Scapegoating Jews During the COVID-19 Pandemic

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Abstract

Historically, Jews have been scapegoated for a variety of social, economic, and political ills. During the COVID-19 pandemic, there was considerable misinformation and disinformation, especially on social media, linking Jews to the pandemic. This paper uses Democracy Fund + UCLA Nationscape Survey Project data to test whether objective trends in the pandemic severity and Google searches linking Jews with COVID-19 affected attitudes toward Jews. Time series analysis indicates death rates and Google searches resulted in less positive attitudes towards Jews, but despite being statistically significant, impacts were substantively small. The conclusion puts the findings into context.

Keywords: Scapegoating Theory, antisemitism, COVID-19 pandemic, George Soros, Google Trends

Introduction

The World Health Organization characterized the information environment of the COVID-19 pandemic as an infodemic of misinformation, disinformation, and fake news (Richtel 2020). The COVID-19 pandemic, the infodemic environment, and government policies have increased social tensions and hatreds among Americans and other peoples around the world. Among the more pernicious claims is that Jews caused or worsened the COVID-19 pandemic, for instance, to poison gentiles and to make money (Gerstenfeld 2020). A second charge claims that Jewish financier George Soros, along with Microsoft founder Bill Gates, supported tests for the COVID-19 virus to implant microchips into people (Fichera 2021). Where these two charges were more commonly held among those on the political right and far-right, other linkages between Jews and COVID-19 seemed rooted on the political left. This left-leaning, third trope focused on Ultra-Orthodox Jews as COVID-19 spreaders, a
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perspective seemingly held among secular Jews in Israel and liberals in the U.S. and UK, especially in area proximate to large Ultra-Orthodox communities, like New York and London (Gilman 2021; Xun and Gilman 2021a; Xun and Gilman 2021b). Another trope suggested that Israel was the source for COVID-19, as Israel strategically used COVID-19 to weaken its adversaries, especially in the Middle East (Topor 2020).

The COVID-19 pandemic is not the first large-scale health crisis blamed on Jews. The Black Plague of 1346–1353 is perhaps the most famous, with many cities in Europe expelling their Jewish residents (Finley and Koyama 2018; Jedwab, Johnson, and Koyama 2017; Cohn Jr. 2007). Jews have been scapegoated for a variety of reasons besides pandemics and plagues, such as economic downturns, droughts, and social upheavals (Anderson, Johnson, and Koyama 2017; Bilewicz and Krzeminski 2010; Gibson and Howard 2007; Grosfeld, Sakalli, and Zhuravskaya 2020). This paper asks whether American voters became more antisemitic in response to COVID-19 and the COVID-19 infodemic. Hence, this research speaks to the broader literature on antisemitism, linking it to one of the most momentous events in modern world history.

Testing for the effects of COVID-19 and COVID-19 infodemics on antisemitic attitudes is not straightforward. First, direct public opinion data linking COVID-19 to attitudes towards Jews is lacking. A search of the Roper Center data archive (ropercenter.cornell.edu) failed to locate a single question referring to Jews as a source of or blame for COVID-19. Second, there is a dynamic element to the COVID-19 pandemic, with cycles in cases and deaths. The impact of the pandemic on antisemitic attitudes may depend on such cycles. Thus, temporal data may be necessary to assess accurately and precisely the effects of the pandemic on antisemitic attitudes.

Rarely, however, is there data on antisemitic attitudes that are temporally refined enough to allow dynamic analysis. Most public opinion surveys with questions on antisemitism are asked only once, or if repeated, are done with wide time intervals, usually years, like the American National Election Study’s feeling thermometer toward Jews (at best every two years) or the Gallup Poll question on willingness to vote for a Jewish candidate for president (at best annually) (Smith and Schapiro 2019; J.E. Cohen 2018).

Fortuitously, the Democracy Fund + UCLA Nationscape Survey Project (voterstudygroup.org) ran a weekly poll of Americans from July 2019 through January 2021, which overlaps with the COVID-19 pandemic from its outbreak in January 2020 through the first weeks of the Biden administration in January 2021. Fifty-eight of these polls asked

1 Xun and Gilman (2021a) discuss other groups also blamed by some for the spread of COVID-19 besides Ultra-Orthodox Jews, namely, Asians especially Chinese from Wuhan, China; African-Americans in the United States and Black/Asian/mixed ethnic communities in the United Kingdom; and White right-wing groups in the United States and Europe, all groups with low vaccination rates. Unfortunately, Xun and Gilman have little survey data on how widespread is blame towards these groups for COVID-19. Freeman, et al. (2022) estimate that 20 percent blamed Jews for COVID-19 in the United Kingdom, but their methods have been sharply criticized McManus, D’Ardenne, and Wessely (2022). Sutton and Douglas (2022), relying on a convenience sample in the UK, find only 2–3 percent blaming Jews and overall belief in COVID-19 conspiracies is much lower than reported in the news media. But it is unclear how representative the Sutton-Douglas sample is of the population. Using a representative sample, Garry et al. (2020) find only 10 percent in the UK blame Jews for COVID-19.
respondents two questions often used to tap into attitudes towards Jews, favorability toward Jews, and respondents’ perception of discrimination toward Jews. For perhaps the first time, we can trace attitudes towards Jews in small, discrete time units over a relatively lengthy period.

