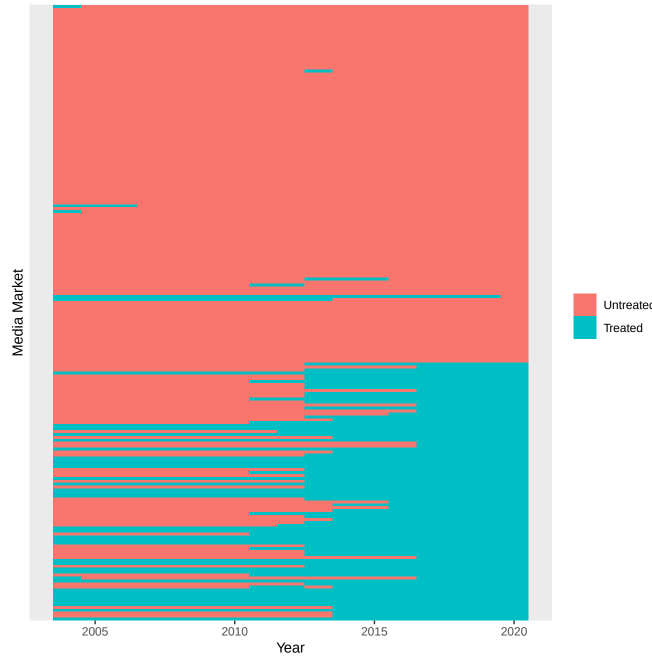
I create a record of Sinclair's station ownership over time from the company's yearly filings with the Securities and Exchange Commission, which enumerate all the stations owned by the company at the end of each year. This strategy has previously been used by Miho (2018) to track Sinclair Expanison over the period of 1995-2017. A map of the media markets Sinclair either purchased or sold a station in can be seen in in figure 1a. A chart showing when each station became treated can be seen in 1b.

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. The SEC dataset has an advantage over this dataset as it is open-access, and can be published freely alongside the research.

(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




### 3.1.1 Does Sinclair Have a Racial Bias?

Previous quantitative research has shown that when Sinclair buys a station, its coverage shifts sharply rightwards. I make the case 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.

assume 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 we would expect to see no difference in levels of racial resentment between Sinclair and non-Sinclair media markets.

So, it must be asked: does Sinclair coverage have a racially-conservative bent? Admittedly, there have been no large-scale analyses of the effects of Sinclair ownership on coverage of racial issues. Nonetheless, I submit that there is evidence to show Sinclair Stations cover racial issues in a more conservative light than they would absent Sinclair ownership.

Previous research has demonstrated that Sinclair acquisition of a network is associated with a sharp rightwards shift in its coverage (Martin and McCrain, 2019). I argue this effect extends to its framing of racial issues.

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).

## 3.2 Measuring Racial Animus

Measuring racial resentment is difficult. Overt expressions of racism are severly 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 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 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.

### 3.3 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. 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).

The core assumption of this strategy is that Google searches for the word [Word 1] reflect 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 offer several reasons to suggest that searches for racial epithets well proxy racial animus in an area, namely: searches are conducted in private, and are not subject to the same social-desirability biases as traditional, survey-based measures; and measurements of area-level racism obtained from Google trends data correspond well to traditional survey-based and non-survey-based measures of racial animus.

