Google Insights and U.S. Senate Elections: Does Search Traffic Provide a Valid Measure of Public Attention to Political Candidates?*

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Objective. To propose a new indicator of public attention to electoral candidates based on the relative pattern of Internet queries for opposing candidates. *Methods.* To demonstrate the validity of this measure, we use ordinary least squares regression and an F-ratio test. *Results.* We find that this measure, based on Google Insights data, behaves in a manner consistent with a valid measure of public attention. Moreover, this finding holds when the measure is included in a standard model used to explain U.S. Senate election outcomes. *Conclusion.* The Google Insights measure of relative public attention shows the shifts in public attention as the campaign is waged and is consistent with how we would expect to see such a measure behave. This research opens numerous avenues for research in the campaigns and elections subfield.

In 2010, a little-known Republican state senator from Massachusetts, Scott Brown, won a special election to replace Senator Ted Kennedy. His path to victory was unforeseen by many pundits—as of two weeks prior to the January 20 election, no poll had Brown within nine points of his Democratic opponent, Martha Coakley.[1] In the last week of the campaign, however, Brown surged to tie or moved ahead in almost every poll. Brown's come-from-behind win shocked politicos across the country. Implicit in postelection analysis was the idea that Brown was able to get voters to pay attention to his message in an effort to change the dynamics of the race.[2] Though intriguing, narratives like this remain speculative because election scholars have yet to develop a metric capable of monitoring public attention to political candidates throughout campaigns. Accordingly, it is difficult to determine *if* and *when* public attention

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[1] See <http://www.realclearpolitics.com/epolls/2010/senate/ma/massachusetts_senate_special_election-1144.html> for a list of polls conducted on the Brown–Coakley race. Accessed September 23, 2013.

[2] For an example of such analysis, see <http://www.wordstream.com/blog/ws/2010/01/14/ma-senate-race-poll-scott-brown-trounces-martha-coakley#>.

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shifts during a given election. It is even more challenging, then, to explain *why* attention changes and *what* affect these changes have on fundraising, voter enthusiasm, turnout, and/or election outcomes.

To fill this gap, we propose a new indicator of public attention to electoral candidates based on the relative pattern of Internet queries for opposing candidates. We develop and validate an example metric by comparing Google Insights data to outcomes in 160 Senate elections between 2004 and 2012 and find that the search-based measure demonstrates a high degree of predictive validity and utility. Accordingly, we advocate its use in future research on the causes and consequences of attention shifts during the campaign season.

Public Attention

At the individual level, *attention* denotes the cognitive resources—time and other—that individuals selectively devote to processing information about a particular object (Ripberger, 2011). In other words, attention represents the cognitive process wherein a person concentrates on or "attends to" one object in his or her environment while ignoring others. *Public attention*, then, characterizes the aggregate distribution of individual attention in a given population. In most instances, it is measured in relative terms—on average, how much time do people spend thinking about one object as opposed to other objects?

In the context of elections, candidates are the objects that members of the public attend to. Returning to the 2010 special election, for example, Massachusetts voters spent some time thinking about both Brown and Coakley. In the beginning of the race, election watchers claim that Coakley received more attention than Brown. As the race progressed, however, the tides of attention are said to have turned toward Brown and away from Coakley.

To evaluate this proposition, we need a measure of public attention that continuously monitors and aggregates the cognitive resources that potential voters devote to processing information (i.e., thinking) about one candidate as opposed to another throughout the course of a campaign. Unfortunately, these data are difficult to collect. It would require that we "get into the heads" of individual people and document what they are thinking about at a given point in time. Given the impractical nature of this task, researchers have developed a number of proxies.