The next section of this paper briefly reviews the empirical work on antisemitism, especially regarding survey research on antisemitic attitudes, which helps to situate the research reported here into the larger literature on antisemitism. Then I present the main theoretical frameworks employed here—scapegoat theory and terror management theory—which, while derived from different research traditions, overlap, at least pertaining to antisemitism attitudes. A discussion of the Nationscape data follows, and then the data analysis is presented. The conclusion puts the findings into perspective and makes suggestions about future research.

The State of Antisemitism and Antisemitism Research

How much antisemitism is there in the world and the U.S.? Answering this question requires a definition of antisemitism and ways of operationalizing the definition—an operational definition will suggest types of data and methods for collecting that data. However, there is considerable controversy over defining antisemitism and the meaning/relevance of different types of data (Enstad 2021; Fein 1987).

For purposes here, it is best to start with a simple definition that can encompass several perspectives, but that is also specific enough to guide empirical research. Thus, I define antisemitism as hatred, dislike, and/or actions against Jews and/or Jewish institutions, merely because they are Jewish. Thus, a person can express antisemitism though opinions and behaviors. And rather than thinking of someone as antisemitic or not, it is useful to conceptualize antisemitism as a scale, following Staetsky’s (2017) elastic view, that people vary in their degree of antisemitism.

Enstad (2021; Smith and Schapiro 2019; Aronson et al. 2022) identifies several manifestations of antisemitism, 1) from events, which can range from violent to verbal (Feinberg 2020; Feinberg and Stewart 2019); 2) to attitudes towards Jews such as from polls; 3) to Jewish experiences and perceptions of antisemitism (J.E. Cohen 2010; Rebhun 2014; Kremelberg and Dashefsky 2016; Kremelberg 2009; A.B. Becker 2020; Wright et al. 2021). Further, antisemitism can be express in the media and on the internet (Zannettou et al. 2020).

The literature on antisemitism that investigates one or more of these forms is too large to review here comprehensively (see Enstad 2021). As this study employs public opinion data to study antisemitic attitudes, I will only refer to such research. An important question concerns how to measure antisemitism with public opinion polls (Levin, Filindra, and Kopstein 2022). The protean nature of antisemitism further complicates writing survey questions regarding antisemitism. Antisemitism was long associated with Christianity, but in the middle-late nineteenth century, although religious antisemitism remained potent, antisemitism associated with the political left and right emerged. In the 1980s, the new antisemitism emerged, which connects attitudes towards Israel and the Israel-Palestinian conflict with attitudes towards Jews, which survey questions developed in the 1940s and 1950s were unable to tap. The protean quality of antisemitism limits the ability to compare the incidence and level of antisemitism across time (Laqueur 2006).

A second question concerns the geography of antisemitism. Most research employing survey questions analyze responses for only one or a few nations (Enstad 2021, but see Tausch
2016, 2014 for an exception). There are three major efforts to measure antisemitism across a large number of countries, the Antidefamation League ADL Global 100 project (global100.adl.org/map), the Pew Global Attitudes surveys (pewresearch.org/global/database), and the World Values surveys (worldvaluessurvey.org/wvs.jsp). The ADL 100 uses a scale based upon ten questions. Pew and World Values employ single items, a favorability question for Pew and willingness to have a Jewish neighbor for World Values. Despite differences in questions, countries analyzed, and data collection dates, there is broad agreement about the global geography of antisemitism. Antisemitism is lower in North America and Western Europe and is highest in North Africa and the Middle East. Pew and World Values also have repeated surveys in some countries, showing aggregate stability in levels of antisemitism over the past two decades.

This study uses the Nationscape data to test for the effects of the COVID-19 pandemic on Americans’ attitudes toward Jews. Thus, this study investigates the sources of antisemitism attitudes, one type data on antisemitism. But like much research on antisemitism, which tends to use data from only one nation (Enstad 2021), this study is restricted to the case of the United States. Yet this study makes two contributions to the study of antisemitic attitudes, the ability to analyze weekly trends in antisemitic opinion and linking the COVID-19 pandemic to those trends.

Theory and Hypotheses

Scapegoating, and the related theory, terror management, provide the theoretical foundations for this study. From an intergroup conflict perspective, scapegoating occurs when members of one group blame members of another group for their problems, frustrations, misfortunes, etc. Scapegoating is viewed as a type of prejudice because the scapegoat target is not the source of the misfortunes of the members of the frustrated group (Allport, Clark, and Pettigrew 1979; Bettelheim and Janowitz 1964). Scapegoating has been associated with social and economic stress, especially when such changes are rapid and when relatively advantaged groups see their position being threatened (Green, Glaser, and Rich 1998; Becker, Wagner, and Christ 2011; Bukowski et al. 2017).

