Trending in the Right Direction: Using Google Trends Data as a Measure of Public Opinion During a Presidential Election

Jordan T. Wolf

Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Arts
In
Communication

John C. Tedesco, Chair
Katherine E. Haenschen
Daniel J. Tamul

April 27, 2018
Blacksburg, Virginia

Keywords: Google, polling, public opinion, 2016 election

Trending in the right direction: Using Google Trends data as a measure of public opinion during a presidential election

Jordan T. Wolf

ACADEMIC ABSTRACT

During the 2016 presidential election, public opinion polls consistently showed a lead in the popular vote and Electoral College for Hillary Clinton over Donald Trump. Following Trump's surprise victory, the political pundits and public at large began to question the accuracy of modern public opinion polling. Fielding a representative sample, convoluted and opaque methodologies, the sheer amount of polls, and both the media's and general public's inability to interpret poll results are among the flaws of the polling industry. An alternative or supplement to traditional polling practices is necessary. This thesis seeks to investigate whether Google Trends can be effectively used as a measure of public opinion during presidential elections. This study gathers polling data from the 2016 presidential election from states that were considered swing states. Specifically, this study examines six total polls, three from states that swung in the way the polls predicted they would – Nevada and Virginia –and three from states that swung against the prediction – Michigan, Wisconsin, and Pennsylvania. Answers to the "Most Important Issue" question in each poll are compared to their corresponding topics in Google Trends by calculating Pearson product moment correlations for each pair. Results indicated that in states that swung as predicted, Google Trends was an effective supplement to traditional public opinion polls. In states that did not swing as predicted, Google Trends was not an effective supplement. Implications of these results and future considerations for the polling industry and Google are discussed.

Trending in the right direction: Using Google Trends data as a measure of public opinion during a presidential election

Jordan T. Wolf

GENERAL AUDIENCE ABSTRACT

During the 2016 presidential election, public opinion polls consistently showed a lead in the popular vote and Electoral College for Hillary Clinton over Donald Trump. Following Trump's surprise victory, the political pundits and public at large began to question the accuracy of modern public opinion polling due to the number of issues that were made apparent during this election cycle. An alternative or supplement to traditional polling practices is necessary. This thesis seeks to investigate whether Google Trends can be effectively used as a measure of public opinion during presidential elections. This study looks at answers to the "Most Important Issue" question in polls in states that swung as predicted and states that swung against their predictions. The answers to this question in each poll are compared to their corresponding topics in Google Trends to determine how similar public opinion was in polls to what people in those states were searching on Google over the same period of time. Results indicated that in states that swung as predicted, Google Trends was an effective supplement to traditional public opinion polls. In states that did not swing as predicted, Google Trends was not an effective supplement. Implications of these results and future considerations for the polling industry and Google are discussed.

TABLE OF CONTENTS

List of Figures

List of Tables

Introduction

What went wrong? It was all but a certainty that the sun would rise on November 9, 2016 and former Secretary of State and Democratic Party nominee Hillary Clinton would be the President-Elect of the United States. Nearly every poll leading up to Election Day showed Clinton taking home an Electoral College victory. That outcome, of course, did not happen. Hillary Clinton is not the President of the United States.

The 2016 election was unprecedented in many regards. On one side, we saw the first woman, Clinton, to lead a major party ticket and saw the first reality television show host, Donald Trump, to lead a major party ticket on the other side. Many polling sites consistently showed a comfortable Clinton lead not only in the popular vote margin but also, albeit somewhat competitive, in the Electoral College as well (Trende, 2016). Among pollsters, academics, and data-driven prognosticators, Clinton was predicted to win the election with confidence levels varying from 71 to 99 percent (Katz, 2016). The polling and data aggregation website FiveThirtyEight, in the weeks before the election, even released an article detailing possible scenarios that could play out on Election Day with four of the five scenarios leading to a Clinton victory (Wasserman, 2016).

To the general shock of the polling industry, Trump won the Electoral College and therefore the Presidency. Clinton did win the popular vote by slightly more than two percentage points (CNN, 2016). Even though most polls and poll aggregating services predicted a Clinton popular vote lead, most overestimated the amount of her lead (Rivers, 2016), and therefore incorrectly predicted the Electoral College results.

Immediately following the election, the Trump victory, an unexpected result, was met with quick blame assigned to the polling industry. Specific methodological flaws like low response rate were cited as a reason for this failing (Cassino, 2016) along with critiques that the industry as a whole simply needed to do a better job of informing the public what it was they were actually seeing in specific polls (Cillizza, 2016; Shepard, 2016).

As further proof that this result came as a shock and was somewhat suspect, following the election, the House of Representatives, the Senate, and the Department of Justice, via an appointed special counsel, all opened investigations into alleged Russian interference in the election. This election was also widely discussed on social media, even more so than the 2012 election, with 40 million tweets sent about the election by 10 p.m. on Election Day (Isaac & Ember, 2016).

Trying to pin Clinton's electoral loss on one single cause of error is difficult. A multitude of issues likely contributed, including but not limited to Russian influence and interference, the rise of fake news, decisions regarding which swing states to visit (or not visit) in the final days, and a heightened state of racial tension throughout the country. Notwithstanding any of these issues, polling of this election was still found to be slightly off, especially due to an underestimation of Trump support in Michigan, Pennsylvania, and Wisconsin (Kennedy et al., 2018).

As its name implies, the job of an opinion poll is to accurately portray the opinions of a representative sample of a population, whether it measures preference for a political candidate, the most important issue on voters' minds, or the perception of the job that an elected official is doing, among other uses. To accomplish this, pollsters typically employ one of two methods: phone-based surveys, such as random digit dialing, or online polling. These public opinion polls are not insulated from their fair share of problems.

Among the concerns facing public opinion polling, fielding a representative sample is often costly and time consuming (Wang, Rothschild, Goel, & Gelman, 2015). This has been somewhat quelled with the advent of online polling and the ability to draw from a bigger population in a shorter amount of time, but it is far from perfect. Indeed, unless online polling organizations are careful and willing to invest the necessary financial support to conduct a representative poll, an unrepresentative sample will likely be the result (Johnson, 2002). Another problem of modern public opinion polling is a lack of methodological transparency and convoluted predictive models that make the task of finding out what went wrong with a poll especially difficult. When coupling these problems with a vast increase in the number of overall polls and the inability of the media and the public to accurately interpret them, it is clear that modern public opinion polling is not entirely reliable.

Perhaps the most damning indictment of these polls is that being asked questions from a third-party lends itself to social desirability bias. This bias is the idea that a respondent will want to answer a question in the most socially desirable way (Randall & Fernandes, 1991). regardless if polling is done in a traditional format such as a phone survey or online (Dodou & de Winter, 2014). Because polls are administered by people or organizations, respondents may not give their true answer out of fear of being judged for their opinions. The respondent reverts back to the answer that most closely resembles the societal norm or expectation. Online polling is just as likely to be subject to social desirability bias, possibly because respondents are aware that their responses and data, even though collected digitally, are monitored, stored, and shared just as it would be if it were conducted offline (Dodou & de Winter, 2014). This bias is being discussed as one possible explanation for polling being off in the 2016 election; people may not have wanted to truthfully answer that they supported Trump because they did not want to be associated with his racist, misogynistic, anti-Islamic, authoritarian, uninformed rhetoric which did not conform to societal standards (Klar, Weber, & Krupnikov, 2016).

To remove something like social desirability bias from polling is difficult. The nature of polls are such that respondents know that they are part of a poll and may consciously change their answer to save embarrassment or reputational harm. Removing this other party – the polling organization – from the equation theoretically would produce only the actual opinion of the respondent and not the socially desirable answer that the respondent suspects most conforms to social norms. Take, for example, the news of Cambridge Analytica and their data harvesting operation on Facebook. People were more likely to allow access to their information to a non-human entity – like a Facebook application – and not really pay much attention to the implications of that access (Rosenberg & Dance, 2018). It would follow that a non-human solution where people don't necessarily think about the implications of leaving a trace of data may be better.

A creative solution that addresses the shortcomings of polls and removes awareness of a third party is necessary. As seen in the proliferation of technology and Internet usage over the past nearly two decades, society as a whole continues to utilize the Internet in great numbers; in 2013 nearly 75% of all American households used the Internet (File & Ryan, 2014). Using a search engine continues to be the most popular online activity among Americans (Purcell, 2011). Internet users tend to use search engines for information seeking (Rose & Levinson). Google is still the most popular search engine, dominating the market share by an extremely large margin (NetMarketShare, 2017). Google, and more specifically Google's search engine, may be the answer to the pollster's conundrum.

Search engines, including Google, are primarily used as a means to seek information or increase knowledge; approximately two thirds of users consider these search engines to be unbiased (Purcell, Brenner, & Rainie, 2012). Search engines are often utilized to seek information about policy issues, especially with a triggering event in the news that mentions that topic or issue (Trevisan, Hoskins, Oates, & Mahlouly, 2018). Search engine use is also positively correlated to political knowledge (Stephens et al., 2014). Outside of a specifically political context, research has also shown that people turn to search engines when seeking health information and that those searches tended to increase when particular health issues were mentioned in the news (Brigo & Erro, 2016). In an even broader context, searches can be more like a confession or a way to type out something, as shown through the thousands of searches for "I am sad," or "I regret having children," that are made every year (Stephens-Davidowitz, 2017). Essentially, searches can be a strong substitute for social desirability bias-influenced responses in traditional public opinion polls.

When attempting to look at Google as more than just a search engine and more as a powerful tool that can help us explain things that we otherwise are not able to, Seth Stephens-Davidowitz said it best in his book, *Everybody Lies*, suggesting that, "The everyday act of typing a word or phrase into a compact, rectangular white box leaves a small trace of truth that, when multiplied by millions, eventually reveals profound realities," (Stephens-Davidowitz, 2017).

This information seeking via Google searches creates a digital trace, or record, of information that researchers can use to find insights about things that matter to or spark curiosity in the people making these searches. A Google search is a direct measure of what someone types into their computer or smart device. A public opinion poll subjects respondents to the selective measure of asking a question and requiring a response from a predetermined list of options. The idea that someone is not telling another person or a polling organization what, for example, is the thing that they are most concerned about in this country but are simply confiding in a search engine on their web browser means that maybe searches can be used as a way to get a more accurate view of public opinion devoid of the worry that respondents may have just been feeding pollsters the answer that they want to hear.

Even if not supplementing traditional public opinion polling as a whole, Google searches give the possibility of measuring sentiment that may otherwise go unnoticed. The availability of technology and the insights that big data can provide may mean that traditional public opinon polling is no longer the standard-bearer when it comes to informing campaigns or the public.

Literature Review

Polling History and the 2016 Presidential Election

Predictive polling – trying to make forecasts and predictions on elections based on polling data – is rooted in scientific methods. It famously gained a spotlight in presidential elections during the 1936 election between Franklin D. Roosevelt and Alfred Landon. Polling wasn't especially robust prior to and during this time and it was limited methodologically (Hillygus, 2011). Charles Gallup used a quota-controlled sample to accurately predict the election with a smaller sample than *Literary Digest* – which famously but incorrectly predicted that Alfred Landon would handily defeat incumbent Franklin D. Roosevelt (Hillygus, 2011). Gallup's quota sampling consisted of choosing an exact number, or quota, of certain demographic groups to survey based on proportions in the population as a whole, thus creating a representative sample; conversely, *Literary Digest* used a sample based on automobile registration lists and telephone directories which were inherently biased towards higher income individuals and therefore not representative (Bethlehem, 2009). Other early approaches to forecasting elections included the identification of bellwether localities, or areas of the country whose vote proportions closely match those of the country as a whole (Bean, 1948) and surveying them as a measure of possible election results, as it is more efficient and reasonable than focusing on the entire country. Far from an exact science, professional pollsters have made many incorrect predictions by utilizing inaccurate or incomplete methods (Hillygus, 2011; Jacobs, 2005).

Many factors have to be considered when examining polls such as the sample, the data collection method, and what the results are actually showing, among other factors. It is naïve to assume that any two polls that one may see are the same. A large reason for this is a lack of methodological transparency and lack of poll aggregation (Hillygus, 2011). Polling aggregation is the concept of combining results of polls and averaging them by taking the mean of all results or by weighting them based on sample size, type of survey, etc. (Pasek, 2015). This aggregation allows the public to see moving averages of all polls over a period of time and can downplay the significance of a single outlier poll. When polls differ from actual results, it can be hard to pinpoint what specifically about the methodology was wrong because of the large number of factors that go into the design of any predictive aggregation model used by pollsters. There could be one or many methodological issues in a single poll that make the entire model inaccurate overall. Coupled with the nearly impossible task of predicting future behavior on a grand scale, choosing a representative sample of likely voters is a very important consideration that pollsters must keep in mind when designing predictive models (Hillygus, 2011).