One such proxy, for example, uses media coverage to estimate the amount public attention that a given object (candidate) is likely to have received at a given point in time. The theoretical motivation for this proxy is fairly simple—all else equal, objects that receive more attention from the media tend to receive more attention from the public than objects that are covered less frequently (Iyengar and McGrady, 2007; McCombs and Shaw, 1972). Though useful, recent research indicates that the empirical correlation between media and public attention to political figures is relatively weak (Kiousis and McCombs, 2004). Thus, analysts have used other proxies, like name recognition to indirectly measure public attention to political figures (i.e., Kiousis and McCombs, 2004). Again, however, these measures are suboptimal for a variety of theoretical and practical reasons. On theoretical grounds, awareness (name recognition) is a necessary but not sufficient condition for attention, which requires a higher form of selective cognition. Recognizing that an object exists requires little if any thought. As such, measures that conflate the two generate observational error that is difficult to identify and therefore combat. On practical grounds, surveys that gauge name recognition (like the American National Election Survey) cover relatively few candidates and are infrequently administered. This limits the number of races that researchers can study and the type of questions they can answer.

In light of these limitations, we borrow from recent research on public health (e.g., Ginsberg et al., 2009; Brownstein, Freifeld, and Madoff, 2009), agenda setting (e.g., Ripberger, 2010; Weeks and Southwell, 2010; Scheitle, 2011; Granka, 2013; Mellon, 2013), and consumer/investor behavior (e.g., Choi and Varian, 2009, 2012; Da, Engelberg, and Gao, 2011) to propose a new indicator of public attention based on the relative frequency with which members of the public search for information about political candidates on the Internet. All else equal, we suggest that individuals who search for candidates are paying attention to those candidates. As such, candidates who generate more searches generate more attention than their opponents.

The benefits of this measure are threefold. First and foremost, the behavioral processes that motivate individual-level search behavior align rather closely with our conceptualization of public attention. Though individuals approach information seeking on the web with a wide array of distinct motives (e.g., Broder, 2002; Rose and Levison, 2004; Jansen and Booth, 2010), actively typing something into a web browser is necessarily motivated by some degree of thought about a particular object as well as general willingness to invest some effort into processing that thought. In other words, attention motivates search behavior, both of which require active thought rather than passive awareness. Aggregate data on searches are likely to provide some insight into the distribution of collective attention within the population responsible for the searches.

Second, the measure is flexible and dynamic. It can be used to monitor attention to a large number of candidates at specific or repeated intervals of time as well as particular points in geographic space (e.g., city, state, county), which maximizes the number of races that one can study and the type of questions that can be answered. For example, the metric provides data on attention to candidates in local races, which—because they are relatively low in profile—seldom appear in commonly used name recognition surveys, like the ANES. Likewise, the metric repeatedly gauges attention throughout the election season, which allows researchers to answer time-sensitive questions about when attention shifts occur and what factors or strategies contributed to those shifts.

Finally, the data are inexpensive and easily accessible. Google Insights, for example, is freely available (<http://www.google.com/Insights/>) and supported by an impressive set of user-friendly help directories. This allows for straightforward replication of any study that utilizes these data.

Research Design

In light of these benefits, we are optimistic that systematic studies of Internet usage will advance our understanding of the relationship between public attention and elections. Before such analyses can proceed, however, we must step back and evaluate the validity of the indicator. To accomplish this, researchers generally employ a battery of tests that gauge the extent to which newly defined indicators accurately measure the concepts that they purport to measure. The easiest and best tests compare new measures against observations of their underlying concepts. A new metric is valid if it accurately measures the concept. Unfortunately, social scientists work in a world where it is difficult if not impossible to collect objective observations about an underlying concept, like individual thought processes. Accordingly, we commonly conduct indirect assessments of criterion validity by comparing new measures against observable phenomena (criterion) that are external yet theoretically related to the latent construct that one is trying to measure (Carmines and Zeller, 1979). If the new measure is related to the criterion in a way that is consistent with the theory, one can reasonably conclude that it is valid.

Prediction is one of the comparisons that researchers use to statistically assess the relationship between new measures and theoretically-related criterion. Meteorologists, for example, validate newly developed forecasting tools by assessing the accuracy with which outputs at T_1 predict weather patterns at T_2. Pollsters do the same thing—they tune and validate their models by making predictions and then comparing those predictions against electoral outcomes.

In the findings that follow, we chart a similar course. We evaluate the criterion validity of our measure by assessing its ability to predict the outcome of contested races for the U.S. Senate. If the measure provides a valid proxy for public attention, then candidates who receive more attention than their opponent will, on average, receive more votes. From there, we move on to explore the predictive utility of our metric by assessing the extent to which it improves our ability to predict elections after accounting for the standard battery of structural and candidate-specific factors thought to influence Senate election outcomes.

