April 4, 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 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

This analysis relies on the identifying assumption that Google trends searches for the word [Word 1] are an appropriate proxy for the racial animus in an area. If readers are not convinced that that the Google trends data accurately measure racial animus, they will have little reason to accept the results of this analysis. I offer several reasons to suggest that Google trend data can be used as a proxy for racial animus, and some caveats associated with using the data.

[1] 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 ".

If readers do not find the Google trends data a convincing proxy for racial animus, they have little reason to accept the results of this analysis. As such, I give several reasons to suggest that Google trends data can be used to measure racial animus.

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.

[1] Stephens-Davidowitz 2014 evidences this claim by reporting statistics for pornography searches. Today, searches for "porn" and "news" are relatively commensurate, yet only 14% of GSS respondents tell the GSS they have visited a website in the past 30 days.

3 Methods

3.1 Tools Used

Surveys of major social science journals routinely fail to reproduce the findings of a plurality or majority of papers from the supplementary code and data provided (Nuijten, Hartgerink, et al. 2015; Nuijten and Polanin 2020; Eubank 2016).

Failures to replicate are often due to coding errors or mistakes in transcribing the results of a calculation into a published manuscript (Eubank 2016, p. 276).

I use Kintr to integrate statistical calculations into the paper, eliminating the possibility of transcription errors (Xie 2014). To ensure that the methods of this paper have been properly implemented and the finding 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]

3.2 Preregistration

To avoid the possibility of fitting hypotheses to the data after results are known, I created a preregistration plan of my analysis. The plan can be seen in section **??**.

I have made one significant deviation from the preregistration plan. In my preregistration, I describe a strategy to back out a ratio-level measure of the number of searches for [Word 1] in an area from Google trends data. This 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