There are several limitations of scapegoat theory. Studies do not always find scapegoating responses when they might be expected, and it is not always clear why one group is scapegoated but another is not (Gibson and Howard 2007; Green, Glaser, and Rich 1998; Glick 2005). Still, Jews are often scapegoated. Economic shocks have led to mob violence and pogroms against Jews, especially in eastern Europe and under Czarist Russia (Grosfeld, Sakali, and Zhuravskaya 2020; Kopstein and Wittenberg 2018). When weather patterns negatively affected crop yields and prices, Jews were scapegoated and expelled from many affected European locales (Anderson, Johnson, and Koyama 2017). Jews at times were scapegoated because they were believed to be powerful (Bilewicz and Krzeminski 2010; Bramoullé and Morault 2017; Brustein and King 2004).

Outbreaks of contagious diseases also have led to Jews being scapegoated. Most famously, many cities in Europe expelled Jews in reaction to the Black plague. Expulsion was more likely where the plague was more severe, where Jews did not play a vital economic role, and where that economic role did not threaten non-Jewish populations (Finley and Koyama 2018; Jedwab, Johnson, and Koyama 2019; Johnson and Koyama 2019, 2017; Moore 2008; Cohn Jr.
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2007, 2018; Voigtlander and Voth 2012). Other pandemics have also led to scapegoating of certain groups, including Jews, such as the influenza pandemic of 1918, typhus outbreaks in the U.S. in the late nineteenth and early twentieth centuries, and the cholera eruption in 1830s Italy (Jedwab et al. 2021; Jones 2005; Markel 1999; Martin 2019).

Another theory, terror management, is compatible with scapegoating and may be relevant to the COVID-19 pandemic. Cohen, et al. apply terror management theory (TMT) to antisemitism (F. Cohen et al. 2009) and Pyszczynski, et al (2021) apply TMT to the COVID-19 pandemic. Terror management theory is rooted with the idea that concern with one’s mortality can cause anxiety. People will look for ways to reduce that anxiety, sometimes by seeking reassurance from in-group members who share the same cultural values and worldview. Since Jews commonly are viewed as an outgroup, they pose a potential threat due to their distinctive cultural values and worldviews. Subsequently, non-Jews hostility toward Jews should increase as mortality anxiety rises. Cohen and colleagues, through a series of experiments, show an association between higher levels of mortality anxiety and hostility toward Jews.

The COVID-19 pandemic may have intensified mortality anxiety. Individuals have been bombarded with news about the COVID-19 pandemic, such as case and death reports, economic fallout, shortages of necessities like toilet paper, burnout among health care workers, increased crime rates, and other forms of social upheaval. Individuals too may personally know victims of COVID-19. This environment may heighten mortality anxiety (Pyszczynski et al. 2021; Barnes 2021; Courtney, Goldenberg, and Boyd 2020). Thus, according to the terror management hypothesis, individuals whose mortality concerns have risen due to COVID-19 should also show higher levels of antisemitic attitudes.

From COVID-19 to Antisemitism

Two mechanisms might link COVID-19 with antisemitism. The first looks at objective indicators of the severity of the COVID-19 pandemic, here measured as caseloads and deaths. Considerable research across a range of disciplines has found that individual opinion and behavior may respond to changes in objective conditions. For instance, studies find that as inflation or unemployment changes, so does voter concern with those economic conditions (Page, Shapiro, and Dempsey 1987; Conover, Feldman, and Knight 1986). As the COVID-19 virus spreads, and cases and deaths rise, more individuals will confront the effects of the virus, which in turn may spark an increase in antisemitic opinion, blaming Jews for the virus and its severity.

A second mechanism has to do with the diffusion of communication that blames Jews. Contrary to the objective conditions' hypothesis, people do not always discriminate between actual and fake information (Bryanov and Vziatysheva 2021; Anthony and Moulding 2019; Bronstein et al. 2019). The COVID-19 information environment has been characterized as an infodemic, that is, there is much false and misleading content, some of which blames Jews or highly visible Jewish personalities. Social media, the internet, and some cable television

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2 They further contend that mortality concerns and antisemitism will be associated with greater hostility toward Israel. The present research cannot test that hypothesis.
channels have been found to be major conduits for COVID-19 misinformation (Evanega et al. 2020; Cuan-Baltazar et al. 2020). This study uses internet search activity as an indirect method for measuring individuals’ exposure to misinformation.

Data

The dependent variable for this study is an index of antisemitic opinion constructed from the Democracy Fund + UCLA Nationscape Survey Project, here called Nationscape. The Nationscape project consists of weekly polls of Americans from July 2019 through January 2021. Approximately 5,000 respondents were surveyed each week, for a total of over 500,000 respondents, making it one of the largest scholarly data collections of Americans’ attitudes ever conducted.