Data and Methods

The criterion variable in this study is the percentage of the two-party vote that Democratic candidates received in the 2004–2012 Senate elections.

Consistent with previous research, we exclude special elections and uncontested races (e.g., Stewart, 1989; Abramowitz, 1988). This yielded an *n-size* of 160 races, 92 of which were won by the Democratic candidate; the mean vote share was 51.54 percent and the standard deviation was 13.85.

Aggregate data on Internet search behavior were collected using Google Insights. This decision was made for three reasons: first, Google is the most widely used search engine in the United States.[3] As such, collecting data on Google rather than Microsoft or Yahoo searches yields the largest cross-section of the Internet-using population. Second, the vast majority of social scientists who have used search-based measures of public attention have used Google Insights, indicating that the data provided by the service are reliable (e.g., Mellon, 2012; Scheitle, 2011; Granka, 2013; Reilly, Richey, and Taylor, 2012; Pelc, 2012; Weeks and Southwell, 2010). Finally, we used Google Insights because it is freely available and easy to access, which enhances the ability of future researchers to replicate and expand upon our work.

Collecting data by way of Google Insights involves a two-step process. First, users are prompted to enter up to five search terms or keywords that they would like to analyze. Second, users are asked if they would like to filter their query by geographic location, category, or timeframe. With this information, Google Insights generates a data set that estimates search volume for the specified keywords during the specified time and within the specified region. These estimates represent *relative* volumes that are normalized and scaled such that 100 reflects the highest amount of search volume within the specified geographic and temporal constraints (Carneiro and Mylonakis, 2009).[4]

To measure relative public attention to each candidate in each Senate race, we entered the first and last name of each candidate as keywords in Google Insights. We then filtered our results by the state in which the campaign was waged and the timeframe of January through November of each election year. After downloading our results, we computed a public attention score for each candidate by averaging the amount of relative attention that he or she received between January and November. Relative public attention, which is the variable that we used in subsequent analysis, was calculated by subtracting the attention score of the Republican candidate from the attention score of the Democratic candidate. A positive attention margin indicates that the Democratic candidate received more public attention than the Republican candidate. In the 160 Senate races included in this analysis, the attention margin ranged from −73.1 to 63.64, the mean was 1.96, and the standard deviation was 22.96.

To assess the predictive validity of our measure we used ordinary least squares (OLS) regression to predict (M1) the Democratic candidate's share of

[3]According to a recent report, roughly 19.4 billion Internet searches were conducted in July 2013. Approximately 13 billion (67 percent) of these searches were conducted on Google sites, followed by 3.5 billion (18 percent) on Microsoft sites, and 2.2 billion (11 percent) on Yahoo sites (comScore, 2013).

[4]For more on how Google Insights estimates search volume, see Choi and Varian (2011).

the two-party vote in each election as a function of the attention margin. If the measure provides a valid proxy for public attention, then (H_1) *there will be a positive and statistically significant relationship between these two variables*. To assess the predictive utility of our measure, we used OLS regression to estimate two additional models. The first of these (M2) establishes a baseline prediction by regressing the Democratic candidate's share of the two-party vote on the standard battery of structural and candidate-specific factors thought to influence Senate election outcomes. The second (M3) adds the search-based public attention margin to the baseline model.[5] If the measure is useful, then (H_2) *the relative increase (from M2 to M3) in the residual sum-of-squares between the two models will be greater than the relative increase in degrees of freedom.* In other words, the F ratio, defined as:

$$F = \frac{(SS_{\mathrm{M2}} - SS_{\mathrm{M3}}) / (DF_{\mathrm{M2}} - DF_{\mathrm{M3}})}{SS_{\mathrm{M3}}/DF_{\mathrm{M3}}},$$

will be positive and statistically significant.

Findings

Figure 1 displays the bivariate association between the number of searches for the Democratic candidate (relative to the Republican candidate) and the percent of the two-party vote that the Democratic candidate received on Election Day. A quick look at this plot suggests that the two variables are positively related; as searches go up, votes go up.