Figure 1: Illustration of Scaling Algorithm

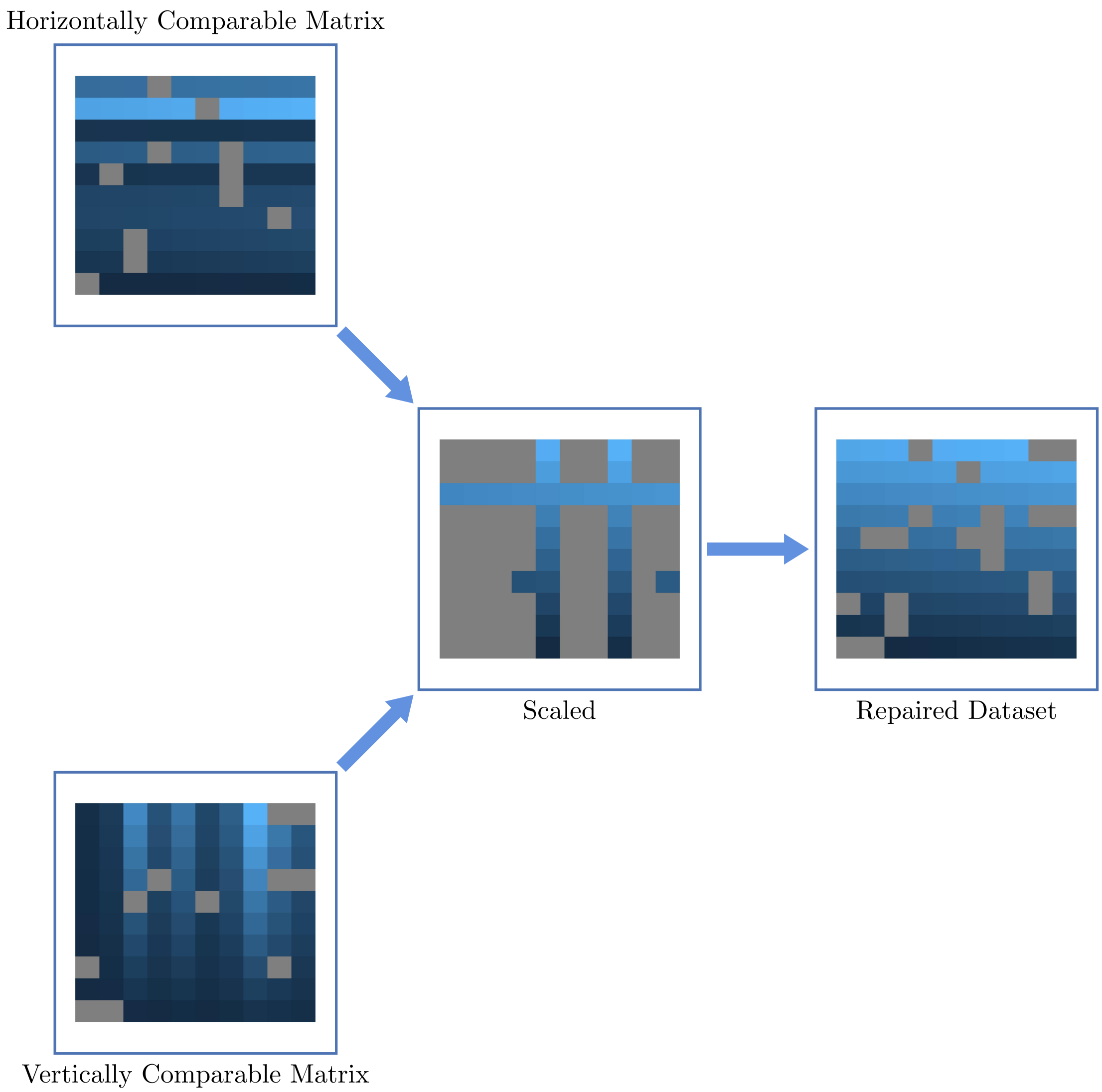


Figure 2: Sinclair News Anchors Reading a “Must-Run” Script (May 2018)

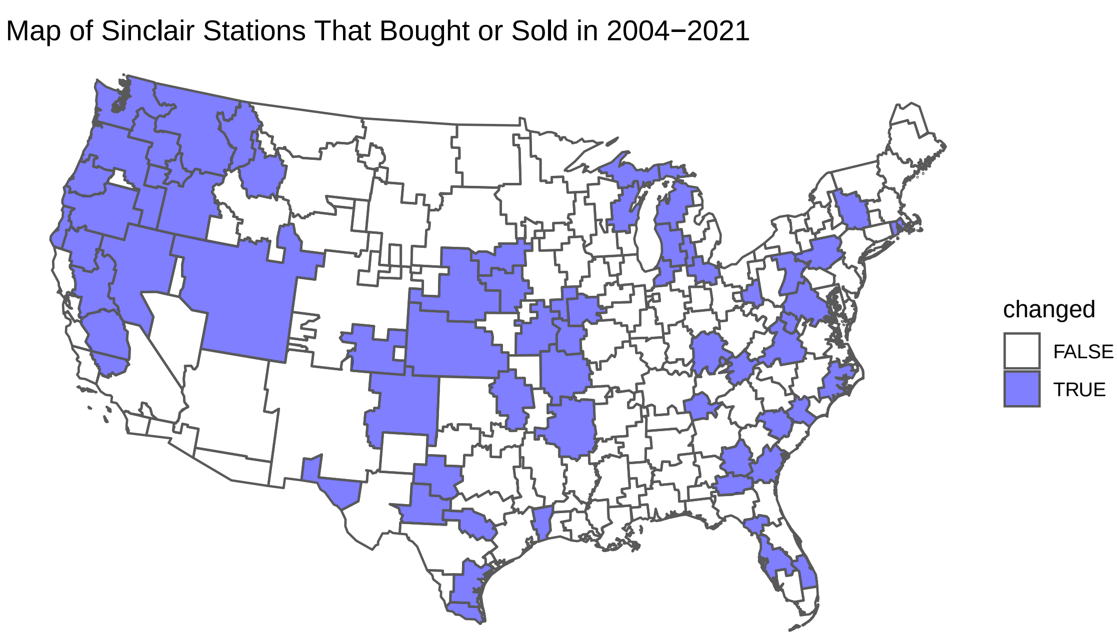
(a) Images of 30 of 210 Sinclair Station Hosts Reading a Must-Run Script (Burke 2018)