Nationscape asked respondents two questions to measure attitudes toward Jews:

1. Favorability: Here are the names of some groups that are in the news from time to time. How favorable is your impression of each group or haven’t you heard enough to say? – Jews

2. Discrimination: How much discrimination is there in the United States today against each of the following groups? – Jews

The two Jewish items were not asked across all waves. These items, however, were asked beginning with the 22nd wave (December 12–18, 2019), and asked continuously until the end of the data collection. Together, there are over 340,000 responses to these questions once removing Jewish respondents.

The favorability question has five response categories: Very favorable (5), somewhat favorable (4), somewhat unfavorable (2), very unfavorable (1), and haven’t heard enough (3). The “haven’t heard enough” category is kept and recoded as the midpoint; numbers in parentheses are the coding categories used here. The “haven’t heard enough” cases are kept because they make up about 20 percent of the responses. There are also five categories for the discrimination question: a great deal (5), a lot (4), a moderate amount (3), a little (2), and none at all (1).

Table 1. Distribution of Attitudes Toward Jews, Nationscape Study

<table>
<thead>
<tr>
<th>Discrimination</th>
<th>n</th>
<th>Percent</th>
<th>Favorability</th>
<th>n</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>A great deal</td>
<td>46,639.29</td>
<td>13.52</td>
<td>Very favorable</td>
<td>110,479.16</td>
<td>32.95</td>
</tr>
<tr>
<td>A lot</td>
<td>70,146.48</td>
<td>20.33</td>
<td>Somewhat favorable</td>
<td>116,938.77</td>
<td>34.88</td>
</tr>
<tr>
<td>A moderate</td>
<td>118,018.31</td>
<td>34.21</td>
<td>Somewhat unfavorable</td>
<td>22,675.87</td>
<td>6.76</td>
</tr>
<tr>
<td>A little</td>
<td>80,071.60</td>
<td>23.21</td>
<td>Very unfavorable</td>
<td>13,987.09</td>
<td>4.17</td>
</tr>
<tr>
<td>None at all</td>
<td>30,126.32</td>
<td>8.73</td>
<td>Haven’t heard enough</td>
<td>71,209.12</td>
<td>21.24</td>
</tr>
</tbody>
</table>

Weighted data, Jews excluded from calculations.

An index of antisemitism is constructed by adding respondents’ scores to the two questions. Table 1 presents (weighted) distributions of the two questions. Overall, Americans have positive attitudes toward Jews, with a mean favorability score of 3.86 and a mean discrimination score of 3.07. The correlation between the two questions is quite modest, only
0.13 (Pearson’s r), which is highly statistically significant because of the massive n (p = 0.000). Although related, the two items appear to be picking up different dimensions of attitudes toward Jews.

Figure 1 presents a histogram of the Index of Antisemitism. The index displays a positive tilt, with a mean score of 6.93 out of a possible 10. Notably, no Americans hold the most antisemitic scores (0 or 1), with only tiny percentages holding highly negative scores of 2 or 3. Defining philosemitism when a person has a score of 6 or greater, 81.6 percent of Americans are philosemitic, compared to 10.4 percent who are neutral (5), with another 8 percent antisemitic (scores less than 5). Consistent with other studies of attitudes towards Jews, these data indicate positive sentiment of American voters toward Jews.

The Nationscape opinion data are aggregated by week for the time series analysis. Weekly data are used because Google Trend Search data cannot be disaggregated in units smaller than weeks. To measure objective conditions, I use weekly counts of cases and deaths from USA Facts (usafacts.org), which presents the Centers for Disease Control COVID-19 data in an easy-to-use format. I use Google Trends (trends.google.com/trends) to track search interest in the COVID-19 pandemic and searches that blame Jews and/or George Soros. Although Google searches do not measure exposure to content about the pandemic or that the searcher blamed Jews or Soros for the pandemic, Google searches show an aggregate interest in the topic. Stephens-Davidowitz (2017, 2019) argues that internet searches often are more revealing and truthful about behavior than survey self-reports and have been used in some recent studies on antisemitism.

I ran two searches on Google Trends, one simply for “covid” and the other for the combination of Jews and George Soros with Covid: “Jews covid + Soros covid + jews covid + soros covid.” The simple “covid” search measures an interest in, perhaps concern with, the COVID-19 pandemic. The combination search aims to specifically link COVID-19 with Jews and/or George Soros.
Trends in Antisemitism Across the COVID-19 Pandemic

Figures 2a and 2b present plots of the weekly trends in the favorability and discrimination items. A locally weighted scatterplot smoother (lowess) is overlaid to see the trend more clearly. Both the favorability and discrimination trend lines vary within a tight range, from about 3.8 to nearly 4.0 for favorability and from about 3.0 to 3.2 for discrimination. Temporal patterns are discernible and clear if we focus on the lowess smoothed line. Favorability shows a very slight decline from January 2020 until late spring, when the favorability ratings begin to rise, and continue rising until summer 2020. Then the favorability ratings start receding, falling back to the levels early in the series, at the beginning of the COVID-19 outbreak. In contrast, discrimination sympathy begins to erode with the COVID-19 outbreak in early 2020 in an almost steady, incremental fashion. The discrimination scores appear to reach a plateau in spring 2020, remaining at that level until late fall 2020, when another drop in discrimination sympathy commences. Unlike the favorability trends, discrimination sympathy never recovers to early 2020 levels. The two series are weakly and insignificantly correlated at the weekly level ($r = 0.08$, $p = 0.52$).