Currently, polling is shifting from phone-based interviews to largely digital, online polling methods (Hillygus, 2011; Jacobs, 2005; Panagopoulos, 2009). The shift to mostly online polling and subsequent ease in ability to aggregate polls online and rise of polling aggregators means that the volume of available data has skyrocketed (Blumenthal, 2014). Aggregation of polls by websites such as FiveThirtyEight.com, RealClearPolitics.com and others has led to a simplified way for the public to view polling data and less of a reliance on any single poll by capturing unprecedented numbers of both state and national polls to give a more direct and accurate sense of elections (Panagopoulos, 2009). These outlets take polls that measure the same thing and combine the results, giving certain weight to each poll based on sample size, credibility of the polling organization, timeliness of the poll, etc. Aggregation websites also allow the public to see a broader picture of the polling landscape. Journalists and other members of the media who are not highly trained in polling methods no longer have to act as gatekeepers of polling information and subjectively choose which poll will be reported (Hillygus, 2011).

There has been a considerable rise in the sheer number of polls over the past 30 years. For trial heat polls, a measure of support for a hypothetical candidate for an election, an approximate 900 percent increase was seen between 1984 and 2000 (Traugott, 2005). There is also an availability of aggregate data from the emergence of aggregation websites. It should be noted though, that aggregation has seen its share of drawbacks even when considering that they allow more informed predictions to be made than could be made by relying on any single poll. Despite the increased availability of polling information, Jacobs (2005) argues that the media and campaign officials often do not have the background and knowledge necessary to interpret the polling data in a useful manner. When important information like polling data is so visible and readily available, it can be tempting to report on that information without first seeking to understand it.

A larger variability in methods as referenced by Hillygus (2011) can also lead to the inaccurate reporting of otherwise accurate numbers which is especially disappointing when polls have the ability to be more accurate and predictive than they were previously. This was seen in the most recent presidential election in 2016 where, overall, the national polls were among the most accurate in estimating the popular vote since 1936 (Kennedy et al., 2018). Despite this, the sheer amount of data available from polling aggregators and the lack of understanding of polling methodology by key personnel inside campaigns and in the media lead to an overall misunderstanding and distrust of the industry as a whole. In fact, in the Pew Research Center's quadrennial post-election evaluation, respondents gave an average grade of a D+ to pollsters in assessing their performance during the election (PewResearchCenter, 2016).

Polling Methods

The question or questions being asked in a poll are of special importance because they form the actual content of the poll. Traditionally, many election and public opinion polls used the standard verbal scale or options (dichotomous response, Likert-type, etc.) when asking survey questions (Delavande & Manski, 2010). This leaves respondents limited in the choice they can make. In these verbal responses, respondents can only choose a predetermined selection (likely, strongly agree, candidate A, etc.). An issue associated with these types of questions, other than the limiting factor, is that the possible responses are not inherently equal. Delavande and Manski (2010) illustrate this by offering an example of being able to choose very likely, fairly likely, not too likely and not at all likely in one survey, but not being able to equate those if the same question was asked and responses of definitely, probably, probably not and definitely not were used instead. This methodology only allows an ordinal responses; that is, the degree of difference between choices is unknown.

Probabilistic polling, on the other hand, is a methodology that takes a self-report measure of the percentage of likelihood that a respondent will perform a certain action and in what direction they would perform that action (Delavande & Manski, 2010). In the context of an election, a probabilistic methodology would consist of asking which candidate a respondent supported and then give a percentage to the likelihood that they would ultimately vote for that candidate. For example, if a pollster used a probabilistic method for a 2016 general election poll, they would first ask respondents what percentage chance there was, from 0 to 100, that they would vote in the upcoming election and then ask what percentage chance, from 0 to 100, there was that they would vote for the candidate that they most supported – Clinton or Trump. The method was tested on a large scale and in a presidential election during the 2008 presidential election (Delavande & Manski, 2010).

Delavande and Manski (2010) found that probabilistic polling more accurately predicted both voting behavior and likelihood to vote compared to traditional verbal methods of polling. They asked respondents what percentage chance there was, from 0 to 100, that they would vote in the election and then asked the percentage chance, from 0 to 100, that they would vote for McCain or vote for Obama. They compared these results to the results when asking respondents to respond with a typical verbal scale response (Delavande & Manski, 2010). Although this study was particularly relevant to the field as a whole because it was conducted on a national scale for a presidential election, the method itself does not seem to be widely used. The University of Southern California/L.A. Times Daybreak tracking poll was seen as an outlier during the campaign because it consistently showed a Trump victory, but the poll's reliance on a probabilistic polling methodology helped it to predict the result (NorthwesternInstituteForPolicyResearch, 2016). While they were able to predict the Electoral College outcome correctly using this method, their popular vote margin was also incorrect. Additionally, they don't utilize state-by-state results in their poll and instead use a national sample, so perhaps part of the method is sound, but more considerations and changes should be addressed.

Monitoring the effectiveness and transparency of polling methodology is crucial in legitimizing the field in the eye of the public. The American Association for Public Opinion Research has published a Survey Disclosure Checklist as part of their Code of Ethics which outlines elements of a survey that must be disclosed by researchers when disseminating reports to the public (AAPOR, 2009). Among the requirements are the name of the survey sponsor, the name of the organization that conducted the survey, an explanation of how respondents were selected, the method or mode of data collection, estimates of sampling error, and a description of how the data were weighted, among others (AAPOR, 2009). Education on these guidelines is crucial to media outlets who report on polls in order for polling to be used more effectively as an accurate resource for the public's knowledge. Although some outlets may be aware of the guidelines and include some or all information specified in them, the information may be included at the bottom of the article (e.g. Bradner (2016); Hartig, Lapinski, and Psyllos (2016)) where a reader may not see it.

In discussing the 2016 presidential election specifically, journalists and other political observers have rightly stated that the polls were off, but offered a few possible explanations as to why this was the case. These explanations include a lack of polling in key swing states, which were states that had a fairly even chance to swing to either party and decide the election, reliance on telephone surveys, and ineffective methodologies (Cillizza, 2016; Graff, 2016a; Rivers, 2016; Shepard, 2016). Even though some reactions and conclusions focused on the implications towards the result of the election itself (Miller, 2016), the fact that polls were off in general will have a negative domino effect on all questions included in them – not only the, "Which candidate will you vote for," question but also, "What is the most important issue," questions. Broadly speaking, polls were off as a whole in terms of predicting the Electoral College outcome, while the measure of the national popular vote was not; a YouGov article points to polls disproportionately overestimating support for Clinton (Rivers, 2016) and the AAPOR published similar findings (Kennedy et al., 2018). The same YouGov article also introduces the idea that herding – basing weighting of data decisions to better match the results of similar studies – or similarity in methods accounted for results being untrue or unrepresentative as support for candidates or issues was not accurately captured (Rivers, 2016). These surveys will likely always be subject to some degree of measurement error such as random error, or inherent unpredictability of responses even from the same population (J. Taylor, 1997), and sampling error, or basing the sample on an unrepresentative subset of the population (Särndal, Swensson, & Wretman, 2003).

Telephone surveys tend to skew towards more highly educated respondents. In general, studies have found that respondents are more likely to answer surveys if they possess higher education levels than those who possess low education levels and thus surveys tend to over represent respondents with higher education (Chang & Krosnick, 2001; Holbrook, Krosnick, & Pfent, 2007; Mulry-Liggan, 1983). Adjusting raw polling data to weight for this overrepresentation of college educated respondents is crucial, but the report by Kennedy et al. (2018) found that many did not do that, and thus support for Clinton was inaccurate and overestimated. Another obstacle stems from the considerable decrease in response rate for telephone surveys over the past 20 years; response rates for telephone surveys have dropped from approximately 36 percent in 1997 to just 9 percent in 2016 (Keeter, Hatley, Kennedy, & Lau, 2016)

Even before Election Day, it was apparent to some that traditional polling methods being used in key states were suspect. Graff (2016b) detailed inaccuracies of polling during the primaries in Michigan, which included outdated telephone survey methods that have yielded lower response rates in recent years, inaccurate or unrepresentative samples as a result of methodologies that over represent certain demographics, and general disarray and disorganization of previously collected voter information that amplified these weak methods. Graff suggests that big data-driven methods could provide better poll results.

The 2016 presidential election – one that was all but given to Hillary Clinton based on pre-election polling (Katz, 2016) – showed the public once again that there are fatal flaws in the polling industry as a whole. Among the concerns may be the fact that social desirability bias played a key role in pre-election polling because some Trump supporters had a tendency to repress their support for Trump as it was seen as the more socially undesirable behavior and was at least partially responsible for some of the projections that showed a decisive Clinton win (Klar et al., 2016).

Social Desirability Bias And The Bradley Effect

Biases as a whole are systematic errors that result in deviations from the truth in results and observations (Higgins & Altman, 2008). In polling, biases can be found when respondents give answers skew the actual results based on any number of factors. Social desirability bias is a phenomenon in which research subjects give or choose answers and responses that conform to socially desirable standards rather than ones that are reflective of their true feelings (Grimm, 2010). In the context of a survey, survey respondents will respond to questions according to societal norms and expectations rather than their true personal beliefs because of a fear of reputational damage – the fact that they hold a potentially morally reprehensible view is now known –or embarrassment (Stout & Martin, 2016). Social desirability bias is a widely researched phenomenon and is not strictly limited to one area or method of study. Research has shown the psychological phenomenon to be present using web-based experimentation, survey responses, telephone response and face-to-face interviews with results showing that the bias is consistent throughout methods of experimentation (Fisher, 1993; Holbrook, Green, & Krosnick, 2003; Persson & Solevid, 2014; Powell, 2013).

Social desirability bias seems to be a pervasive bias that is evident throughout many polling subjects including same-sex marriage, voter turnout reports, feelings regarding a black political candidate, ethical decision making and vote-buying practices (Gonzalez-Ocantos, de Jonge, Meléndez, Osorio, & Nickerson, 2012; Holbrook et al., 2003; Powell, 2013; Randall & Fernandes, 1991). Fisher (1993) and Holbrook et al. (2003) suggest that social desirability bias is strongly tied to the type of questioning employed by the researchers or by the method of conducting the study. Indirect questioning is a method in which researchers ask respondents structured questions from the perspective of groups to which the respondent does not belong (Anderson, 1978; Calder & Burnkrant, 1977). Indirect questioning is seen to reduce social desirability bias in topics that are socially influential but not in ones that are socially neutral (Fisher, 1993). That is, if a subject is one that is widely considered to be sensitive when discussed socially (think gun control, abortion, drug use, etc.) an indirect line of questioning by researchers can lead to more accurate responses that are actually reflective of participants' true attitudes and beliefs.

Immediately after the election as pollsters tried to assess their shortcomings, the thought that a "silent majority" type of voter that was unwilling, or not contacted by pollsters, to express their support for Trump was yet another cause of inaccurate predictions (Graff, 2016a). This could have been attributable to voters that decided their choice in the final week of the campaign, who in states such as Pennsylvania and Wisconsin chose Trump by margins of 17 and 30 points, respectively (Kennedy, 2018). This is particularly relevant because of the decision by then-FBI Director James Comey on October 28, 2016 to reexamine claims that Clinton mishandled classified information on a private server (Helderman, Zapotosky, & Horwitz, 2016). Additionally, this "shy Trump supporter" phenomenon could have been attributable to respondents in polls simply not wanting to admit their socially undesirable support for Trump. While some have refuted this theory (Coppock, 2017), others have experimentally tested that there was indeed a "shy Trump supporter" effect where respondents felt less comfortable admitting their support for Trump, especially to pollsters via telephone (Darling, 2017). These shifts in public opinion and voting preference may not have had a chance to be reflected in election polling because this revelation was so close to Election Day.

Additionally, some experimental methodologies can lead to higher rates of socially desirable responses. Telephone surveys are more likely to generate socially desirable responses from respondents, perhaps due to the greater trust and rapport and more effective nonverbal cues inherent in face-to-face interviews (Holbrook et al., 2003). The authors studied factors such as survey length and general satisfaction with the polling experience and warned against generalizing all findings, but did find significance in telephone surveys seeing social desirability bias as being more evident than in face-to-face interviews (Holbrook et al., 2003). Research investigating the rigors of with sampling methods is abundant, but methodological approaches accounting for social desirability bias are somewhat limited, although Holbrook's study does serve as a good launching pad.

Social desirability bias has been tested outside of political contexts which somewhat supports the notion that it is a widespread and generalized phenomenon rather than a statistical anomaly present only in election polling. Randall and Fernandes (1991) outlined the presence of social desirability having an effect on self-reporting of ethical conduct. The study tied self-reporting of perceptions of highly unethical conduct to socially desirable traits as reported by respondents; this includes image management and perceived item desirability. Researchers have also found socially desirability bias to be present in measures of dietary intake (Hebert, Clemow, Pbert, Ockene, & Ockene, 1995), in the measurement of risk behaviors conducive to the development of sexually transmitted diseases (Gregson, Zhuwau, Ndlovu, & Nyamukapa, 2002), motivations to work (Antin & Shaw, 2012), and family planning studies (Stuart & Grimes, 2009) among others. Findings such as these add to theoretical understanding of social desirability bias as something rooted in personal characteristics and spread out over a wide range of research areas.