(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)



4 Results

Racially Charged Search Rate = β_1(Sinclair Present)+β_2(DMA fixed effects)+β_3(year fixed effects)

Table 1: Fixed-Effect Model Results

	Dependent variable:	
	Frequency of Google Searches for [Word 1]	
	(1)	(2)
Sinclair Present	-0.122^{*}	-0.068
	(0.065)	(0.107)
Constant	-0.212	41.959
	(0.234)	(126.128)
Year Fixed Effects	Yes	Yes
Region Fixed Effects	Yes	Yes
Region / Year Fixed Effects	No	Yes
Observations	3,570	3,570
R^2	0.240	0.309
Adjusted R^2	0.188	0.214
Residual Std. Error	0.901 (df = 3343)	0.887 (df = 3134)
F Statistic	4.668^{***} (df = 226; 3343)	3.229^{***} (df = 435; 3134)
Note:		*p<0.1; **p<0.05; ***p<0.01

4.1 Indentification Asssumption

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

Racially Charged Search Rate = β_1(Sinclair Present)+β_2(DMA fixed effects)+β_3(year fixed effects)+β_4(Year / D

Figure 3: Fixed-Effects Estimates of the effect of Sinclair Acquisition on Rate of Racially Charged Google Searches

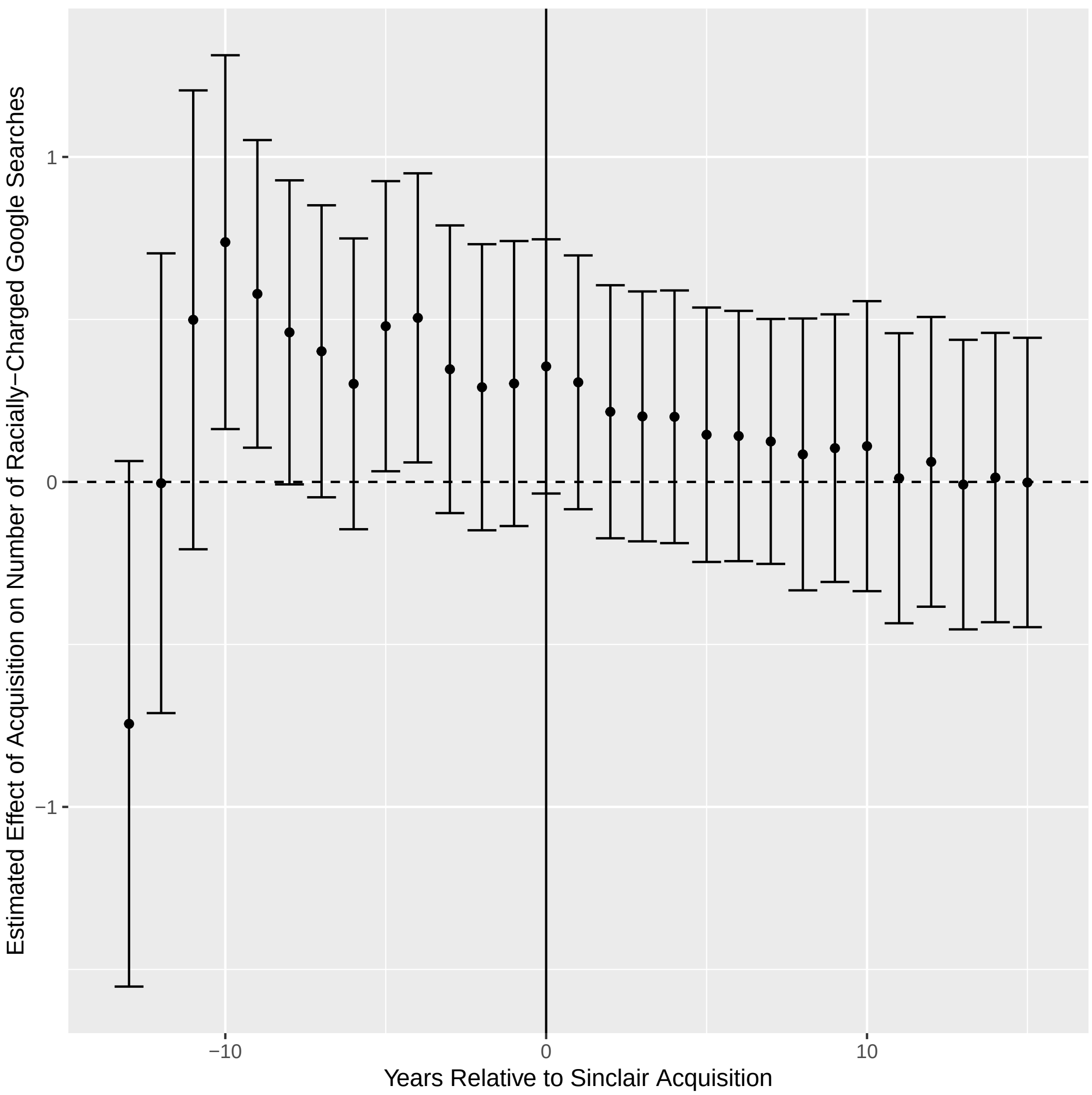
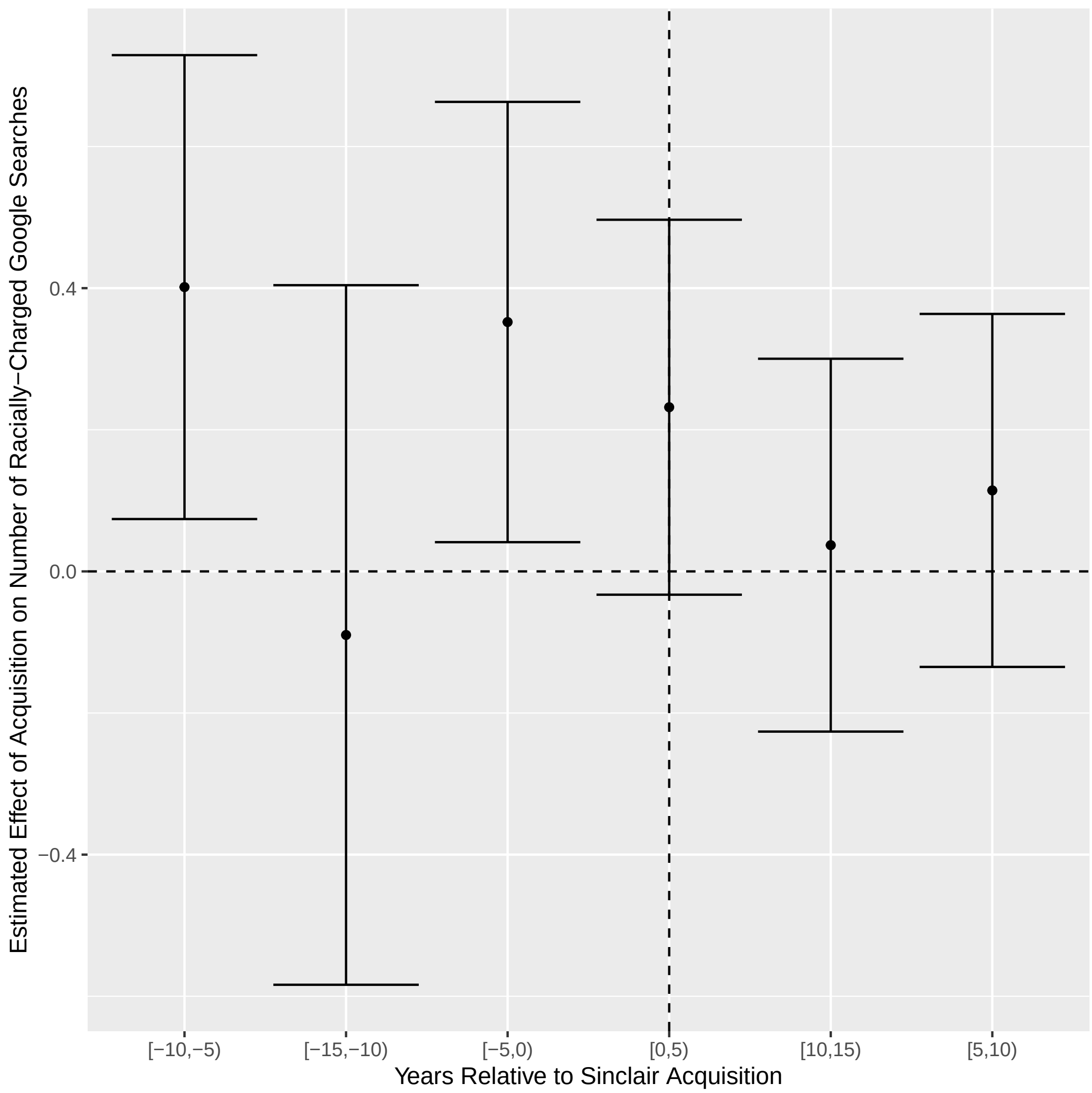