The two survey items appear to tap different, albeit related dimensions of antisemitic opinion. Thus, it is important to combine the two into one index, which provides us with the most information about peoples’ attitudes. Multiple items are preferable to single items for measuring complex attitudes, such as antisemitism (Curtis and Jackson 1962; Balch 1974; Sullivan 2017). Figure 3 plots the trend for the antisemitism index, again using the lowess smoother.

Variation in the antisemitism index is tightly bounded from about 6.8 to 7.1 on the 10-point scale. The series starts at a high point of 7.1 in January 2020, then slides until mid-spring 2020. It stays at this level for a brief time, followed by an uptick, which peaks in mid-late

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3 Time series data, especially when based on survey data, contain noise, which may make it difficult to visualize any trends or patterns. Lowess smoothing is a regression process where one obtains smoothed values by running a regression, regressing the favorability or discrimination values, on a time counter. The regression uses several data points near the one being smoothed, and the impact of each data point is weighted by how close the data point is to the one being smoothed (see Cleveland 1981).
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summer 2020; this peak sits below the level early in the series. Then in fall 2020, the index again wanes, and continues to slide until the end of the series in January 2021. Despite these visually detectable trends, the variation in attitudes towards Jews is tightly bounded. Are these visual trends systematic and associated with the COVID-19 pandemic, or are they short-term and random fluctuations?

Figure 3. Trends in the Antisemitism Index

Note: Lowess smoothing. Data from Nationscape. See text for details.

Time Series Properties of the Antisemitism Index

Prior to assessing the causal relationship of variables in a time series, it is necessary to inspect the data series’ temporal properties. Doing so will help distinguish whether two series are causally related or the correlation between them is spurious. First, we ask, is the series, especially the dependent variable, stationary? Stationarity means that the variables does not trend over time. (Technical details of this part of the analysis are presented in the Appendix.) Analysis indicates the antisemitism index is stationary. Visual inspection of Figure 3 also supports this conclusion: The series declines, stays steady, rises, and declines again. A non-stationary series would show continual growth or decline.

Second, do past values of a series affect current values, autocorrelation? If a series is autocorrelated, it violates the regression requirement of independence of observations. When autocorrelation exists, past values affect current values, thus the observations are not independent. Diagnostics suggests the presence of two types of autocorrelation—a first-order autoregression and a first-order moving average process. First-order autocorrelation happens when the prior period’s value ($t-1$) affects the current value ($t$). A moving average process exists when the prior period’s errors affect current errors. The analysis below applies corrections for first-order autocorrelation and first-order moving average.

4 In other words, if we regress the current value of a series on past values, a moving average process exists when the errors (or residuals) in the series are correlated. Residuals or errors are the differences between the observed
Independent Variables: Objective Indicators and Google Searches

![Figure 4. Weekly Trend in Covid Cases and Deaths](image1)

Figure 4. Weekly Trends in COVID-19 Cases and Deaths. Source: USA Facts from official CDC sources.

![Figure 5. Trends in Google Searches for Covid and Combination Jewish/Soros with COVID-19](image2)

Figure 5. Trends in Google Searches for Covid and Combination Jewish/Soros with COVID-19. Source: Google Trends. Calculated by the author.

Figures 4 and 5 plot the trends in the four independent variables: the weekly number of new cases and the weekly number of new deaths on Figure 4; weekly Google trend searches values and statistically predicted values. If autocorrelation is present, current values are a function of past values. Note the difference between the values in the series and errors in the values of the series.

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for “covid” and weekly trend searches for “Jews covid + Soros covid + jews covid + soros covid” on Figure 5. On Figure 4, the left y-axis is for cases and the right-side y-axis for deaths.

Weekly trends in cases and deaths correlate strongly (r = 0.81, p = 0.000). (Table 2 presents the correlations for all four variables.) Both deaths and cases cycle over time, with peaks and valleys that we have become familiar with. Deaths spiked upward in spring 2020, receding as warm weather appeared, but surged upward again as winter 2020-21 approached. Cases show a similar time path. It may not be possible to include both in the same equation because they are so highly correlated.

Table 2. Correlations of Independent Variables used in the Analysis

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<tbody>
<tr>
<td>(1) Weekly Deaths</td>
<td>0.81 (0.00)</td>
<td></td>
<td>-0.36 (0.01)</td>
<td>-0.23 (0.10)</td>
</tr>
<tr>
<td>(2) Weekly Cases</td>
<td></td>
<td>-0.40 (0.00)</td>
<td></td>
<td>-0.27 (0.05)</td>
</tr>
<tr>
<td>(3) Google Search-COVID-19</td>
<td></td>
<td></td>
<td></td>
<td>0.71 (0.00)</td>
</tr>
<tr>
<td>(4) Google Search- Jew/Soros Plus COVID-19</td>
<td></td>
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</table>

Note: Pearson Product Moment Correlations. Significance level in parentheses.