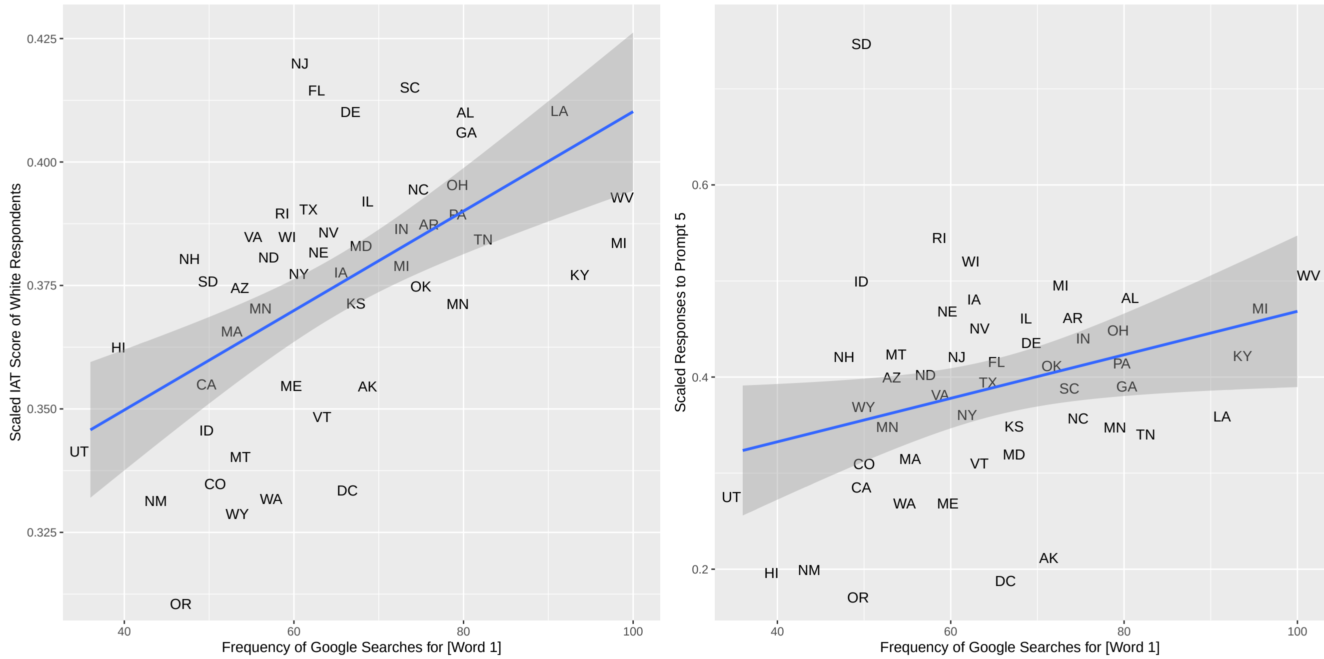
First, Google searches do not suffer from the same social censoring as traditional measures of public opinion that rely on face-to-face or over-the-phone interviews. Overt expressions of racism are no longer socially palatable in the U.S., Social desirability bias is a pressing concern when it comes to measuring racial animus; research has repeatedly demonstrated that (Kuklinski, Cobb, and Gilens, 1997)

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. [1]

A pressing concern is that searches for the word "[Word 1] " might not actually measure racial animus but, in fact, reflect users learning about the term. Indeed, "Definition of [Word 1] " and "what does [Word 1] mean" are both among the top 5 search queries related to term. 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: 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." Stephens-Davidowitz (ibid.) evidences this claim by reporting strong correlations between opposition to interracial marriage 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 white respondents in a state on the IAT. Following practices of other research using IAT data (Connor et al., 2019, p. 206) I use the scores of only white respondents.

[1] Stephens-Davidowitz, 2014 evidences this claim by reporting statistics for pornography searches. 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.




## 3.4 Scaling Google Trends Data:

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 of search volume that is comparable both between regions and between times.

$$\text{Search Volume in Region } r \text{ at Time } t = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{\text{Search Volume in Region } r \text{ at Time } t}{\text{Search Volume in Region } i \text{ at Time } j}$$

With

- regions $1 \ldots J$
- time periods $1 \ldots I$

# 4 Methods

## 4.1 Tools Used

I use Knitr (Xie, 2014) to integrate statistical calculations into the paper, eliminating the possibility of transcription errors. To ensure that the methods 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 for it – I provide a Docker image with the reproducibility materials to ensure others can replicate the calculations on their own systems (Merkel, 2014; Boettiger, 2015). The net 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. [2]

## 4.2 Preregistration

To avoid the possibility of fitting hypotheses to the data after results are known, I created a preregistration plan of my analysis using the Google trends data. The plan can be seen in section **??**. As I decided to conduct the analysis using the project implicit data to confirm the Google trends results, I did not preregister this analysis plan.

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. This original strategy is 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 **??**.