Some research has shown that motivations for producing socially desirable responses are a culturally linked phenomenon. Some research suggests that people in individualistic cultures like the United States tend to report socially desirable responses as an outlet of self-deceptive enhancement (Bernardi, 2006; Lalwani, Shavitt, & Johnson, 2006). This means they enjoy giving an inflated sense of their abilities and like to see themselves in a positive light, regardless of their actual abilities or beliefs, compared to collective cultures that tend to focus on the reputation and abilities of the group rather than the individual (Bernardi, 2006; Lalwani et al., 2006).

While at least one study shows that voter turnout increases among racial minorities in elections in which there is a candidate of the same racial minority (Barreto, Segura, & Woods, 2004), there is surprisingly not an established link for social desirability bias to influence their self-reporting of actual turnout in an election. In studying validated data from two general elections, researchers found no link between over reporting voter turnout by blacks and Latinos when there was a United States House of Representatives candidate of the same race/ethnicity (Stout & Martin, 2016). This means that descriptive representation diminishes social desirability bias, although the Bradley effect – specifically an unusually large tendency to over report support for a black candidate (Stout & Kline, 2008) – suggests that race or other different demographic factors make a difference when considering voting behaviors.

Scholars believe that social desirability bias to over report support for a black candidate can be a cause for a large difference between pre-election polls and actual results (Payne, 2010). Tom Bradley is the namesake of this particular type of social desirability bias called the Bradley effect. In 1982, the then-mayor of Los Angeles enjoyed a comfortable margin in pre-election polling, but was stunningly defeated on election night. Similarly, Douglas Wilder, a Virginia gubernatorial candidate in 1989 showed a lead of 15 points in polls leading up to the election but only won by a total of 6,700 votes, prompting some to rename this as the Wilder effect (Hopkins, 2009). Both candidates were black and, put simply, both of these "effects" refer to "the difference between the share of the electorate voicing support for a black candidate in a survey and the share casting ballots for that candidate," (Hopkins, 2009).

In recent presidential elections involving Barack Obama in 2008 and 2012, this effect could have been a factor, but it's important to refrain from assuming this is a sole factor without giving proper consideration to other factors that affect polling and political election cycles. Among other factors that affect elections regardless of race, the need to consider front-runner polling declines as Election Day nears (Hopkins, 2009). Hopkins asserts that in the 1989 Virginia gubernatorial race, while there was slight evidence of a statistical shift because of race, a decline was inevitable because of Wilder's pre-election standing as a front-runner throughout (Hopkins, 2009).

The Bradley effect, with the exception of Wilder, seemed to be a one-off type of statistical anomaly rather than a tried and true theory that formed the basis for research and ways of thinking about polling methods. That is, the effect was either not present because minority candidates became more common, or people were not overreporting support as they had in the past. Perhaps though, it was and is still present, but the media simply stopped covering it for a period of time. After Bradley's defeat, the media seemed to forget about the phenomenon, mentioning it less than 100 times from then until the 2008 New Hampshire primary election (Payne, 2010). With the rise in popularity of Barack Obama and his corresponding presidential campaign, the first black nominee for a major party, suddenly the Bradley effect was beginning to gain a foothold in conversation once again.

In the first ten months of 2008, the Bradley effect had been cited in television, blogs and radio nearly 1,000 times (Payne, 2010). With limited research and limited mentions of this phenomenon directly prior to the presidential campaign, one can postulate that its inclusion in media dialogue leading up to the election was done so out of necessity to understand race as a possible underlying factor. With the nature of modern media outlets, viewership and website visits are essential to generating advertising revenue. Going along with the uncertainty of the validity of the theory past the few instances roughly 20 years prior, media outlets gave a roughly equal amount of time to supporters and detractors of the theory (Hopkins, 2009). Payne (2010) suggests that the theory's presence in dialogue on the campaign was mostly a tool the media used to give reason and rationale to incorporating race and latent racism into their coverage and a frame for explaining possible feelings on the campaign.

Hopkins (2009) and Payne (2010) both suggest and offer evidence to support the fact that, while the Bradley/Wilder effect was a significant factor at play in the 1980s, its effects are not as evident in more recent elections at the local and state level as well as it not being significant in the 2008 election outside of media dialogue. Heerwig and McCabe (2009) also suggest that this type of underlying racism is somewhat more indicative on levels of education.

In short, the Bradley effect was a relevant area of political polling research necessary to accurate understanding and interpretation in elections around the 1980s, though some newer research tends to shift the academic opinion to one that discredits it as not of particular relevance and reminding us that elections are complex so many factors must be considered to accurately isolate the effect and credence has to be given to the fact that racial attitudes have fluctuated over the past 30 years. Though, given the variability of this effect and the context of the 2016 presidential election, a type of Bradley effect or signs of social desirability bias may be making new headway into polling.

Concerning the Bradley effect, it seems to come and go in waves in terms of the public's perception of its existence. As referenced before, the media may have a part in making this bias known if it truly does persist through election cycles. With heightened racial attitudes and awareness on a national level, perhaps it is time to reconsider and revisit this theory once again. Future research on the most recent presidential election should also be looked at through the lens of this phenomenon. Even though there was not a candidate of a racial minority group, this election saw the first woman nominee for a major political party. The possibility that there could have been a gender-related Bradley-like effect in this election certainly adds to the already mounting evidence that the polls were less than stellar during the 2016 election cycle.

Current research on election polling in the United States is wide and varied. A few important considerations regarding the field as a whole have been covered. Social desirability bias, research has shown, definitely has an impact on polling of any type and any type of election cycle is not immune to it. The Bradley effect is also a big consideration especially when there is a minority candidate. Polling methods themselves, research has shown, are also subject to biases and inaccurate samples that taint the results. Even when they have a large predictive power, an unfamiliarity because of cloudy methodology can lead to inaccurate interpretation of polls by the public. The way in which questions are asked is also subject to debate.

Clearly, election polling in the United States is certainly not an exact science. There are many considerations to account for when creating a survey, interpreting its results and then disseminating the information in a clear manner. Even by doing all of those things and thinking that all errors or sources of bias may have been accounted for, it is likely impossible to know for certain. Perhaps a different way of examining public opinion is necessary to explore going forward.

Digital Trace Data

Google and other websites are able to offer insights in to a variety of fields and contexts because users leave a digital record of their activity, a concept referred to as digital trace data (Howison, Wiggins, & Crowston, 2011). This digital trace data has been hailed as the driving force of a “measurement revolution” (Kleinberg, 2008). Though studied in the field of politics and public opinion on Twitter by examining mentions, retweets, and followers (Freelon, 2014; Jungherr, 2015; Jungherr, Schoen, Posegga, & Jürgens, 2017), the idea can be applied to anything digital in which some type of record, such as a search, is performed. Interactions with some type of online platform or service, like Facebook, Twitter, Google, etc. by a user leave traces of data that show a record of online behavior or actions (Howison et al., 2011; Jungherr & Jürgens, 2013). Digital trace data gathered from online sources has been especially helpful in understanding or predicting behaviors including future box office performance (Asur & Huberman, 2010), identifying and predicting areas of influenza outbreaks (Ginsberg et al., 2009), and predicting election outcomes (Mavragani & Tsagarakis, 2016).

An additional characteristic of digital trace data, and one that makes it both appealing and daunting for researchers, is that it already exists with the online service and is not contingent on research designs or laboratory methods (Howison et al., 2011). It is appealing because there is now a large trove of data available on human behavior that was simply not available before. It can be daunting and frustrating because, instead of shaping research around questions and collecting necessary data, often researchers utilizing digital trace data must shape their research around the data and determine what questions they can answer (Jungherr, 2017).

A drawback of digital trace data is also largely dependent on the medium or source in which it was recorded (Jungherr, 2017). This is useful if the source is highly descriptive of group or sample in which the researcher wishes to study, but can present problems if they are seeking to make generalizable claims (Jungherr & Theocharis, 2017). This idea that researchers can capture all of the data available is referred to as n=all (Mayer-Schönberger & Cukier, 2013). Although a novel and exciting catchphrase at first, n=all is unfortunately not accurate, as any digital trace data has technical limitations based on user base, platform limitations, and ability of the source to gather all available data from their own databases, among others (Jungherr, 2017). Additionally, the mirror fallacy of digital trace data refers to the idea that researchers see digital traces as absolutely reflective of users actual behaviors or intentions (Jungherr, 2017). Researchers need to be careful in their interpretation of findings using digital trace data. It is crucial to not only analyze the data on its face and instead investigate outside influence or other factors that may cause the result.

Despite its drawbacks, digital trace data can be especially useful, particularly if its drawbacks are kept in mind and accounted for. It can be and has been used in political contexts in order to predict or uncover otherwise unattainable insights (Freelon, 2014; Jungherr, 2015; Sinclair & Wray, 2015; Swearingen & Ripberger, 2014). Some have argued that digital trace data collected via Twitter may not be especially useful in measuring certain political characteristics or motivations (Jungherr, 2015). A source of digital trace data that is widely used and has been proven to have many practical applications is Google.

Google Trends

Google Trends is a publicly available tool made by Google that allows users to compare the relative search interest for a term or a topic in different geographic regions over a period of time. In its earliest iterations in 2006, the Google Trends utility suggested it was good for telling someone what was popular at the time – whether it be celebrities, fashion, movies or television – to settle debates or answer a trivia question. After combining the original Trends tool with a different, similar tool aimed more towards marketers called Google Insights for Search, Google made its Trends platform easier and more intuitive to delve into search data (Google, 2012). A growing body of research has shown the usefulness of this tool to provide answers to complex problems in a variety of areas.

Google Trends has found itself as a new and emerging tool to capture insights into public sentiment or behavior. Applications can range from housing focused issues, like using the tool to predict trends in the housing market (Askitas, 2016) and observing search terms that coincided with the housing market crash to better “nowcast” a recession (Chen, So, Wu, & Yan, 2015) to health related issues such as using search terms to detect outbreaks of influenza (Ginsberg et al., 2009) and improving estimates of suicide amongst a population (Kristoufek, Moat, & Preis, 2016).

On a non-national level scale in the United States, Google Trends has also been used as a measure of public attention in U.S. Senate races (Swearingen & Ripberger, 2014), and as a key tool at the state level, even in races of the same political party (Sinclair & Wray, 2015).

There have also been many international applications in using Google Trends as a supplement or a main tool to predict election outcomes. This has been seen by using Google searches to successfully predict the Greek Referendum (Askitas, 2015; Mavragani & Tsagarakis, 2016) and in examining three German elections in 2005, 2009 and 2013 and comparing results to Trend data in order to form a predictive algorithm (Polykalas, Prezerakos, & Konidaris, 2013).

The research of Seth Stephens-Davidowitz from approximately 2013 onward has been a key contributor to the field of Google Trends research. He has used Google Trends to show that American parents still largely think in terms of classic gender roles (Stephens-Davidowitz, 2014b). Searches about pregnancy around the world were also explored, showing differences, based on their country, in how people inquire about what they can or cannot eat during pregnancy and how to do certain things while pregnant (Stephens-Davidowitz, 2014c). Search data was also used to examine which parts of the country may have a higher amount of gay men than reported in surveys (Stephens-Davidowitz, 2013a).

An emerging application of Google Trend data has been in a political context. One of the more interesting findings in this field was using Google search data to explore whether racial animus negatively affected Barack Obama's vote shares in the 2008 and 2012 election. Stephens-Davidowitz (2014a) found that a negative predictor of votes for Obama was an area's racially charged search rate. In both elections, roughly four percentage points of the national popular vote were lost by Obama because of continued racial animus. While this and previously mentioned findings are key to the field, some still criticize his work. Generally, Google searches can be made by those of any age, making findings about elections somewhat questionable, searches can be made by a person any number of times, and researchers cannot specifically know the intent of the search term (Greenfield, 2011).

Additionally, Google search data can be used to predict an area's turnout on election day. Stephens-Davidowitz (2013b) showed that examining Google searches for "vote" or "voting" in the month before an election compared to the same month in the lead up to a previous election explained up to over 40 percent of change in state-level turnout. By overlaying the results with media market-level demographic data, predicting the composition of the electorate was also possible (Stephens-Davidowitz, 2013b).

Summary and Research Question

Where does this leave traditional public opinion polling? Especially when it comes to issues-based polling, research has suggested that Google Trends may be a much better alternative to traditional survey data (Mellon, 2013). Given the high costs, unrepresentative samples, and general difficulty associated with traditional polling methods, Google Trends seems like an answer to traditional survey methodological problems, but investigation is necessary.