The two Google search trends follow a similar path but differ considerably from the objective measures. Before proceeding, Google Trends does not provide search numbers, only percentages that are normed against the period with the highest number of searches, which receives a score of 100 percent. A score then of 20 percent indicates that the number of searches during that period was only 20 percent of the highest number of searches.

Like the objective measures, the two Google searches are highly correlated (r = 0.71, p = 0.000). Unlike the objective measures, which show oscillating cycles over the year, both Google search trends show their acmes in March 2020, shooting up from low levels in January 2020. Then both abruptly decline, with some minor oscillations thereafter. It should be noted that even these lower levels of searches for “covid” and combined with a Jewish reference, while small in percentage, may still represent many millions of searches due to the massive search volume on Google. It is safe to say, however, that search interest in “covid” and covid-19-Jewish combinations quieted down considerably after a flurry of search interest early in the pandemic. Finally, the correlations between the objective measures and Google searches are not as high as within those two groups, ranging from about 0.23–0.40, of course being negative since they peak at different times of the year.

Statistical Analysis

The Appendix reports details of the statistical analysis; the discussion here summarizes results of that analysis. The estimation equation can be expressed as such:

\[
\text{Antisemitism Index} = \text{COVID-19 Cases} + \text{COVID-19 Deaths} + \text{COVID-19 Searches} + \text{Combination COVID-19 Searches}
\]
There is little guidance on the speed with which the independent variables may affect antisemitism attitudes. The impact may be quite swift or delayed. To test between these possibilities, the analysis estimated equations with the independent variables having a contemporaneous weekly effect, a one-week lagged effect, or a longer lagged effect. Another concern is whether the series is heteroskedastic or not. Heteroskedasticity refers to the spread of the values of the residuals across values of the dependent variable, for instance, that variability is low when the dependent variable values are low, but the residuals high when the values of the dependent variables are high.

Turning to the results, the cases variable displays the wrong sign no matter the estimation particulars, whether robust regression is used, the lag structure, and whether corrections for autoregression are employed or not. As cases rise, antisemitism levels fall. Multicollinearity appears the primary reason for the incorrect sign—COVID-19 cases and deaths are highly correlated ($r = 0.80, p = 0.000$). When the estimation employs cases but not deaths, the cases variable does not reach statistical significance with no lag or a one-week lag but is significant with the proper sign with a two-week lag. A comparison of the AIC and BIC statistics for estimations that include or exclude the two-week lag, with the other three variables included, finds better performance (smaller AIC and BIC statistics) without the cases variable. Thus, the cases variable is eliminated from the model. The final model consists of the contemporaneous Google search variables and the one-week lag of deaths, with the autocorrelation corrections applied. Appendix Table 3 presents details of the results and for other estimations used to arrive at this conclusion.

What are the substantive effects of these variables on the antisemitism index? Here I use marginal effects analysis, which compares levels of antisemitism across different levels of the independent variables. Figures 6–8 plot these marginal effects, with the other variables held constant at their means.

![Figure 6. Impact of Google Combination Searches on Antisemitism Index. Source: Google Trends. Calculated by the author and Nationscape. See text for details.](image-url)
Visually comparing across the three figures suggests that Google searches for the combination of “covid” and Jews/Soros has the weakest, albeit statistically significant, effect on antisemitism attitudes. From the minimum percentage of such searches to the maximum (0–100) produces only a 0.05 effect, 6.92 at the minimum to 6.87 at the maximum, which is hardly a substantively significant impact. In contrast, the antisemitism index is more sensitive to “covid” Google searches, although again the impact may not be substantively weighty. From the minimum percentage of such searches to the maximum value, there is a 0.11 shift,
from 6.93 at the minimum to 6.82 at the maximum, about twice the effect of combination searches. Still, in a practical sense, this is hardly powerful.

The antisemitism index is responsive to COVID-19 deaths, lagged one week. When COVID-19 deaths during the past week are at their minimum, no deaths, the antisemitism index score is 6.95, but drops to 6.83, a 0.13 unit drop when such deaths hit their maximum during this period (25166). Again, one may question the substantive import of this movement. Yet these effects, however small, are statistically significant on a modest number of cases (n=52). It can be difficult to reach statistical significance when the n of cases is so small. What about the cumulative effect of the three variables? When all three variables are set at their minimums, the antisemitism index is 6.98, but drops to 6.70, a 0.28 decline, when all are set at their maximum. Arguably this too represents only a slight increase in antisemitism.

Conclusion

Antisemitism among American voters increased slightly during the COVID-19 pandemic, ostensibly because of the worsening of the pandemic and Google searches. Despite the statistically significant association between higher COVID-19 death rates, Google searches for COVID-19, and combination Google searches for Jews/Soros and COVID-19, effects appear substantively slight. Still, results are statistically significant with a relatively small number of cases.