Figure 4: Fixed-Effects Estimates of the effect of Sinclair Acquisition on Rate of Racially Charged Google Searches [Larger Bins]



Code	Word
Word 1	nigger

A Codings for Offensive Words

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B Code In This Document

C Web Scraping Code

C.1 Master Web Scraping Script

```python
#!/usr/bin/python
import glob
import os
import pickle as pkl
from between_regions import between_reigion_many
from in_region import in_region
from utils import itr_split_overlap
import tqdm


def extract_keywords(filename):
    with open(filename, "r") as f:
        keywords = f.read().splitlines()
    return keywords


def get_basename(filename):
    name_w_ext = os.path.basename(filename)
    basename = os.path.splitext(name_w_ext)[0]
    return (basename)


def run_keywords(name, keywords):
    regions = pkl.load(open("data/dma_abbreviations.pkl", "rb"))
    filename = f"data/google_trends_data/{name}_time_serires.csv"
    with open(filename, "w") as f:
        f.write("row,date,score,ispartial,code,term\n")
        for keyword in keywords:
            for region in tqdm.tqdm(regions):
                df = in_region(keyword, region, True, timeframe="all")

                if df is not None:
                    df.to_csv(f, header=False)

    filename = f"data/google_trends_data/{name}_between_regions.csv"
    with open(filename, "w") as f:
        df = between_reigion_many(itr_split_overlap(keywords, 5, 1),
                                  censor=True,
                                  timeframe="all",
                                  geo="US",
```

```
                                  gprop="")
        df.to_csv(f, header=True)


if __name__ == "__main__":
    keyword_files = sorted(glob.glob("data/keywords/*.csv"))
    base_names = [get_basename(filename) for filename in keyword_files]
    keywords = [extract_keywords(filename) for filename in keyword_files]
    first = (list(zip(base_names, keywords)))[0]
    run_keywords(first[0], first[1])
```