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

Figure 3: Illustration of Scaling Algorithm

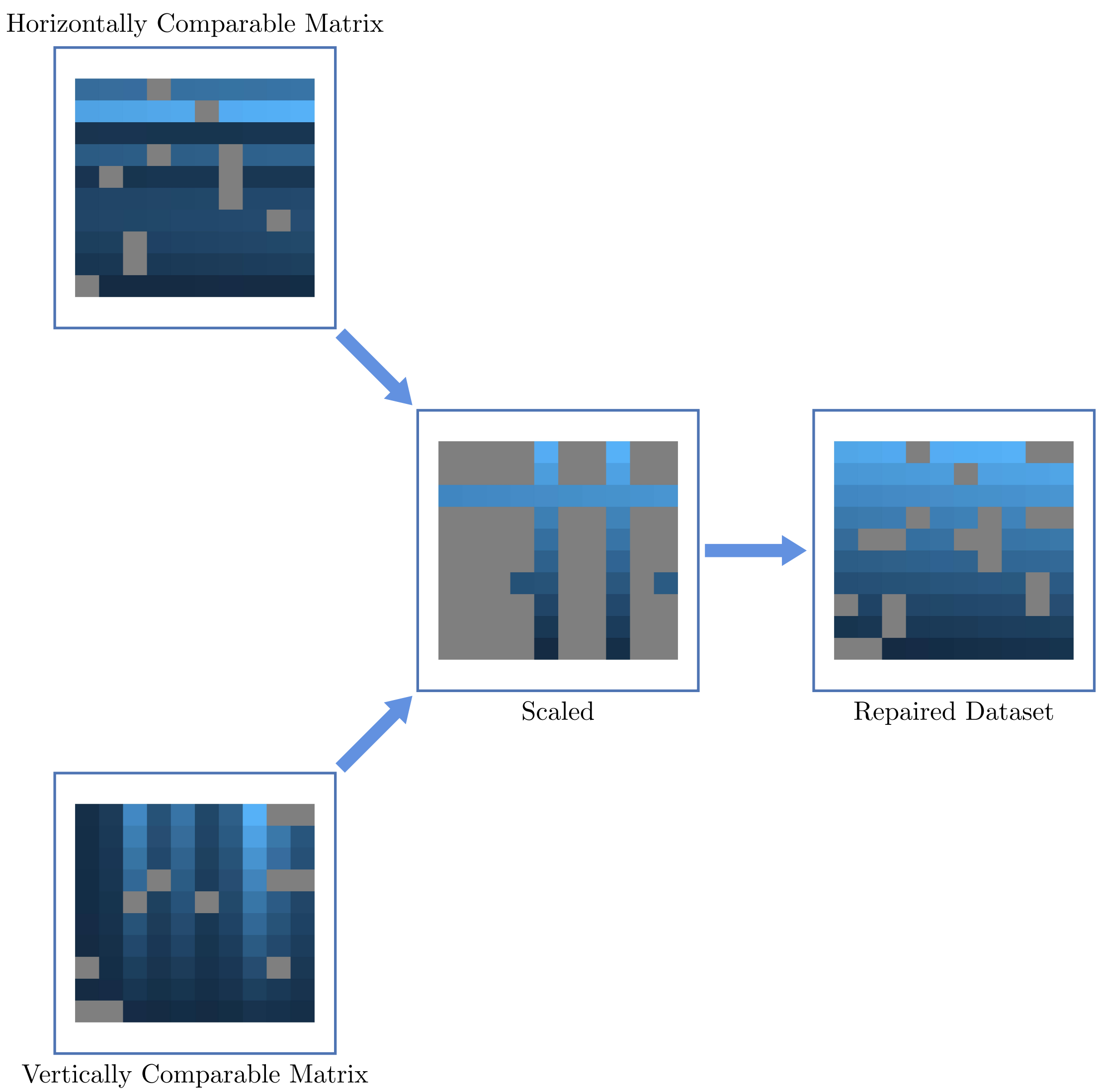


Figure 4: Sinclair News Anchors Reading a "Must-Run" Script (May 2018)


(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)

# 5 Results

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

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Frequency of Searches for [Word 1] | | Frequency of Searches for Words 1-5 | |
| | (1) | (2) | (3) | (4) |
| Sinclair Present | −0.009 | −0.030* | −0.001 | −0.010 |
| | (0.010) | (0.016) | (0.011) | (0.018) |
| Constant | 0.201*** | 23.678 | 0.136*** | 13.430 |
| | (0.036) | (18.785) | (0.040) | (21.272) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Region Fixed Effects | Yes | Yes | Yes | Yes |
| Region Time Trends | No | Yes | No | Yes |
| Observations | 3,570 | 3,570 | 3,570 | 3,570 |
| $R^2$ | 0.234 | 0.349 | 0.226 | 0.329 |
| Adjusted $R^2$ | 0.183 | 0.258 | 0.173 | 0.235 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| (Intercept) | $0.28^{***}$ | $0.29^{***}$ | $0.32^{***}$ | $0.32^{***}$ |
| | (0.00) | (0.01) | (0.00) | (0.01) |
| sinclair_presentTRUE | 0.00 | −0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Region Fixed Effects | Yes | Yes | Yes | Yes |
| 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 |