The 2016 presidential election was not without its problems. Perhaps chief among them was the idea that pollsters simply were not capturing an accurate sample and even if they were, even the best survey methodology can be clouded by social desirability bias. In thinking about the Bradley effect, social desirability bias, and the general problems associated with over reporting support for a minority candidate, it is also possible that this type of effect was present in the 2016 election, albeit not with a minority candidate but with a group – women – who are underrepresented in politics.

Based on the preceding literature, the following research question is proposed:

RQ1: How can Google Trends data be used alongside or in place of traditional public opinion polls?

Testing this research question requires a methodology that examines both traditional public opinion polling and Google Trends data. The 2016 presidential election offers the luxury of polling data collected throughout the campaign and thus a wealth of Google searches over that same period of time.

Methodology

Overview of Methodology

As Google Trends research is a relatively new area of research, an exhaustive database of applicable methodological approaches does not exist. In such situations, a novel approach to analyzing data is necessary. The current study gathers polling data from the 2016 presidential election from states that were considered swing states. Specifically, this study examines states that swung both in the way in which outcomes followed and states that went against the prediction as determined by the polling aggregator RealClearPolitics (RealClearPolitics, 2017). Individual polls from Michigan, Wisconsin, and Pennsylvania are representative of swing states in the unpredicted direction while individual polls from Nevada and Virginia represent swing states in the predicted direction.

The percentage of respondents who indicated a response in the "Most Important Issue"-type question for each poll was compared to the relative search interest ranking from Google Trends for the same topic over the same period of time in the same state. This was the most effective way of capturing interest via Google searches and was effective in capturing a broader conceptualization of each term, such that all related searches for a given topic would be included rather than just a search for that term.

Sample

Of particular interest in this study is the question of whether or not Google data can be used as a supplement to, or a replacement of, traditional public opinion polling. In order to determine whether inaccurate polling contributed to the overall "miss" of the polls during the election cycle, it is useful to examine states where the winner was correctly predicted and states where the winner was incorrectly predicted. For the current study, six total polls have been chosen for analysis. Polls were found by first determining states considered swing states according to RealClearPolitics, which they refer to as "Battleground States." This aggregation site contained multiple polls for each of those 16 states; individual polls in each state were examined to see if a "Most Important Issue"-type question was asked in the poll. The nine total polls across all states meeting this criteria were then separated by states where the outcome followed the prediction and by ones were the result differed from the prediction. This was determined by examining the final result on Election Day and comparing that to the average polling difference between the candidates on the dates in which the poll was conducted. Next, the remaining polls were compared to determine general timeframes that included both a poll from a correctly predicted state and from an incorrectly predicted state. This resulted in three general timeframes and six total polls. The states, dates, and sponsoring organizations for polls from states predicted incorrectly can be seen in Table 1.

Table 1

Polls from states that were predicted incorrectly

	State	**Date**	**Sponsoring Organization**
August	Michigan	Aug. 22 – 24, 2016	Suffolk University
October	Wisconsin	Oct. 4 -5, 2016	Loras College
Late Oct./Early Nov.	Pennsylvania	Oct. 31 – Nov. 1, 2016	Susquehanna Polling and Research & WHTM-TV/ABC27 News

The sample of polls from states predicted incorrectly include a poll conducted in Michigan by Suffolk University from August 22 – 24, 2016, a poll conducted in Wisconsin by Loras College from October 4 – 5, 2016, and a poll conducted in Pennsylvania from October 31 – November 1, 2016 by Susquehanna Polling and Research & WHTM-TV/ABC27 News.

The states, dates, and sponsoring organizations for polls from states predicted correctly can be seen in Table 2.

Table 2

Polls from states that were predicted correctly

	State	Date	Sponsoring Organization
August	Nevada	Aug. 15 – 17, 2016	Suffolk University
October	Virginia	Oct. 2 -6, 2016	Roanoke College
Late Oct./Early Nov.	Virginia	Oct. 29 – Nov. 1, 2016	Roanoke College

The sample of polls from states predicted correctly include a poll conducted in Nevada by Suffolk University from August 15 – 17, 2016, a poll conducted in Virginia by Roanoke College from October 2 – 6, 2016, and a poll conducted in Virginia from October 29 – November 1, 2016 by Roanoke College.

More specifically, these polls were chosen because they represent more than one state and one polling organization in both conditions. Thus, the findings will be more generalizable. These polls also cover the same general timeframes: 1) mid-to-late August, 2) early October, and 3) late October to early November. These comparable polls and dates were identified so that findings are able to account for and control for events that may have swayed public opinion during the campaign.

The comparison search data from Google Trends directly corresponds to the states and timeframe of the polls selected. The results that are generated when comparing searches using the Trends tool are assigned a value of zero to 100. This normalized score is based on relative search interest between those terms given the geographical and time constraints, such that a 100 score would show a term that is very popular while a lesser score, such as 20, would show a term of less interest comparatively (Green, 2017). The tool can also be used to show a comparison between geographic regions for a particular term. For example, a user could compare the interest of a term between states, or between media markets within a state. Google Trends allows users to set geographic and time parameters. It also categorizes search terms into broader “Topics” that include relevant search terms that relate to the topic. For example, queries for, “Obamacare repeal,” “Obamacare senate vote,” and, “Affordable care act,” would all fall under the broader Patient Protection and Affordable Care Act “Topic” in the Trends tool. For each poll, a corresponding Google Trends dataset was generated based on the options given for the “Most Important Issue” question in each poll, the state that the poll was conducted, and the dates that the poll was conducted. The polling data was analyzed based on the percentage of respondents who selected each choice. The Google Trends datasets were analyzed by producing a search interest score for each topic on Google Trends.

Google Trends gives a score of 0 to 100 based on the relative search interest for the terms or topics comparatively based on the geographic and time constraints. The Google Trends datasets were generated by first filtering to the specific state and then to the specific period of time in which the poll was conducted. For example, to generate the dataset for the Suffolk University poll conducted in Nevada from August 15 – 17, 2016, first Nevada was selected as the geographic area and then a custom time range of August 15 – 17, 2016 was entered. After these parameters were set, topics corresponding to the choices of issues in the corresponding poll were chosen. In cases where there wasn’t an exact match from a poll option to a topic in Google Trends, the author chose a topic that most closely resembled the option from the poll. The relative comparative search interest score was recorded for each of these topics.

Because Google Trends only allows five topics or search terms to be compared at a single time, at least one topic remained constant when comparing the rest of the topics to each other. This is an acceptable way to handle this problem with the platform as the nature of Google Trends is that it gives scores to topics or search terms based on relative search interest compared to each other. By keeping at least one search topic constant and rotating the remaining topics, an accurate score for each topic can still be generated as the topics are still being compared to a constant.

Method of Analysis

Data was analyzed using R statistical software. Specifically, a Pearson product-moment correlation coefficient (Pearson's *r*) was produced to show the relationship between the answers chosen in the polls and the search interest of topics on Google Trends.

The Pearson product-moment correlation coefficient produces a score of -1 to 1 that tells both the magnitude and the direction of the relationship between two variables (Onwuegbuzie, Daniel, & Leech, 2007). A score of -1 indicates a completely inverse correlation between the variables while a score of 1 indicates a perfect positive correlation between the variables. A score of 0 indicates no relationship whatsoever between the two variables.

Generally, Pearson product-moment correlation coefficients can be categorized to show the degree of the correlation they represent. Values of *r* less than or equal to 0.35 generally represent weak or low correlations, values in the 0.36 to 0.67 range are modest or moderate correlations, and values from 0.68 to 1.0 are strong or high correlations (R. Taylor, 1990). Additionally to further categorize strong correlations, *r* values 0.90 or above are considered to be very high or very strong correlations (Prion & Haerling, 2014).

Results

The issues for each poll, the corresponding topics for each of these issues, the issue percentages, and their corresponding Google Trends scores for each state and poll can be seen below in Tables 3 – 8.

Table 3

August Suffolk University Michigan poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trends Score
Jobs/Economy (Economy)	21.4	31
Terrorism/national security (Terrorism)	20.0	24
Supreme Court Nominee (Supreme Court)	11.0	7
Healthcare (Patient Protection and Affordable Care Act)	6.8	42
Schools/Education (Education in the United States)	6.2	0
Illegal Immigration (Illegal immigration)	6.0	11
Reducing the national debt (National debt of the United States)	5.4	4
Crime/Guns (Gun violence)	4.4	0
Civil liberties (Civil liberties)	3.2	1
Taxes (Taxation in the United States)	2.2	2
Abortion Policy (Abortion)	2.0	57
Climate Change (Climate change)	1.6	17
Drugs/Opioids (Drug policy)	0.8	0

Note. Poll conducted via live telephone (landline and cell phone) interviews August 22 – 24, 2016 with a sample of 500 likely Michigan general election voters. Margin of error +/- 4.4%. Trends Score calculated on trends.google.com where geographic location was set to Michigan and custom time range was set to August 22 – 24, 2016.

Table 3 shows that likely Michigan general election voters reported Jobs/Economy to be the most important topic closely followed by Terrorism/national security and the Supreme Court Nominee while all other topics received less than seven percent. Meanwhile, Abortion had the highest score on Google Trends followed by Healthcare, and Jobs/Economy while other topics received relatively low scores including some like Schools/Education receiving a score of 0.

Table 4

August Suffolk University Nevada poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trends Score
Jobs/Economy (Economy)	26.0	80
Terrorism/national security (Terrorism)	20.4	13
Supreme Court Nominee (Supreme Court)	10.6	27
Healthcare (Patient Protection and Affordable Care Act)	6.8	13
Illegal Immigration (Illegal immigration)	6.8	13
Reducing the national debt (National debt of the United States)	4.8	0
Schools/Education (Education in the United States)	4.0	0
Crime/Guns (Gun violence)	3.4	0
Taxes (Taxation in the United States)	3.2	0
Civil liberties (Civil liberties)	1.6	0
Climate Change (Climate change)	1.2	0
Drugs/Opioids (Drug policy)	1.2	0
Abortion Policy (Abortion)	0.2	53

Note. Poll conducted via live telephone (landline and cell phone) interviews August 15 – 17, 2016 with a sample of 500 likely Nevada general election voters. Margin of error +/- 4.4%. Trends Score calculated on trends.google.com where geographic location was set to Nevada and custom time range was set to August 15 – 17, 2016.

Table 4 shows that likely Nevada general election voters reported Jobs/Economy to be the most important topic at 26.0% closely followed by Terrorism/national security at 20.4 % and the Supreme Court Nominee at 10.6% while all other topics received less than seven percent. Meanwhile, Jobs/Economy had the highest score on Google Trends by a large margin followed by Abortion, and the Supreme Court Nominee while three other topics – Terrorism, Healthcare, and Illegal Immigration – received scores of 13 with all others receiving a score of 0.

Table 5

October Loras College Wisconsin poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trends Score
Jobs/economy (Economy)	30.2	88
Terrorism/national security (Terrorism)	25.2	21
Healthcare (Patient Protection and Affordable Care Act)	12.8	53
Supreme Court nominee (Supreme Court)	12.6	18
Race relations (Racism in the United States)	3.8	0
Illegal immigration (Illegal immigration)	3.4	24
Climate change (Climate change)	2.4	15

Note. Poll conducted via live telephone (landline and cell phone) interviews October 4 – 5, 2016 with a sample of 500 likely Wisconsin voters. Margin of error +/- 4.4%. Trends Score calculated on trends.google.com where geographic location was set to Wisconsin and custom time range was set to October 4 – 5, 2016.

Table 5 shows that likely Wisconsin voters reported Jobs/Economy to be the most important topic at 30.2% closely followed by Terrorism/national security at 25.2% with Healthcare and Supreme Court nominee both just above 12.0%. The bottom three topics received less than four percent. Meanwhile, Jobs/Economy had the highest score on Google Trends by a large margin followed by Healthcare. Illegal Immigration and Terrorism/national security both received scores just above 20.

Table 6

October Roanoke College Virginia poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trends Score
Economy (Economy)	28.0	84
Healthcare/Obamacare (Patient Protection and Affordable Care Act)	8.0	50
Terrorism (Terrorism)	7.0	33
Honesty/character/corruption (Political corruption)	7.0	0
Immigration (Illegal immigration)	6.0	12
Foreign relations (Foreign relations of the United States)	5.0	0
Education (Education in the United States)	5.0	4
Leadership (Leadership style)	4.0	0
Economic inequality (Economic inequality)	2.0	2
Supreme Court (Supreme Court)	2.0	19
Abortion (Abortion)	2.0	59
Crime/police (Law enforcement)	2.0	10
Budget deficit/debt (National debt of the United States)	2.0	7
Gun control/gun rights (Gun control)	1.0	12
Climate change (Climate change)	1.0	20
Race relations (Racism in the United States)	1.0	0
War (Nuclear warfare)	0.0	7

Note. Poll conducted via live telephone (landline and cell phone) interviews October 2 – 6, 2016 with a sample of 814 likely Virginia voters. Margin of error +/- 3.4%. Trends Score calculated on trends.google.com where geographic location was set to Virginia and custom time range was set to October 2 – 6, 2016.