C.2 Collecting Data for Between-Region Comparisons

```
#!/usr/bin/env python
from pytrends.request import TrendReq
from utils import censor_string
import pandas as pd


def between_region(query, censor, **kwargs):
    pytrends = TrendReq(hl='en-US', tz=360)
    pytrends.build_payload(query, cat=0, **kwargs)
    df = pytrends.interest_by_region(resolution='DMA',
                                     inc_low_vol=True,
                                     inc_geo_code=True)
    df = df.set_index("geoCode")
    df.index.name = 'code'
    if censor:
        df = df.rename(censor_string, axis="columns")
    return (df)


def between_reigion_many(iterable, censor, **kwargs):
    iterable = iter(iterable)
    chunk1 = next(iterable)
    df1 = between_region(chunk1, censor, **kwargs)

    for chunk in iterable:
        chunk2 = chunk
        shared = list(set(chunk1) & set(chunk2))[0]
        if censor:
            shared = censor_string(shared)
        df2 = between_region(chunk2, censor, **kwargs)

        mean1 = df1[shared].mean()
        mean2 = df2[shared].mean()
        normaliation_factor = mean1 / mean2

        df2 = df2 * normaliation_factor
        df2 = df2.drop(columns=[shared])

        df1 = df1.join(df2)

        chunk1 = chunk2

    return (df1)


def create_v_df(term, year):
    timeframe = f"{year}-01-01 {year}-12-31"
    df = between_region([term], False, timeframe=timeframe, geo="US")
    df = df.rename(columns={term: str(year)})
    return df


if __name__ == "__main__":
    dfs = tuple(create_v_df("hello", year) for year in range(2004, 2021))
    df_c = pd.concat(dfs, axis=1)

    df_c.to_parquet("v_matrix.parquet")
```

C.3 Collecting Within-Region Data

```
#!/usr/bin/python
from pytrends.request import TrendReq
```

```python
from utils import censor_string
import time
import pandas as pd
import re
import pickle as pkl


def in_region(query, region, censor, **kwargs):
    """ Returns a set of data showing the popularity of a search term over time

    :query: The search term that time-series data is collected for
    :region: The geographic region to retrieve time-series data for.
    :censor: boolean should the search terms be censored?
    :**kwargs: kwargs to be passed to pytrends.build_payload()
    :returns: DataFrame giving time-series data for the popularity of a
        search term in a given region

    """
    pytrends = TrendReq(hl='en-US', tz=360)
    try:
        pytrends.build_payload(kw_list=[query], geo=f"{region}", **kwargs)
        df = pytrends.interest_over_time()
        if df.empty:

            df = pd.DataFrame()
            df['date'] = pd.period_range(start='2004-01-01',
                                         end='2021-01-01',
                                         freq='M').to_timestamp()
            df['n'] = 0
            df['ispartial'] = pd.Series([True]).bool()

        else:

            df.columns = ["n", "ispartial"]
            df.index.name = 'date'
            df.reset_index(inplace=True)

        df["query"] = query
        df['code'] = re.findall("\d+", region)[0]
        if censor:
            df["query"] = df["query"].apply(censor_string)

        return df
    except:
        if censor:
            print(f"Rate error: {censor_string(query)} in {region}")
        else:
            print(f"Rate error: {query} in {region}")

        time.sleep(60)
        return in_region(query, region, censor, **kwargs)


def to_wide(df):
    """TODO: Turns time-series search popularity data into a 'wide' dataframe to be used in scaling

    :df: 'long' dataframe of search data, as from in_region()
    :returns: 'wide' DataFrame of search data, averaged by year

    """
    print(df['date'])
    df['year'] = pd.DatetimeIndex(df['date']).year
    df['year'] = df['year'].apply(str)
    df = df.groupby(['year', 'code'])["n"].mean()
    df = df.unstack(level=0)
    return (df)


# with open("data/dma_abbreviations.pkl", "rb") as f:
#     dmas = pkl.load(f)

# dmas = dmas

# in_region_dfs = tuple(
#     in_region("economist", dma, True, timeframe="all") for dma in dmas)
# wide_dfs = map(to_wide, in_region_dfs)
```

```
# h_df = pd.concat(wide_dfs).sort_index()
# print(h_df)
```