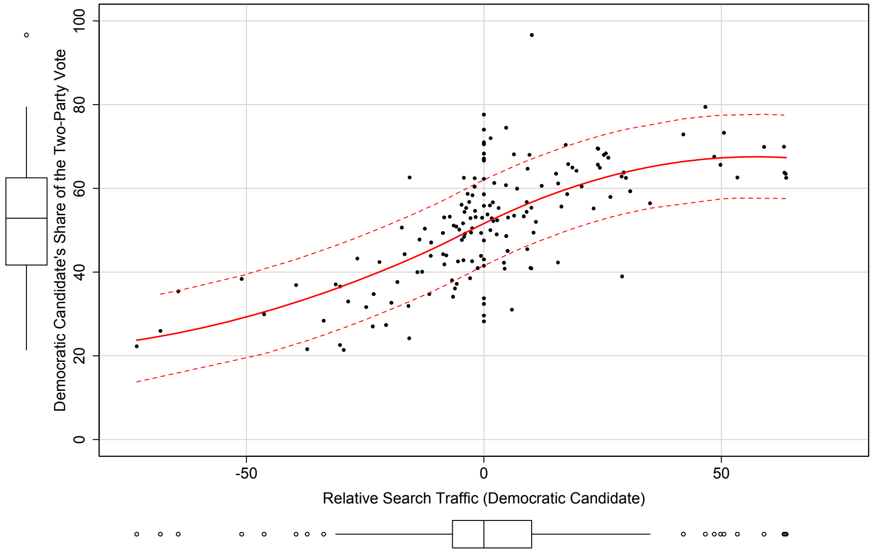
This finding is corroborated in Table 1, which summarizes the estimates derived from Models 1, 2, and 3. Consistent with H_1, the parameters associated with Model 1 (M1) reveal a strong, positive, and statistically significant relationship between the two variables. In races where the Democratic candidate received more searches than the Republican candidate, the Democratic candidate received a significantly higher share of the vote. In fact, search volume alone accounts for almost 45 percent of the variation in Democratic vote share. From this, one can conclude that the search-based measure of public attention systematically predicts the criterion variable in a way that is consistent with our theoretical expectations. This supports our contention that the measure is, indeed, a valid indicator of the public attention.

Having discussed construct validity, we turn now to predictive utility—does the search-based proxy improve our ability to forecast election outcomes? To answer this question, compare the baseline model (M2) to the model that includes the proxy (M3). As expected, the baseline model indicates that marginal fundraising, experience, incumbency, and partisanship significantly influence

[5]See Appendix A for a list of the variables that we included as predictors in the baseline model.

FIGURE 1

Relative Search Traffic vs. Democratic Candidate's Share of the Two-Party Vote



electoral outcomes. All else equal, Democratic candidates receive more votes if they raise more money than their opponent and/or have previous elected experience. They receive relatively fewer votes, by comparison, when their Republican opponent is the incumbent (or a member of the incumbent party) and/or has previous elected experience. Likewise, Democratic candidates receive more votes in left-leaning states and fewer votes in right-leaning states.

Model 3 reveals a similar set of findings, with the exception of two things: the effect of Republican incumbency fades and public attention—as measured using relative search volume—emerges as a significant predictor of the Democratic candidate's share of the two-party vote.[6] Holding the candidate-specific and structural characteristics at their mean, a one point increase in relative search volume corresponds with a 0.11 percent increase in vote share. To put this relationship into perspective, the model predicts that an otherwise average Democratic candidate who generates about as much public attention as his or her opponent is expected to receive roughly 51.3 percent (50.3 percent, 52.3 percent) of the two-party vote.[7] By comparison, a Democratic candidate

[6]Note that none of the explanatory variables listed in M3 are highly correlated with relative attention. The highest correlation is 0.60 (attention vs. net terms), suggesting that public attention is sufficiently unique to the other variables in the models.

[7]Predicted values represent the mean of a distribution of simulated expected values (King, Tomz, and Wittenberg, 2000), along with their 95 percent confidence intervals. Simulations were generated using the "arm" package in R.