Why such small substantive effects? First, American have positive dispositions towards Jews, which may immunize most Americans from scapegoating Jews for the COVID-19 virus and pandemic (J.E. Cohen 2018; Smith and Schapiro 2019; Putnam and Campbell 2012). The few times series of Americans attitudes towards Jews find increasing positivity for most survey items that have been repeated over the past two decades or so (J.E. Cohen 2018; Smith and Schapiro 2019).

Second, many more voters blame the Chinese government for the COVID-19 pandemic, perhaps providing a more compelling scapegoat than Jews (Gilman 2021a; Xun and Gilman 2021b; Sutton and Douglas 2022; McManus, D’Ardenne, and Wessely 2022; Garry, Ford, and Johns 2020). A Fox News poll of June 2021 found 60 percent saying the virus was created in a Chinese laboratory, while 31 percent felt it naturally evolved and spread to humans from an animal market in China (Fox News 2021, Question 27). And, even believers of George Soros’s involvement may not generalize that conspiracy to Jews in general. We lack data on how many individuals believe the Soros related conspiracies nor do we know how many people know that Soros is Jewish. Still, while belief in COVID-19 conspiracies and political orientations affect attitudes and behavior toward COVID-19 and government COVID-19 policies, we know little about the sources and/or effects of the many different COVID-19 conspiracy beliefs (Bavel et al. 2020).

The acceptance of and positivity toward Jews in the U.S. may have provided a barrier against broadly scapegoating Jews for the pandemic. But there may also have been skepticism about the conspiracy tropes linking Jews to the COVID-19 pandemic. Despite the lack of scientific literacy of the U.S. population, there may be enough understanding of the COVID-

---

5 A search of the Roper poll database could not find a single survey question on George Soros.
Scapegoating Jews During the COVID-19 Pandemic

19 virus that it seems unreasonable for most Americans to scapegoat Jews. Even if the population is not sufficiently literate about science, there is a foundation of trust toward scientific authorities, such as the Centers for Disease Control (CDC). A December 2021 poll found 29 percent and 37 percent of respondents having a great deal or a fair amount of trust in the CDC to provide “accurate information about coronavirus or COVID-19,” where 19 percent and 14 percent had not very much or no trust in the CDC. In contrast, there is not much trust in social media as a source of accurate information concerning COVID-19. The same poll found 1 percent with great deal, 13 percent with a fair amount, 41 percent with not very much and 44 percent with no trust in social media to provide accurate information about COVID-19 (Axios 2021, Question 40). Still, the general thrust on scientific literacy of average Americans emphasizes their lack of knowledge, misunderstanding of science, growing distrust of science institutions in and out of government, and increasing politicization of attitudes towards science in the U.S. (Druckman 2022; Suhay and Druckman 2015; Bolsen and Druckman 2018). But trust in science, however limited, has remained relatively high compared to other institutions in the U.S. for the past 40 years (Krause et al. 2019). Yet it may be more the mistrust of social media than trust in scientific authorities that limited or blunted the effect of the COVID-19 infodemic on attitudes towards Jews and perhaps the basic positivity of Americans towards Jews created a sense of skepticism about the COVID-19 conspiracies that implicated Jews.

The combination of positivity toward Jews, modicum of science knowledge, and relative trust toward scientific authorities may only be found in advanced western nations. Hence, the present findings may not replicate to other nations without this constellation of factors, leading to the possibility of a stronger linkage between COVID-19 and antisemitism. Still, it is troubling that this analysis detected a small, statistically significant impact of COVID-19 on antisemitic beliefs. A deeper analysis of these data at the individual level may help identify the types of individuals who scapegoated Jews for COVID-19.

Appendix

Analysis of time series is complicated because the temporal properties of the series can affect results. This appendix reports technical details of the time series analysis used here, diagnosing those issues such as stationarity, serial correlation, the lagged relationship of the independent variables to the dependent variable, and other estimation concerns that may affect results, such as employment of robust standard errors.

Times Series Issues: Stationarity

Two time series may be statistically correlated but are not causally related because a third factor affects both, in other words, the correlation between the two series is spurious. To assess whether the relationship between two series is due to spurious correlation or is casual requires detecting the nature of trends in the series, called stationarity. A stationary series is one without an identifiable trend. The mean value of the series remains the same across different temporal subsets. In contrast, a non-stationary series exhibits a trend or drift, or what econometricians call a unit-root; the mean value of the series differs for different temporal subsets. Most important is diagnosing the dependent variable for stationarity (see Hamilton 2020).
Assessing stationarity employs in formal visual approaches and formal statistical tests. For instance, visually inspecting Figure 3 in the text suggests a stationary series. In the early months of 2020, the series dips (antisemitism increases), then it plateaus before it rises a little (antisemitism decreases) and declines again for the final months of 2020 and the initial months of 2021. These periods of rise, stability, and decline in the antisemitism index also are not of uniform duration, a possible indication that there is no cycle to the changes. Visual inspection of the series suggests a stationary series.