Table 6 shows that likely Virginia voters reported the Economy to be the most important issue at 28.0%. All 16 other issues received less than 10.0% and were fairly evenly spread out from eight percent to 0%. Meanwhile, the Economy also had the highest score on Google Trends by a fairly large margin followed by Abortion and Healthcare/Obamacare.

Table 7

Late October/Early November Susquehanna Polling and Research & WHTM-TV/ABC27 News Pennsylvania poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trends Score
Jobs/Economy (Economy)	25.0	66
Racial tensions (Racism in the United States)	21.0	0
Illegal immigration (Illegal immigration)	19.0	32
Terrorism/national security (Terrorism)	14.0	17
Healthcare/education (Patient Protection & Affordable Care Act) (Education in the United States)[a]	9.0	57
Income inequality (Economic inequality)	5.0	0
Government accountability (Open government)	3.0	0

Note. Poll conducted through live telephone interviews and automated telephone surveys October 31 – November 1, 2016 with a sample of 681 likely Pennsylvania general election voters. Margin of error +/- 3.76%. Trends Score calculated on trends.google.com where geographic location was set to Pennsylvania and custom time range was set to October 31 – November 1, 2016.
[a] Both Google Trends topic scores were combined for the overall Trends Score; the score for the Patient Protection & Affordable Care Act topic was 57, the score of the Education in the United States topic was 0.

Table 7 shows that likely Pennsylvania general election voters reported Jobs/Economy to be the most important topic at 25.0% closely followed by Racial tensions at 21.0%, Illegal immigration at 19.0%, and Terrorism/national security at 14.0%. The bottom three topics received less than 10.0%. Meanwhile, Jobs/Economy also had the highest score on Google Trends and was followed by Healthcare/education. Though Racial tensions was the second most important issue in the poll, it received a score of 0 on Google Trends.

Table 8

Late October/Early November Roanoke College Virginia poll and Google Trends data

Issue (Corresponding topic in Google Trends)	Issue %	Trend Score
Economy (Economy)	24.0	82
Honesty/character/corruption (Political corruption)	10.0	2
Healthcare/Obamacare (Patient Protection and Affordable Care Act)	9.0	38
Immigration (Illegal immigration)	6.0	10
Abortion (Abortion)	5.0	43
Foreign relations (Foreign relations of the United States)	4.0	2
Leadership (Leadership style)	4.0	3
Terrorism (Terrorism)	3.0	18
Supreme Court (Supreme Court)	3.0	21
Education (Education in the United States)	2.0	0
Budget deficit/debt (National debt of the United States)	2.0	5
Climate change (Climate change)	2.0	15
War (Nuclear warfare)	1.0	5
Economic inequality (Economic inequality)	1.0	3
Gun control/gun rights (Gun control)	1.0	12
Race relations (Racism in the United States)	1.0	0
Crime/police (Law enforcement)	1.0	12

Note. Poll conducted via live telephone (landline and cell phone) interviews October 29 – November 1, 2016 with a sample of 654 likely Virginia voters. Margin of error +/- 3.8 %. Trends Score calculated on trends.google.com where geographic location was set to Virginia and custom time range was set to October 29 – November 1, 2016.

Table 8 shows that likely Virginia voters reported the Economy to be the most important issue at 24.0% followed by Honesty/character/corruption at 10.0%. All 16 other issues received less than 10.0% and were fairly evenly spread out from nine percent to one percent. Meanwhile, the Economy also had the highest score on Google Trends at 82, nearly doubling the next closest, Abortion at 43. Though Honesty/character/corruption was the second most important issue in the poll, it received a score of only 2 on Google Trends.

In order to answer RQ1, how Google Trends data can be used alongside or in place of traditional public opinion polls, individual Pearson product-moment correlation coefficients were calculated for each poll and its corresponding Google Trends data. For each of the polls and sets of Google Trends data, a Pearson product-moment correlation coefficient was calculated to compare the relationship between the percentage of respondents in the polls who indicated which topic was the most important issue facing the country and the relative search interest score for that topic on Google Trends.

August

Michigan. A poll conducted by Suffolk University between August 22 and August 24, 2016 surveyed 500 likely Michigan general election voters. When asked, "What do you think is the most important issue facing the next president," respondents could choose one of 13 issues or respond as undecided. For the purposes of this analysis, only the 13 available issues were used to compare with applicable topics in Google Trends. There was a weak positive correlation between the variables but it was not significant, $r(11) = 0.251$, $p = .408$. These results are summarized in a scatterplot (Figure 1).

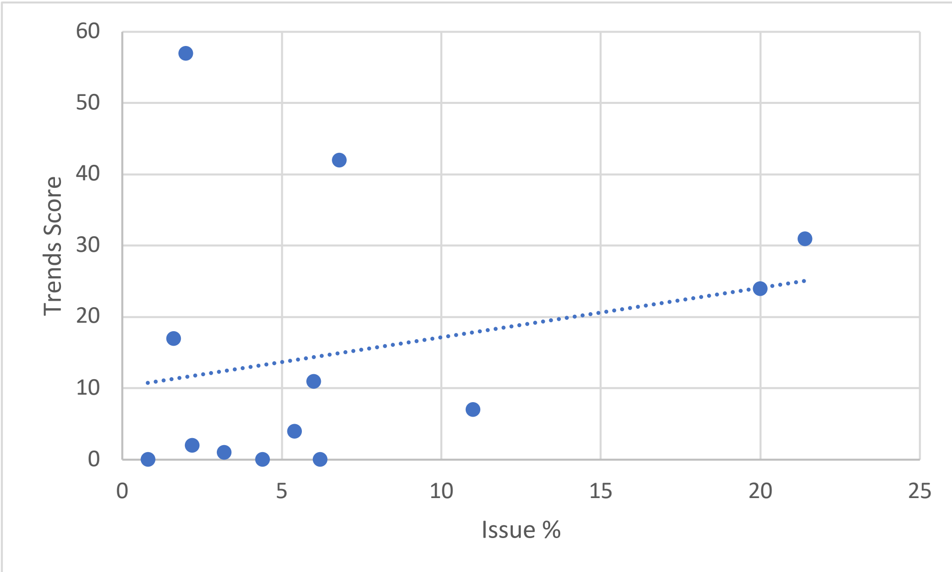

Figure 1. Pearson product moment correlation comparing August Suffolk University Michigan poll and Google Trends data.

Nevada. A poll conducted by Suffolk University between August 15 and August 17, 2016 surveyed 500 likely Nevada general election voters. When asked, "What do you think is the most important issue facing the next president," respondents could choose one of 13 issues or respond as undecided. For the purposes of this analysis, only the 13 available issues were used to compare with applicable topics in Google Trends. There was a significant moderately strong positive correlation between the variables, $r(11) = 0.616$, $p = .025$. These results are summarized in a scatterplot (Figure 2).

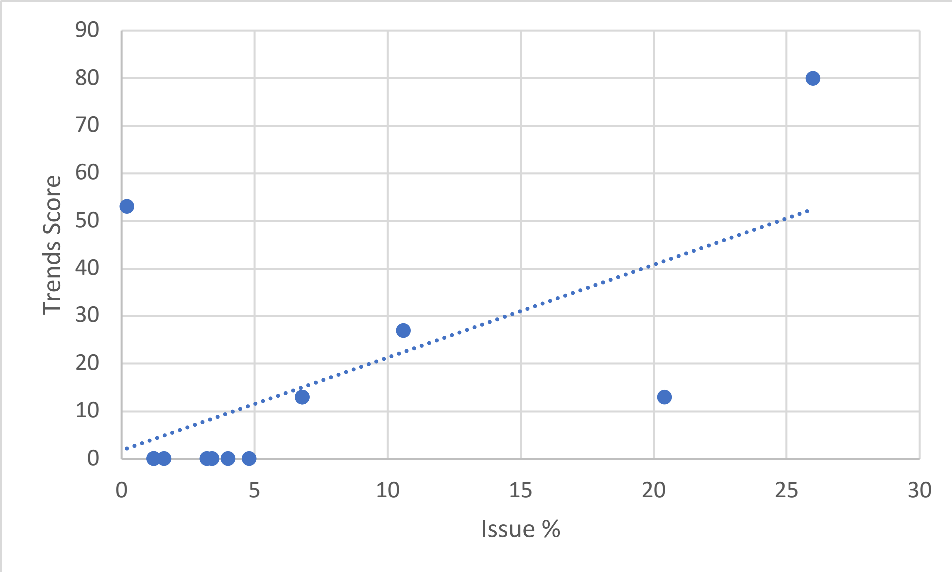

Figure 2. Pearson product moment correlation comparing August Suffolk University Nevada poll and Google Trends data.

October

Wisconsin. A poll conducted by Loras College between October 4 and October 5, 2016 surveyed 500 likely Wisconsin voters. When asked, “From the following list of issues, which is the most important as you make your decision about whom to support for President,” respondents could choose one of 7 issues, respond ‘Other’, or refuse to answer. For the purposes of this analysis, only the 7 available issues were used to compare with applicable topics in Google Trends. There was a strong yet insignificant positive correlation between the variables, $r(5) = 0.703$, $p = .078$. These results are summarized in a scatterplot (Figure 3).

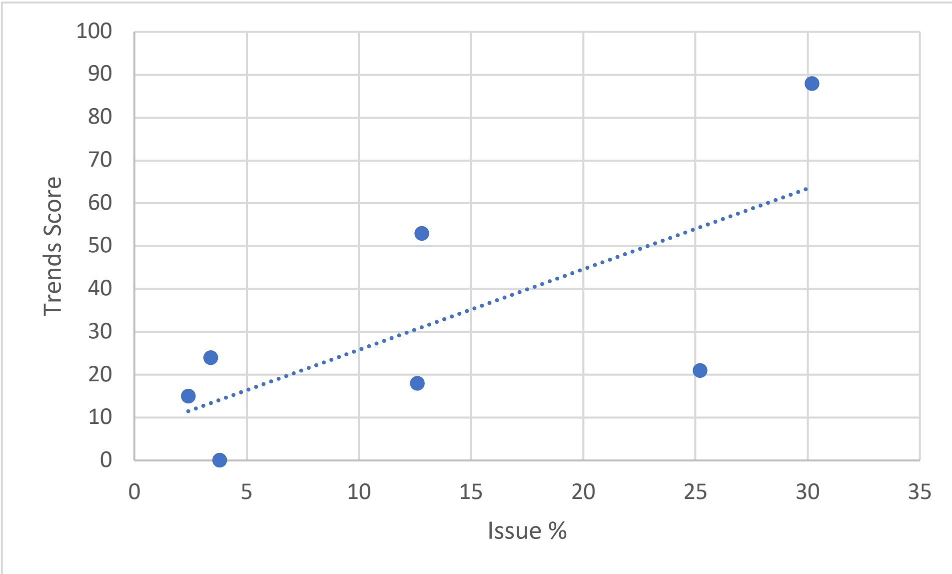

Figure 3. Pearson product moment correlation comparing October Loras College Wisconsin poll and Google Trends data.

Virginia. A poll conducted by Roanoke College between October 2 and October 6, 2016 surveyed 814 likely Virginia voters. When asked, “What is the most important issue to you in this election,” respondents could choose one of 17 issues, respond ‘Other’, ‘Defeating Trump’, ‘Defeating Clinton’, or refuse to answer. For the purposes of this analysis, only the 17 available issues were used to compare with applicable topics in Google Trends. There was a significantly strong positive correlation between the variables, $r(15) = 0.697$, $p = .002$. These results are summarized in a scatterplot (Figure 4).

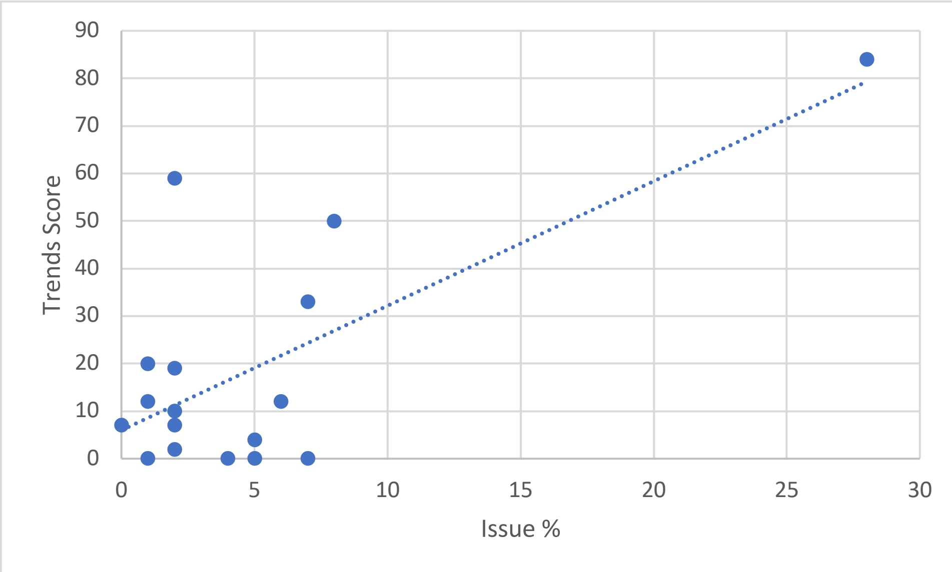

Figure 4. Pearson product moment correlation comparing October Roanoke College Virginia poll and Google Trends data.