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

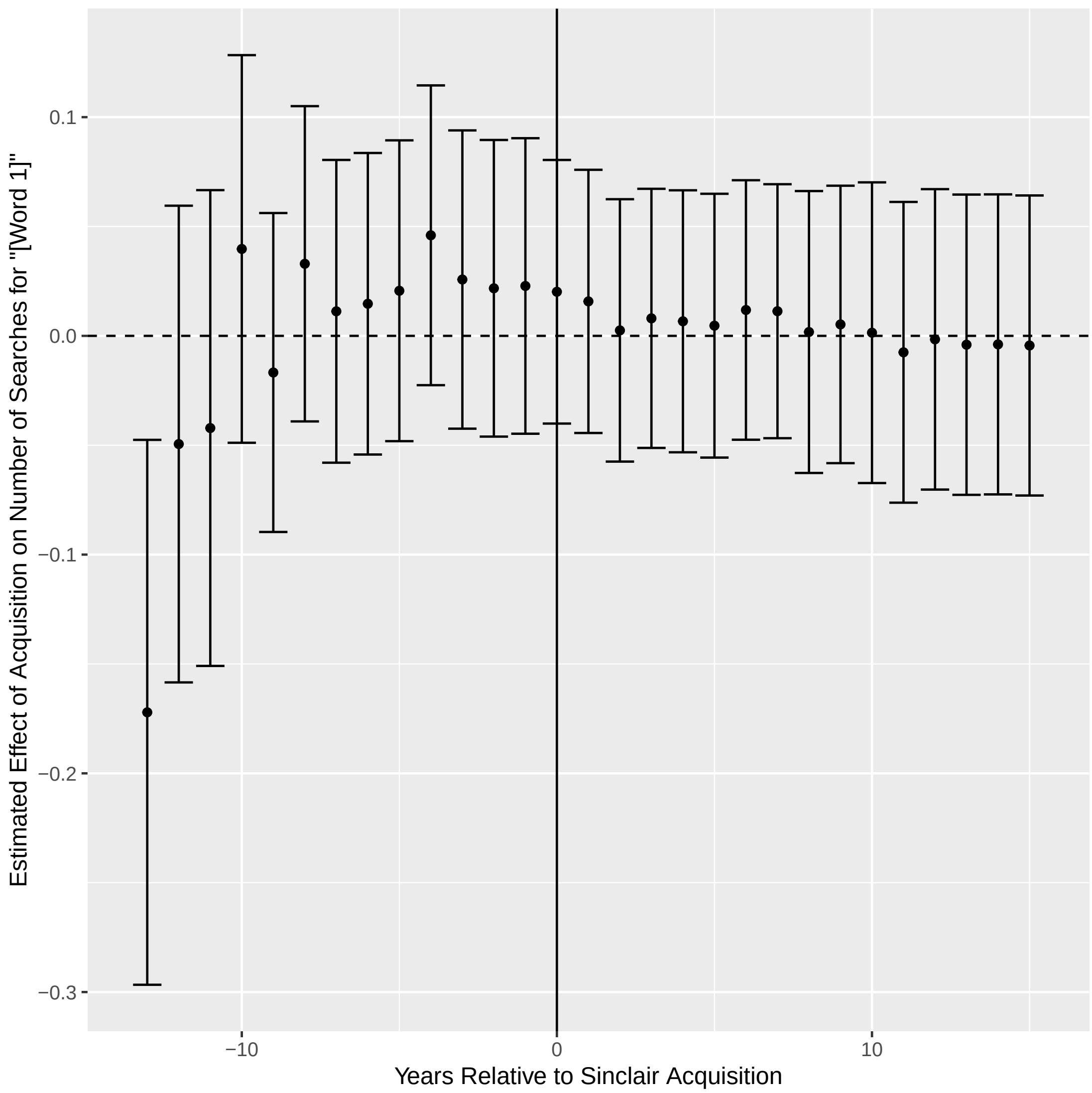
Table 2: Statistical models

## 5.1 Identification Assumption

In this section, I test the indication assumption, the assumption that the treated and control units would have the outcomes if the treatment were absent.

Racially Charged Search Rate = $\beta_1$( Sinclair Present )+$\beta_2$( DMA fixed effects )+$\beta_3$( year fixed effects )+$\beta_4$(Year / D

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



| Code | Word |
|---|---|
| Word 1 | Nigger |
| Word 2 | Coon |
| Word 3 | Kike |
| Word 4 | Spic |
| Word 5 | Spook |

# A Codings for Offensive Words

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# B Code In This Document

# C Web Scraping Code