C.4 Utility Functions

```
#!/usr/bin/python
import itertools as it
import requests
import random


# returns mean of nonzero values in iterator
def mean_nonzero(iterator):
    nonzero = tuple(filter(lambda x: x != 0, iterator))
    if len(nonzero) == 0:
        return None
    elif None in nonzero:
        return None
    else:
        return sum(nonzero) / len(nonzero)


# Returns list of N random words from MIT dictionary
def random_words(n):
    word_site = "https://www.mit.edu/~ecprice/wordlist.10000"

    response = requests.get(word_site)
    words = response.text.splitlines()

    keywords = random.sample(words, n)

    return (keywords)


# Tests if computer is connected to internet (used in tests)
def connected():
    url = "http://google.com"
    timeout = 5
    try:
        requests.get(url, timeout=timeout)
        return (True)
    except (requests.ConnectionError, requests.Timeout):
        return (False)


# Censors strings so that senstive words aren't uploaded to github / used in
# scripts
def censor_string(string):
    return (string[0] + "_" * (len(string) - 2) + string[-1])


# credit to Ilja Everila for this implimentation
# https://stackoverflow.com/questions/48381870/a-better-way-to-split-a-sequence-in-chunks-
    with-overlaps
def itr_split_overlap(iterable, size, overlap):

    if overlap >= size:
        raise ValueError("overlap must be smaller than size")

    itr = iter(iterable)

    next_ = tuple(it.islice(itr, size))

    yield next_

    prev = next_[-overlap:] if overlap else ()

    while True:
        chunk = tuple(it.islice(itr, size - overlap))

        if not chunk:
            break

        next_ = (*prev, *chunk)
        yield next_

```

```
        if overlap:
            prev = next_[-overlap:]
```

D Analysis Code

```
#!/usr/bin/Rscript
# Load Libraries for Analysis
library(tidyverse)
library(lubridate)
library(broom)
# Load utility functions
source("utils.R")

search_data <- read_csv("data/google_trends_data/word_1.csv") %>%
  pivot_longer(-code, names_to = "year", values_to = "word1") %>%
  mutate_all(as.numeric)

stopifnot(nrow(search_data) == 3570)
stopifnot(all(!is.na(search_data)))

write_csv(search_data, "../data/google_trends/word1.csv")

sinclair_data <- read_csv("../data/clean_sinclair_data.csv")
stopifnot(nrow(sinclair_data) == 3570)
stopifnot(all(!is.na(sinclair_data)))

# search_data <- search_data %>%
#   dplyr::select(-data) %>%
#   distinct(term, code, year, .keep_all = TRUE) %>%
#   pivot_wider(names_from = term, values_from = score) %>%
#   mutate(overall_score = rowSums(across(everything()), na.rm = T))
dma_names <- read_csv("data/dma_list.csv")
stopifnot(nrow(dma_names) == 210)

full_data <- search_data %>%
  right_join(sinclair_data) %>%
  full_join(dma_names) %>%
  filter(year != 2021) %>%
  group_by(code) %>%
  mutate(years_before = years_before(sinclair_present)) %>%
  ungroup() %>%
  mutate(sword1 = (word1-mean(word1))/sd(word1)) %>%
  mutate(years_before = relevel(as.factor(years_before),"-99"))

stopifnot(nrow(full_data) == 3570)
stopifnot(all(!is.na(full_data)))

write_csv(full_data, "../data/full_data.csv")

model_1 <- lm(sword1 ~ as.factor(year) + as.factor(code) + sinclair_present, data = full_data
    )
model_1 %>% summary()

model_2 <- lm(sword1 ~ as.factor(year) + as.factor(code) + year:as.factor(code)+ sinclair_
    present, data = full_data)
model_2 %>% summary()

model_3 <- lm(sword1 ~ as.factor(year) + as.factor(code) + as.factor(years_before), data =
    full_data)
model_3 %>% summary()

model_3 %>%
  tidy() %>%
  filter(grepl("years_before", term)) %>%
  mutate(term = as.numeric(gsub("[^0-9\\-]+", "", term))) %>%
  ggplot(aes(x = term, y = estimate)) +
  geom_point() +
  geom_errorbar(aes(ymin = estimate - 1.96 * std.error, ymax = estimate + 1.96 * std.error))
    +
  geom_hline(aes(yintercept=0), linetype=2) +
  geom_vline(aes(xintercept=0))
```