Late October/Early November

Pennsylvania. A poll conducted by Susquehanna Polling and Research & WHTM-TV/ABC27 News between October 31 and November 1, 2016 surveyed 681 likely Pennsylvania general election voters. When asked, "Which one of the following seven issues do you think is the single most important problem facing the country today," respondents could choose one of 7 issues, respond 'None of the above', or refuse to answer. For the purposes of this analysis, only the 7 available issues were used to compare with applicable topics in Google Trends. There was a moderately strong positive correlation between the variables but it was not significant, $r(5) = 0.462$, $p = .296$. These results are summarized in a scatterplot (Figure 5).

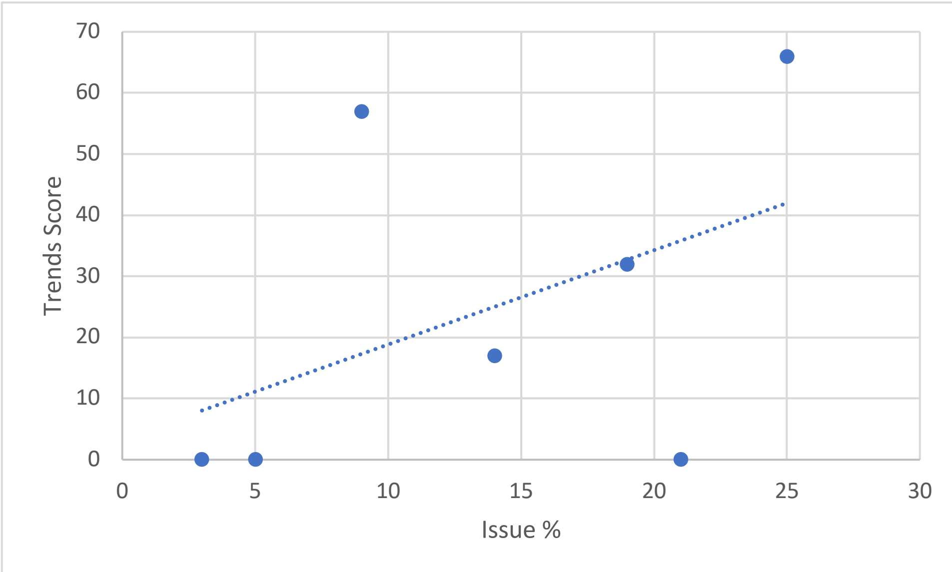

Figure 5. Pearson product moment correlation comparing Late October/Early November Susquehanna Polling and Research & WHTM-TV/ABC27 News Pennsylvania poll and Google Trends data.

Virginia. A poll conducted by Roanoke College between October 29 and November 1, 2016 surveyed 654 likely Virginia voters. When asked, "What is the most important issue to you in this election," respondents could choose one of 17 issues, respond 'Other', 'Defeating Trump', 'Defeating Clinton', or refuse to answer. For the purposes of this analysis, only the 17 available issues were used to compare with applicable topics in Google Trends. There was a significantly strong positive correlation between the variables, $r(15) = 0.808$, $p < .001$. These results are summarized in a scatterplot (Figure 6).

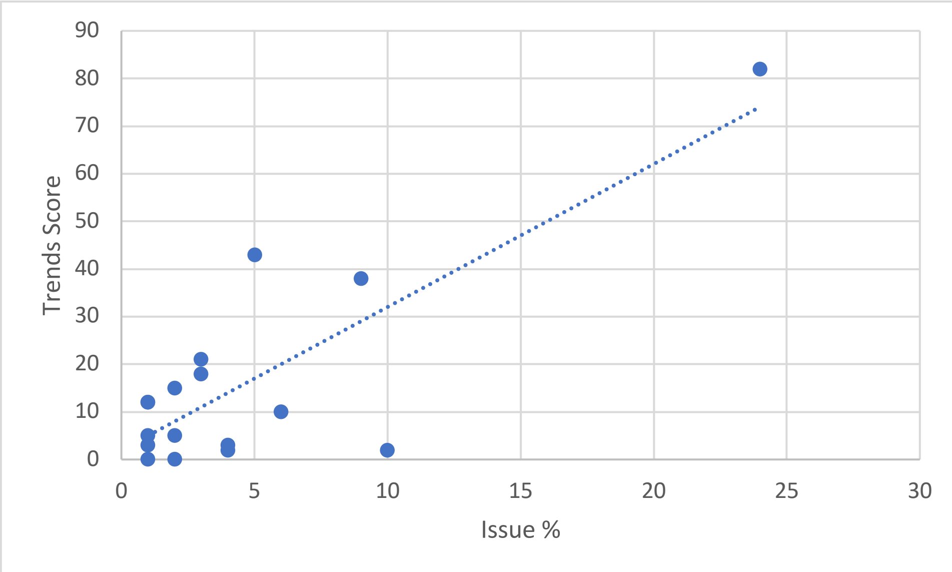

Figure 6. Pearson product moment correlation comparing Late October/Early November Roanoke College Virginia poll and Google Trends data.

Summary of Results

Table 9 shows a summary of the results and includes each state, date of polling, polling organization, statistical values, predicted state vote share according to RealClearPolitics, and actual state vote share according to RealClearPolitics.

Table 9

Summary of results

Date	State	Polling Org.	*r*	*p*	*df*	Predicted state vote	Actual state vote
Aug. 15 – 17, 2016	Nevada	Suffolk University	0.616	.025	11	Clinton +2.3	Clinton +2.4
Aug. 22 – 24, 2016	Michigan	Suffolk University	0.251	.408	11	Clinton +8.5	Trump +0.3
Oct. 2 – 6, 2016	Virginia	Roanoke College	0.697	.002	15	Clinton +6.96	Clinton +5.4
Oct. 4 – 5, 2016	Wisconsin	Loras College	0.703	.078	5	Clinton +5.8	Trump +0.7
Oct. 29 – Nov. 1, 2016	Virginia	Roanoke College	0.808	< .001	15	Clinton +7.53	Clinton +5.4
Oct. 31 – Nov. 1, 2016	Pennsylvania	Susquehanna Polling and Research & WHTM-TV/ABC27 News	0.462	.296	5	Clinton +6	Trump +0.7

Discussion

This study aimed to answer RQ1: *How can Google Trends data be used alongside or in place of traditional public opinion polls?* This study shows that Google Trends data can be used as a supplement to existing polling data, but that it should not replace it entirely. Overall, states that swung as predicted were more reflective of Google Trends data, while states where the result was not as predicted were not reflective, perhaps an indication of bad polling in these states or polls that were subject to biases. This is a study that can add to the growing body of research supporting Google Trends and Google search data in general as a useful tool in a number of contexts. This study also adds credibility to the idea that social desirability bias or a Bradley-like effect was present in polling during this election.

Discussion of Results

These findings seem to imply that the traditional public opinion polls in states that swung as predicted were also more reflective of Google Trends data. The August Suffolk University poll conducted in Nevada, the October Roanoke College poll conducted in Virginia, and the late October/early November Roanoke College poll conducted in Virginia all showed strong correlations to their corresponding Google Trends datasets at a significant level.

If the Clinton campaign did indeed rely on traditional public opinion polling to help shape their campaign strategy, then a practical and logical way to understand this finding is to say that the messaging and overall campaign strategy for Clinton was effective and aligned in those states to reflect what people actually cared about – as evidenced through the combination of traditional polling and Google searches. That is, since Clinton was leading in the polls in Nevada in August, and in Virginia in October and early November and those leads were realized through actual vote totals on Election Day, her general campaign strategy worked; she didn't lose a supposed lead in these states. While there are a myriad of factors to be considered in the scope of a campaign and it's difficult to attribute a vote shift to any one of those factors, campaigning on and speaking about issues that are salient to voters is very important.

Meanwhile, the August Suffolk University poll conducted in Michigan, the October Loras College poll conducted in Wisconsin, and the late October/early November Susquehanna Polling and Research & WHTM-TV/ABC27 News poll conducted in Pennsylvania showed weaker and insignificant correlations to their corresponding Google Trends datasets. It should be noted that in Wisconsin, there was a relatively strong correlation, but only seven issues were included in the poll and the correlation was not statistically significant.

As opposed to the other states, it would appear that the messaging and overall campaign strategy for Clinton was not effective or at least not aligned to the overall interests of the states' electorates. In the states where these polls were conducted, the polling advantage for Clinton at that time was very different from the ultimate difference in votes on Election Day. The average difference in expected vote share based on polls compared to actual vote share on Election Day in these states was 7.333 points. In states that swung as predicted, the average difference was 1.263 points.

Of course, it is necessary to mention Russian cyber meddling when thinking about these results. The potential of Russian influence on the election cannot be understated, especially taking the results of this study into account. A number of ads and pages promoted on Facebook were specifically targeted to key demographic groups in both Michigan and Wisconsin (Raju, Byers, & Bash, 2017). In one study on the reach of disinformation campaigns on Facebook, Russian-linked groups accounted for over 2000 of the ads analyzed in the study, many of which were targeted to voters in key battleground states such as Wisconsin and Pennsylvania (Kim et al., 2018). Additionally, Twitter has notified more than 1.4 million users that they engaged with or were following accounts run by the Russian government-linked Internet Research Agency during the 2016 election (Twitter, 2018). If people were exposed to these ads or pages that may have promoted certain topics, it's likely that they also searched for more information via search engines. The relationship between social media and search engine information seeking has been found to be complementary (Morris, Teevan, & Panovich, 2010), meaning those who find information on search engines will seek confirmation on social media and information found on social media will likely be confirmed via search engines.

The promotion of certain topics by outside actors during the election on social media therefore could have had an effect on what people were searching on search engines such as Google. When considering that, at least on Facebook, Russian-produced ads were able to target specific states (Raju et al., 2010), this study's finding that Michigan, Wisconsin, and Pennsylvania did not have significantly high correlations between what they considered important topics in traditional opinion polls and via Google searches and their actual vote totals swung well against what polls predicted is very notable.

Prior Research & Theoretical Implications

Another interpretation of these findings are in its theoretical implications to support social desirability in the context of polling. Social desirability bias may not have been as pronounced in states that swung as predicted, but it seems to have been at least somewhat relevant in Michigan, Pennsylvania, and Wisconsin in the context of this study. Perhaps the fact that states in this study which swung against polling predictions were not highly or significantly correlated to Google Trends can be attributed to respondents tending to select more socially desirable choices in the "Most Important Issue"-type questions as well as candidate preference in the traditional polls. That is, they felt the need to choose socially desirable choices throughout the survey, including candidate preference, explaining why the predictions were so far off in these three states. This would mean that through an unmediated source – Google – they were more likely to continue seeking information on the topics that they felt were the most important to them. It also shows that the polls as a whole in those states were flawed. Had this analysis been done in real-time as the polls were coming out, it would have been evident that there was a disconnect somewhere and further investigation behind the cause – whether social desirability, constrained choice in the survey question format, or some other fatal flaw – could be done.

These results and the potential presence of social desirability in the polls of swung against predictions can also support the idea of a Bradley-like effect that showed an over reporting of support for Clinton was present in pre-election polls. This means that at least part of the motivation in over reporting support for Clinton was because it was seen as a more socially desirable choice, as she is part of a historically underrepresented group in elected office (CAWP, 2018).

Although there isn't much research suggesting that a primary use of a search engine is because someone is confiding their most important issue facing the country, perhaps this study shows that it is among them. Whether they are seeking more information about the topic or just want to refresh themselves on this topic that is salient, the results indicate that searches in states that swung with the predictions generally aligned with what the polls indicated were the most important issue.

Practical Implications

In regards to the previously stated RQ1, this study shows that Google Trends can be used as a supplement in addition to traditional public opinion polling, but it should not completely replace traditional polling, nor should it be completely ignored. Simply relying on traditional public opinion polls to shape messaging strategy in particular states can give a false sense that the campaign is accurately capturing the sentiment of what is important to residents of that state.

As shown in this study, states that differ in traditional polling and Google search data are at risk of being misunderstood and potentially lost on Election Day. While this was not an exhaustive study of every state because of a limited number of applicable polls for comparison, this study still does not suggest that Google Trends should be the sole tool to replace traditional public opinion polling, it should be a necessary component of any candidate's overall data operation.