More formal statistical techniques for detecting stationarity include the Dickey-Fuller and Phillips-Perron tests. The Dickey-Fuller test suggest the antisemitism index is stationary. Augmented Dickey-Fuller tests, which included up to three lags and a trend found those components to be statistically insignificant, so they were dropped. The Dickey-Fuller statistic is -4.85, which is smaller than the 1 percent critical value of -3.57. Stationarity is indicated when the test statistic is smaller than the critical value. The Phillips-Perron test confirms the Dickey-fuller results. In this case, the Phillips-Perron test indicated a significant one-period lag (coefficient = 0.44, p < 0.000). Both test statistics indicate a stationary series. The Z(\rho) is -29.82 with a 1 percent critical value of -25.87, and the Z(t) test is -4.75 with a 1 percent critical value of -4.14.

**Time Series Issues: Autocorrelation**

Having established the stationarity of the antisemitism index, it is necessary to address the issue of serial correlation, whether past values of a series affect current values. Serial correlation violates the regression requirements of independence of observations, which can bias statistical results. There are two forms of serial correlation, autocorrelation and moving average processes. Autocorrelation is the correlation of current values of a series with past values. The moving average process is the correlation between current values and past values, controlling for the correlation of all other values in the series. Like for stationarity, visual and formal methods are used to assess serial correlation.

Appendix Figure 1. ACF Plot of Antisemitism Index.
Visual inspection utilizes the ACF and PACF plots, the former for autocorrelation and the latter for the moving average process, which are presented with Appendix Figures 1 and 2. The ACF plots shows that the first-order autocorrelation falls outside of the greyed confidence band, while all other autocorrelations fall within the band, indicating that only the first-order autocorrelation is statistically significant. Thus, there appears to be an AR1 process in the series. The PACF plot is somewhat more complex, revealing a significant first-order moving average correlation, as well as significant correlations at the 5, 8, 24, and 26 lags. Finally, Bartlett’s white noise test, plotted on Appendix Figure 3, indicates the series is not white noise, with several frequencies falling outside of the 95 percent confidence band. All the visual inspections suggest presence of some form of serial correlation.
ARIMA modeling allows the application of both AR and MA processes simultaneously. Appendix Table 1 presents several estimations from Arima modeling of the antisemitism index, with and without robust standard errors. Not all estimations are shown. The Arima model indicates presence of an AR1 and MA1 process, and the possibility of a more complex MA process. Later analyses find results using robust standard errors are superior and that the residuals using the simpler AR(1) MA(1) are white noise.

### Appendix Table 1. ARIMA Models for Antisemitism Index

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Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1

**Estimation Issues: Lags of the Predictor Variables and Robust Regression**

How quickly do the independent variables influence the dependent variable, the antisemitic index? Their effects can be contemporaneous, lagged, or some combination. A contemporaneous effect is felt during the same week, while lagged effects are the effects of independent variables from previous weeks. Appendix Tables 2 and 3 provide results of estimations that vary the temporal effects of the independent variables. Further, robust regression is utilized, even though there does not appear to be heteroskedasticity in the residuals. Angrist and Pischke recommend routinely reporting robust standard errors (Angrist and Pischke 2008).
The heteroskedastic robust standard errors consistently reach significance, which is not the case when using non-robust standard errors. This is an odd finding, since robust standard errors are usually larger than OLS standard errors, leading the former to accept the null hypothesis of no effects more often than when using OLS standard errors. The best fitting equation without any insignificant variables is Model 4, Appendix Table 3.

Appendix Table 2. Comparing Contemporaneous and Lagged Independent Variables on the Antisemitism Index

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Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1
Appendix Table 3. Estimations Employing Contemporaneous and Lagged Independent Variables on the Antisemitism Index (Excluding Weekly Cases)

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Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1

Analysis of the Residuals

Finally, the analysis inspects the residuals from Model 4, Appendix Table 3 to insure they are white noise, that is, they are random, with a single N (0, sigma2) distribution. Appendix Figure 4 plots the residuals using Bartlett’s periodogram white noise test. As the figure attests, the residuals fall within the +/- 0.05 confidence band, indicating they are white noise. And Bartlett’s B is insignificant at 0.06 (p = 0.08), confirming they are white noise. The Portmanteau Q test statistic is white noise for all lags from 0 through 5: Q lag(0) = 27.4, p = 0.29; Q lag(1) = 0.14 = 0.71, p = ; Q lag(2) = 0.23, p = 0.89; Q lag(3) = 2.10, p = 0.55; Q lag(4) = 2.51, p = 0.64; Q lag(5) = 3.64, p = 0.60.
Appendix Figure 4. Bartlett’s White Noise Test for Appendix Table 3, Model 4, using Robust Standard Errors

Biblography


Axios 2021. Axios/Ipsos Coronavirus Index, 31119088.00039, conducted by Ipsos. Roper Center for Public Opinion Research, Cornell University.


Scapegoating Jews During the COVID-19 Pandemic


Scapegoating Jews During the COVID-19 Pandemic