D.1 Utility Functions

```r
#!/usr/bin/Rscript
censor_string <- function(string) {
  substr(string, 2, nchar(string) - 1) <- paste0(rep("_", nchar(string) - 2), collapse = "")
  names(string) <- NULL
  return(string)
}
censor_string <- Vectorize(censor_string, USE.NAMES=F)

years_before <- function(bool) {
  if (any(bool)) {
    out <- numeric(length = length(bool))
    start <- min(which(bool))

    before <- (seq(start, 1) - 1) * -1
    if (start != length(bool)) {
      after <- seq(1, length(bool) - start)
    } else {
      after <- c()
    }


    out <- c(before, after)
  } else {
    out <- rep(-99, length(bool))
  }

  return(out)
}
```

E Unit tests

E.1 For Python Code

```python
#!/usr/bin/python
import unittest
import pandas as pd
from between_regions import between_region
from utils import connected


@unittest.skipIf(not connected(), "not connected to the internet")
class TestBetweenRegion(unittest.TestCase):
    def test_between_region_uncensored(self):

        result_1 = between_region(["socks"],
                                  censor=False,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        result_2 = between_region(["socks", "shoe", "fish"],
                                  censor=False,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        expected_1 = pd.read_parquet(
            "tests/test_data/between_region_1_uc.parquet")
        expected_2 = pd.read_parquet(
            "tests/test_data/between_region_2_uc.parquet")

        self.assertTrue(expected_1.equals(result_1))
        self.assertTrue(expected_2.equals(result_2))

    def test_between_region_censored(self):
        result_1 = between_region(["socks"],
                                  censor=True,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        result_2 = between_region(["socks", "shoe", "fish"],
                                  censor=True,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
```

```python
                                  gprop="")

        expected_1 = pd.read_parquet(
            "tests/test_data/between_region_1_c.parquet")
        expected_2 = pd.read_parquet(
            "tests/test_data/between_region_2_c.parquet")

        self.assertTrue(expected_1.equals(result_1))
        self.assertTrue(expected_2.equals(result_2))
```

```python
#!/usr/bin/python
import unittest
from utils import itr_split_overlap, censor_string


class TestItrSplitOverlap(unittest.TestCase):
    def test_itr(self):
        test_list = ["one", "two", "three", "four", "five"]

        expected_result = [('one', 'two'), ('two', 'three'), ('three', 'four'),
                           ('four', 'five')]
        self.assertEqual(expected_result,
                         list(itr_split_overlap(test_list, 2, 1)))

        expected_result = [('one', 'two', 'three', 'four'),
                           ('two', 'three', 'four', 'five')]
        self.assertEqual(expected_result,
                         list(itr_split_overlap(test_list, 4, 3)))

    def test_exceptions(self):
        with self.assertRaises(ValueError):
            test_list = ["one", "two", "three", "four", "five"]

            list(itr_split_overlap(test_list, 2, 3))


class CensorString(unittest.TestCase):
    def test_censor(self):
        self.assertEqual("h_y", censor_string("hey"))
        self.assertEqual("f____r", censor_string("fender"))
        self.assertEqual("fr", censor_string("fr"))
```

E.2 For R Code

```r
library(testthat)
source("../../utils.R")

test_that("censor string works", {
      expect_equal(censor_string("hey"),"h_y")
      expect_equal(censor_string("hy"),"hy")
      expect_equal(censor_string("watermelon"),"w________n")
      expect_equal(censor_string("fantastic"),"f_______c")
})

test_that("censor string vectorized correctly", {
      expect_equal(censor_string(c("hello","there")),c("h___o","t___e"))
      expect_equal(censor_string(c("watermelon","paper")),c("w________n","p___r"))
})

test_that("years before works", {
  expect_equal(years_before(c(F, F, F, T, T)), c(-3, -2, -1, 0, 1))
  expect_equal(years_before(c(F, F, F, F, T)), c(-4, -3, -2, -1, 0))
  expect_equal(years_before(c(T, T, T, T, T)), c(0, 1, 2, 3, 4))
})
```