An additional practical implication made even more apparent in this study is that campaign messaging needs to take a state-by-state approach. The nature of the Electoral College means that each state should be considered individually based on what issues voters find to be the most important. Approaching and implementing a blanket national messaging strategy, while good for consistency, becomes ineffective if polling or other methods like Google search data show that voters in Michigan are interested in different topics than those in Nevada, for example. Google Trends also allows trends to be identified at the media market leveling, meaning that messaging can be further tailored in conjunction with polling results to specific areas of a particular state.

Limitations

There are a few limitations of this study to note. The largest limitation was the amount of applicable polls in swing states. In many cases, there were no traditional public opinion polls that asked the "Most Important Issue"-type question, especially in the swing states being examined. This is important to note because in situations where there is no available data via traditional polls, the findings of this study show that Google search data can give a somewhat accurate, fairly highly correlated idea of what poll responses to these questions may be. While it is unquestionably better to use traditional polls and Google data in conjunction with one another, if there is no traditional polling data available, Google data can at least be used to get a somewhat representative snapshot of public opinion.

A similar limitation regarding the polls was the limited number of choices for "Most Important Issue"-type questions in traditional polls. Coupled with the fact that there were a limited number of polls to choose from, some of the polls included in this analysis had a small choice of response and subsequently a small corresponding Google Trends dataset. Additionally, most polls allowed respondents to answer as 'Undecided,' 'Other,' or refuse to respond. There was no corresponding topic in the Google Trends datasets to account for these responses. An advantage of Google Trends in response to these limitations is that it can allow campaigns to compare many topics, including ones not asked in polls. This gives a broader picture of what is relevant to respondents – especially if there is a high percentage of respondents who answered 'Other' in the polls.

Future Research and Recommendations

This study can be used as a basis for future avenues of research in this growing area of scholarly research on Google search data. While this study took the relative pulse of public opinion during three general timeframes during the election, it would be especially useful if a future study compared Google search data to exit polling. Specifically, an exit poll should ask which one topic or issue was the most important issue that factored in to a voter's decision. An exit poll with this type of question will allow a study similar in design to this one to be done. Based on some of the previously discussed limitations, allowing this answer to be open-ended may result in a more accurate corresponding Google Trends dataset. This kind of information can give campaigns a sense of what types of issues are persistent throughout campaigns and what types of issues should be addressed in the immediate days prior to Election Day.

One of the biggest recommendations to the polling industry that should come from this study is to continue to evolve with technology. The industry depends on a reconsideration of existing practices or it risks being replaced by possibly more accurate indicators such as Google Trends. Random digit dialing and telephone interviews in general may not produce the most accurate results any longer. As an industry, perhaps it is time to factor in new methodologies like web search data. Again, this can be done in conjunction with existing methodologies and different methodologies can be weighted and reported thusly, but the industry itself must take note of its shortcomings and then adapt and evolve to stay relevant.

A specific action made clear in this study that pollsters can take in improving their polls is to include more issues or topics in their "Most Important Issue"-type questions. This will allow a better comparison to be made to Google search data and will generally give a more accurate representation of issues that matter to voters. Being exhaustive in choices in their other poll questions outside of "Most Important Issue"-type questions is also important and recommended.

This study also made apparent that Google has many opportunities to aid in gauging public opinion and assisting researchers. The relatively short period of time that traditional public opinion polls analyzed in this study were conducted – typically two to four days – meant that the corresponding Google Trends datasets only reflected searches in those states over the same two to four day period. In all cases, there were never enough searches for any topic to give a detailed breakdown of the specific search terms for those topics. It would be especially helpful if Google lowered the threshold of searches to display this type of insight, as researchers could greatly benefit to know the exact search terms contained in a topic and which ones were searched more often than others in each state.

Similarly, Google would serve the academic sphere well if they optimized Google Trends to the needs of researchers or created a new platform for this purpose. While Google AdWords and Google Analytics are great tools with impressive insights, they are largely specific and targeted towards marketers. Google should work with the academic community – specifically those who have undertaken research utilizing Google search data – to create a platform that can aid researchers in advancing the collective knowledge of how Google search data can help to explain human behaviors.

Conclusion

This study generally showed that traditional public opinion polling in states that swung as predicted in the 2016 presidential election was significantly highly correlated to the corresponding Google Trends data in those states over the same periods of time as the polls. In states that swung against the predictions, traditional public opinion polling was not significantly correlated to the corresponding Google Trends data in those states over the same periods of time as the polls. These findings add credibility to the idea that Google search data should be used by campaigns in conjunction with traditional public opinion data to get a more accurate overall picture of public opinion in individual states during the course of an election.

References

AAPOR. (2009). Survey Disclosure Checklist. Retrieved from https://www.aapor.org/Standards-Ethics/AAPOR-Code-of-Ethics/Survey-Disclosure-Checklist.aspx

Anderson, J. C. (1978). The validity of Haire's shopping list projective technique. *Journal of Marketing Research*, 644-649.

Antin, J., & Shaw, A. (2012). *Social desirability bias and self-reports of motivation: a study of amazon mechanical turk in the US and India.* Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.

Askitas, N. (2015). Calling the Greek Referendum on the nose with Google Trends. *Institute for the Study of Labor*.

Askitas, N. (2016). Trend-Spotting in the Housing Market. *Cityscape, 18*(2), 165.

Asur, S., & Huberman, B. A. (2010). *Predicting the future with social media.* Paper presented at the Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology-Volume 01.

Barreto, M. A., Segura, G. M., & Woods, N. D. (2004). The Mobilizing Effect of Majority-Minority Districts on Latino Turnout. *American Political Science Review, 98*(1), 65-75. doi:10.1017/S0003055404001005

Bean, L. H. (1948). How to predict elections.

Bernardi, R. A. (2006). Associations between Hofstede's cultural constructs and social desirability response bias. *Journal of Business Ethics, 65*(1), 43-53.

Bethlehem, J. (2009). The rise of survey sampling: Statistics Netherlands.

Blumenthal, M. (2014). Polls, forecasts, and aggregators. *PS: Political Science & Politics, 47*(2), 297-300.

Bradner, E. (2016). Clinton leads Trump, two new polls show. Retrieved from https://www.cnn.com/2016/10/16/politics/hillary-clinton-donald-trump-presidential-polls/index.html

Brigo, F., & Erro, R. (2016). Why do people google movement disorders? An infodemiological study of information seeking behaviors. *Neurological Sciences, 37*(5), 781-787. doi:10.1007/s10072-016-2501-5

Calder, B. J., & Burnkrant, R. E. (1977). Interpersonal influence on consumer behavior: An attribution theory approach. *Journal of Consumer Research, 4*(1), 29-38.

Cassino, D. (2016). Why Pollsters Were Completely and Utterly Wrong. *Harvard Business Review*. Retrieved from https://hbr.org/2016/11/why-pollsters-were-completely-and-utterly-wrong

CAWP. (2018). Women in Elective Office 2018. Retrieved from http://www.cawp.rutgers.edu/women-elective-office-2018

Chang, L., & Krosnick, J. A. (2001). *The representativeness of national samples: comparisons of an RDD telephone survey with matched Internet surveys by Harris Interactive and Knowledge Networks.* Paper presented at the Conference of the American Association for Public Opinion Research.

Chen, T., So, E. P. K., Wu, L., & Yan, I. K. M. (2015). The 2007–2008 U.S. Recession: What did the real-time Google Trends data tell the United States? *Contemporary Economic Policy, 33*(2), 395-403. doi:10.1111/coep.12074

Cillizza, C. (2016). Winners and losers from the 2016 election. Retrieved from The Washington Post website: https://www.washingtonpost.com/news/the-fix/wp/2016/11/09/winners-and-losers-from-the-2016-election/?utm_term=.4a2df94e699c

CNN. (2016). 2016 Election Results. Retrieved from http://www.cnn.com/election/results

Coppock, A. (2017). Did Shy Trump Supporters Bias the 2016 Polls? Evidence from a Nationally-representative List Experiment *Statistics, Politics and Policy* (Vol. 8, pp. 29).

Darling, J. E. (2017). Could "Shy" Trump Voters' Discomfort With Disclosing Candidate Choice Have Skewed Telephone Polls? Evidence from the USC Election Poll. Retrieved from http://evidencebase.usc.edu/could-shy-trump-voters-discomfort-with-disclosing-candidate-choice-skew-telephone-polls-evidence-from-the-usc-election-poll/

Delavande, A., & Manski, C. F. (2010). Probabilistic polling and voting in the 2008 Presidential Election: Evidence from the American Life Panel. *The Public Opinion Quarterly, 74*(3), 433-459. doi:10.1093/poq/nfq019

Dodou, D., & de Winter, J. C. F. (2014). Social desirability is the same in offline, online, and paper surveys: A meta-analysis. *Computers in Human Behavior, 36*, 487-495. doi:10.1016/j.chb.2014.04.005

File, T., & Ryan, C. (2014). Computer and Internet Use in the United States: 2013. *American Community Survey Reports, ACS-28*. Retrieved from https://www.census.gov/content/dam/Census/library/publications/2014/acs/acs-28.pdf

Fisher, R. J. (1993). Social Desirability Bias and the Validity of Indirect Questioning. *Journal of Consumer Research, 20*(2), 303-315. doi:10.1086/209351

Freelon, D. (2014). On the Interpretation of Digital Trace Data in Communication and Social Computing Research. *Journal of Broadcasting & Electronic Media, 58*(1), 59-75. doi:10.1080/08838151.2013.875018

Ginsberg, J., Smolinski, M. S., Brilliant, L., Patel, R. S., Mohebbi, M. H., & Brammer, L. (2009). Detecting influenza epidemics using search engine query data. *Nature, 457*(7232), 1012-1014. doi:10.1038/nature07634

Gonzalez-Ocantos, E., de Jonge, C., Meléndez, C., Osorio, J., & Nickerson, D. W. (2012). Vote Buying and Social Desirability Bias: Experimental Evidence from Nicaragua. *American Journal of Political Science, 56*(1), 202-217. doi:10.1111/j.1540-5907.2011.00540.x

Google. (2012). Insights into what the world is searching for -- the new Google Trends. Retrieved from https://search.googleblog.com/2012/09/insights-into-what-world-is-searching.html

Graff, G. (2016a, Nov 15). How pollsters missed the 'Bowling Alone' voters that handed Trump the presidency. Retrieved from https://www.wired.com/2016/11/pollsters-missed-bowling-alone-voters-handed-trump-presidency/

Graff, G. (2016b, June 6). The polls are all wrong. A startup called Civis is our best hope to fix them. Retrieved from https://www.wired.com/2016/06/civis-election-polling-clinton-sanders-trump/

Green, J. A. (2017). *Google Trends as an Influence Bellwether: Did the Email Server Really Sink Hillary in 2016?* Paper presented at the American Political Science Association Annual Conference, San Francisco, CA.

Greenfield, R. (2011). Some Limitations of Using Google to Find Racist Voters. Retrieved from https://www.theatlantic.com/politics/archive/2011/12/some-limitations-using-google-find-racist-voters/334853/

Gregson, S., Zhuwau, T., Ndlovu, J., & Nyamukapa, C. A. (2002). Methods to reduce social desirability bias in sex surveys in low-development settings: experience in Zimbabwe. *Sexually transmitted diseases, 29*(10), 568-575.

Grimm, P. (2010). Social desirability bias. *Wiley international encyclopedia of marketing*.

Hartig, H., Lapinski, J., & Psyllos, S. (2016). Poll: Clinton Maintains Solid National Lead. Retrieved from https://www.nbcnews.com/storyline/data-points/poll-clinton-maintains-solid-national-lead-n667751

Hebert, J. R., Clemow, L., Pbert, L., Ockene, I. S., & Ockene, J. K. (1995). Social Desirability Bias in Dietary Self-Report May Compromise the Validity of Dietary Intake Measures. *International Journal of Epidemiology, 24*(2), 389-398. doi:10.1093/ije/24.2.389

Heerwig, J. A., & McCabe, B. J. (2009). Education and Social Desirability Bias: The Case of a Black Presidential Candidate. *Social Science Quarterly, 90*(3), 674-686. doi:10.1111/j.1540-6237.2009.00637.x

Helderman, R. S., Zapotosky, M., & Horwitz, S. (2016). Computer seized in Weiner probe prompts FBI to take new steps in Clinton email inquiry. Retrieved from https://www.washingtonpost.com/politics/fbi-to-conduct-new-investigation-of-emails-from-clintons-private-server/2016/10/28/0b1e9468-9d31-11e6-9980-50913d68eacb_story.html?noredirect=on&utm_term=.dd9abe8eb620

Higgins, J. P., & Altman, D. G. (2008). Assessing Risk of Bias in Included Studies. In J. P. Higgins & S. Green (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions*.

Hillygus, D. S. (2011). The evolution of election polling in the United States. *The Public Opinion Quarterly, 75*(5), 962-981. doi:10.1093/poq/nfr054

Holbrook, A. L., Green, M. C., & Krosnick, J. A. (2003). Telephone versus Face-to-Face Interviewing of National Probability Samples with Long Questionnaires: Comparisons of Respondent Satisficing and Social Desirability Response Bias. *The Public Opinion Quarterly, 67*(1), 79-125.

Holbrook, A. L., Krosnick, J. A., & Pfent, A. (2007). The causes and consequences of response rates in surveys by the news media and government contractor survey research firms. *Advances in telephone survey methodology*, 499-528.

Hopkins, D. J. (2009). No More Wilder Effect, Never a Whitman Effect: When and Why Polls Mislead about Black and Female Candidates. *The Journal of Politics, 71*(3), 769-781. doi:10.1017/S0022381609090707

Howison, J., Wiggins, A., & Crowston, K. (2011). Validity issues in the use of social network analysis with digital trace data. *Journal of the Association for Information Systems, 12*(12), 767.

Isaac, M., & Ember, S. (2016, Nov. 9). For Election Day Influence, Twitter Ruled Social Media. *New York Times,* p. B3.

Jacobs, L. R. (2005). Polling Politics, Media, and Election Campaigns. *Public Opinion Quarterly, 69*(5), 635-641. doi:10.1093/poq/nfi068

Johnson, D. W. (2002). Elections and public polling: Will the media get online polling right? *Psychology and Marketing, 19*(12), 1009-1023. doi:10.1002/mar.10050

Jungherr, A. (2015). Predictor of Electoral Success and Public Opinion at Large *Analyzing Political Communication with Digital Trace Data: The Role of Twitter Messages in Social Science Research* (pp. 189-210). Cham: Springer International Publishing.

Jungherr, A. (2017). Normalizing digital trace data. *Digital Discussions: How Big Data Informs Political Communication*.

Jungherr, A., & Jürgens, P. (2013). Forecasting the pulse: How deviations from regular patterns in online data can identify offline phenomena. *Internet Research, 23*(5), 589-607. doi:doi:10.1108/IntR-06-2012-0115

Jungherr, A., Schoen, H., Posegga, O., & Jürgens, P. (2017). Digital Trace Data in the Study of Public Opinion:An Indicator of Attention Toward Politics Rather Than Political Support. *Social Science Computer Review, 35*(3), 336-356. doi:10.1177/0894439316631043

Jungherr, A., & Theocharis, Y. (2017). The empiricist's challenge: Asking meaningful questions in political science in the age of big data. *Journal of Information Technology & Politics, 14*(2), 97-109. doi:10.1080/19331681.2017.1312187

Katz, J. (2016). Who will be President? Retrieved from The New York Time website: https://www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html

Keeter, S., Hatley, N., Kennedy, C., & Lau, A. (2016). What Low Response Rates Mean for Telephone Surveys. Retrieved from The Pew Research Center website: http://www.pewresearch.org/2017/05/15/what-low-response-rates-mean-for-telephone-surveys/

Kennedy, C., Blumenthal, M., Clement, S., Clinton, J. D., Durand, C., Franklin, C., . . . Wlezien, C. (2018). An Evaluation of the 2016 Election Polls in the United States. *Public Opinion Quarterly, 82*(1), 1-33. doi:10.1093/poq/nfx047

Kim, Y. M., Hsu, J., Neiman, D., Kou, C., Bankston, L., Kim, S. Y., . . . Raskutt, G. (2018). The Stealth Media? Groups and Targets Behind Divisive Issue Campaigns on Facebook.

Klar, S., Weber, C. R., & Krupnikov, Y. (2016). Social Desirability Bias in the 2016 Presidential Election *The Forum* (Vol. 14, pp. 433).

Kleinberg, J. (2008). The convergence of social and technological networks. *Communications of the ACM, 51*(11), 66-72.

Kristoufek, L., Moat, H. S., & Preis, T. (2016). Estimating suicide occurrence statistics using Google Trends. *EPJ Data Science, 5*(1), 1-12. doi:10.1140/epjds/s13688-016-0094-0

Lalwani, A. K., Shavitt, S., & Johnson, T. (2006). What Is the Relation Between Cultural Orientation and Socially Desirable Responding? *Journal of Personality and Social Psychology, 90*(1), 165-178. doi:10.1037/0022-3514.90.1.165

Mavragani, A., & Tsagarakis, K. P. (2016). YES or NO: Predicting the 2015 GReferendum results using Google Trends. *Technological Forecasting and Social Change, 109*, 1-5. doi:10.1016/j.techfore.2016.04.028

Mayer-Schönberger, V., & Cukier, K. (2013). Big data: A revolution that will transform how we live, work, and think. *Houghton Mifflin Harcourt*.

Mellon, J. (2013). Where and When Can We Use Google Trends to Measure Issue Salience? *PS: Political Science and Politics, 46*(2), 280-290. doi:10.1017/S1049096513000279

Miller, S. (2016). Post-election, Day 2: World papers, leaders react. Retrieved from USA Today website: https://www.usatoday.com/story/news/world/2016/11/10/world-reaction-trump-papers/93594464/

Mulry-Liggan, M. H. (1983). *A comparison of a random digit dialing survey and the current population survey.* Paper presented at the Proceedings of the American Statistical

Association, Section on Survey Research Methods. Washington, DC: American Statistical Association.

NetMarketShare. (2017). Desktop Search Engine Market Share. Retrieved from http://www.netmarketshare.com/search-engine-market-share.aspx?qprid=4&qpcustomd=0

NorthwesternInstituteForPolicyResearch. (2016). Polling by Probabilities? Retrieved from http://www.ipr.northwestern.edu/about/news/2016/manski-probabilistic-polling.html

Onwuegbuzie, A. J., Daniel, L., & Leech, N. L. (2007). Pearson Product-Moment Correlation Coefficient. In N. J. Salkind (Ed.), *Encyclopedia of measurement and statistics* (pp. 751-755): Sage Publications.

Panagopoulos, C. (2009). Polls and Elections: Preelection Poll Accuracy in the 2008 General Elections. *Presidential Studies Quarterly, 39*(4), 896-907. doi:10.1111/j.1741-5705.2009.03713.x

Pasek, J. (2015). Predicting Elections: Considering Tools to Pool the Polls. *Public Opinion Quarterly, 79*(2), 594-619. doi:10.1093/poq/nfu060

Payne, J. G. (2010). The Bradley Effect: Mediated Reality of Race and Politics in the 2008 U.S. Presidential Election. *American Behavioral Scientist, 54*(4), 417-435. doi:10.1177/0002764210381713

Persson, M., & Solevid, M. (2014). Measuring Political Participation--Testing Social Desirability Bias in a Web-Survey Experiment. *International Journal of Public Opinion Research, 26*(1), 98-112. doi:10.1093/ijpor/edt002

PewResearchCenter. (2016). Low Marks for Major Players in 2016 Election — Including the

Winner. Retrieved from http://assets.pewresearch.org/wp-content/uploads/sites/5/2017/01/10125033/11-21-16-Updated-Post-Election-Release.pdf

Polykalas, S. E., Prezerakos, G. N., & Konidaris, A. (2013). *An Algorithm based on Google Trends' data for future prediction. Case study: German Elections.* Paper presented at the Signal Processing and Information Technology (ISSPIT), 2013 IEEE International Symposium on.

Powell, R. J. (2013). Social Desirability Bias in Polling on Same-Sex Marriage Ballot Measures. *American Politics Research, 41*(6), 1052-1070. doi:10.1177/1532673X13484791

Prion, S., & Haerling, K. A. (2014). Making Sense of Methods and Measurement: Pearson Product-Moment Correlation Coefficient. *Clinical Simulation in Nursing, 10*(11), 587-588. doi:https://doi.org/10.1016/j.ecns.2014.07.010

Purcell, K. (2011). Search and email still top the list of most popular online activities. Retrieved from http://www.pewinternet.org/2011/08/09/search-and-email-still-top-the-list-of-most-popular-online-activities/

Purcell, K., Brenner, J., & Rainie, L. (2012). *Search Engine Use in 2012 : Pew Internet & American Life Project Reports;2012 SRI R8588-1.98*. Retrieved from http://www.pewinternet.org/2012/03/09/search-engine-use-2012/

Randall, D. M., & Fernandes, M. F. (1991). The Social Desirability Response Bias in Ethics Research. *Journal of Business Ethics, 10*(11), 805-817. doi:10.1007/BF00383696

RealClearPolitics. (2017). General Election: Trump vs. Clinton. Retrieved from https://www.realclearpolitics.com/epolls/2016/president/us/general_election_trump_vs_clinton-5491.html#polls

Rivers, D. (2016, Nov 11). First thoughts on polling problems in the 2016 U.S. elections. Retrieved from https://today.yougov.com/news/2016/11/11/first-thoughts-polling-problems-2016-us-elections/

Rose, D., & Levinson, D. (2004). *Understanding user goals in web search*.

Rosenberg, M., & Dance, G. J. X. (2018). 'You Are the Product': Targeted by Cambridge Analytica on Facebook. Retrieved from https://www.nytimes.com/2018/04/08/us/facebook-users-data-harvested-cambridge-analytica.html

Särndal, C.-E., Swensson, B., & Wretman, J. (2003). *Model assisted survey sampling*: Springer Science & Business Media.

Shepard, S. (2016). How could the polling be so wrong? Retrieved from Politico website: https://www.politico.com/story/2016/11/how-could-polling-be-so-wrong-2016-231092

Sinclair, B., & Wray, M. (2015). Googling the Top Two: Information Search in California's Top Two Primary. *California Journal of Politics and Policy, 7*(1), 0_1. doi:10.5070/P2cjpp7125443

Stephens, M., Yoo, J., Mourao, R. R., Vu, H. T., Baresch, B., & Johnson, T. J. (2014). How App Are People to Use Smartphones, Search Engines, and Social Media for News?: Examining Information Acquisition Tools and Their Influence on Political Knowledge and Voting. *Journal of Information Technology & Politics, 11*(4), 383-396. doi:10.1080/19331681.2014.951137

Stephens-Davidowitz, S. (2013a, December 8). How Many American Men Are Gay? *New York Times,* p. SR5.

Stephens-Davidowitz, S. (2013b). *Who Will Vote? Ask Google*.

Stephens-Davidowitz, S. (2014a). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics, 118*(Supplement C), 26-40. doi:10.1016/j.jpubeco.2014.04.010

Stephens-Davidowitz, S. (2014b, January 19). Google, Tell Me. Is My Son a Genius? *New York Times,* p. SR6.

Stephens-Davidowitz, S. (2014c, May 18). What Do Pregnant Women Want? *New York Times,* p. SR6.

Stephens-Davidowitz, S. (2017). *Everybody lies: big data, new data, and what the Internet can tell us about who we really are*. New York, NY: Dey St.

Stout, C. T., & Kline, R. (2008). Ashamed not to vote for an African-American; ashamed to vote for a woman: An analysis of the Bradley effect from 1982-2006.

Stout, C. T., & Martin, P. J. (2016). Does descriptive representation lead to social desirability bias? Over-reporting of voting among blacks and Latinos in the United States. *Research & Politics, 3*(2), 205316801664197. doi:10.1177/2053168016641974

Stuart, G. S., & Grimes, D. A. (2009). Social desirability bias in family planning studies: a neglected problem. *Contraception, 80*(2), 108-112.

Swearingen, C. D., & Ripberger, J. T. (2014). Google Insights and U.S. Senate Elections: Does Search Traffic Provide a Valid Measure of Public Attention to Political Candidates? *Social Science Quarterly, 95*(3), 882-893. doi:10.1111/ssqu.12075

Taylor, J. (1997). *Introduction to error analysis, the study of uncertainties in physical measurements*: University Science Books.

Taylor, R. (1990). Interpretation of the Correlation Coefficient: A Basic Review. *Journal of Diagnostic Medical Sonography, 6*(1), 35-39. doi:10.1177/875647939000600106

Traugott, M. W. (2005). The accuracy of the national preelection polls in the 2004 presidential election. *Public Opinion Quarterly, 69*(5), 642-654.

Trende, S. (2016). It Wasn't the Polls That Missed, It Was the Pundits. Retrieved from RealClearPolitics website: https://www.realclearpolitics.com/articles/2016/11/12/it_wasnt_the_polls_that_missed_it_was_the_pundits_132333.html

Trevisan, F., Hoskins, A., Oates, S., & Mahlouly, D. (2018). The Google voter: search engines and elections in the new media ecology. *Information, Communication & Society, 21*(1), 111-128. doi:10.1080/1369118X.2016.1261171

Wang, W., Rothschild, D., Goel, S., & Gelman, A. (2015). Forecasting elections with non-representative polls. *International Journal of Forecasting, 31*(3), 980-991. doi:https://doi.org/10.1016/j.ijforecast.2014.06.001

Wasserman, D. (2016, Oct. 15). You'll likely be reading one of these 5 articles the day after the election. Retrieved from https://fivethirtyeight.com/features/youll-likely-be-reading-one-of-these-5-articles-the-day-after-the-election/