TABLE 1

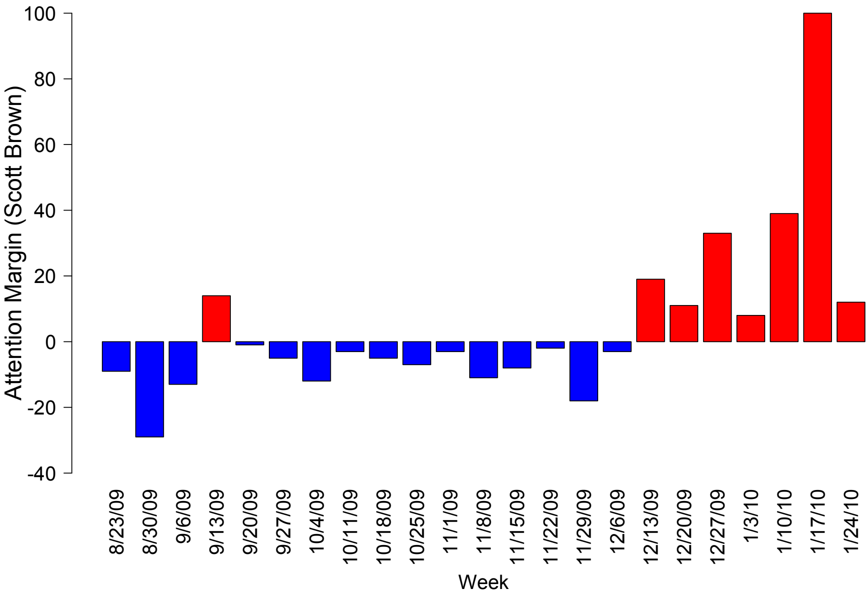
Public Attention and Senate Election Outcomes

	M1	M2	M3
Candidate Qualities			
Fund-raising margin ($100k)		0.02**	0.02*
		(0.01)	(0.01)
Net terms		0.28	0.13
		(0.40)	(0.38)
Experience—Democrat		5.53**	4.83**
		(1.72)	(1.66)
Experience—Republican		−8.48***	−8.08***
		(1.49)	(1.43)
Incumbent (Democrat)		3.72	2.79
		(1.93)	(1.87)
Incumbent (Republican)		−4.52*	−3.37
		(1.88)	(1.83)
Scandal—Democrat		1.28	0.43
		(3.08)	(2.96)
Scandal—Republican		3.63	4.08
		(2.45)	(2.35)
Structural			
Media market diffusion index (100k)		0.08	0.10
		(0.06)	(0.06)
Partisanship		0.40***	0.36***
		(0.08)	(0.08)
2004		−0.22	−1.00
		(1.83)	(1.77)
2006		3.43	2.42
		(1.84)	(1.78)
2008		3.52	1.95
		(1.86)	(1.83)
2010		−5.91**	−6.21***
		(1.78)	(1.71)
Public attention			
Relative search traffic	0.40***		0.12***
	(0.04)		(0.03)
Other			
Constant	50.75***	32.19***	34.94***
	(0.82)	(4.41)	(4.29)
Model statistics			
N	160	160	160
F-statistic	126.50***	35.70***	37.15***
RSS	16,931.90	6,856.40	6,261.80
MAE	7.86	4.85	4.65
Adjusted R^2	0.44	0.75	0.77

Dependent variable: percentage of two-party vote for Democratic Party candidate. One-tailed test where directionality specified.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

FIGURE 2

Relative Public Attention in the 2010 MA Special Election



who generates more attention than his or her opponent (by one standard deviation) is expected to receive roughly 54.2 percent (52.4 percent, 56.0 percent) of the two-party vote. In a competitive election, 3 percentage points can mean the difference between winning and losing a race.

Moving now to model fit, the mean absolute error (MAE) and residual sum of squares (RSS) associated Models 2 and 3 show that adding the search-based measure of public attention improves the predictive accuracy of the forecast. The baseline MAE without the indicator is 4.85 percent whereas the model with the indicator has an MAE of 4.65 percent, which represents a 4 percent improvement. Consistent with H_2, this improvement yields an F ratio of 13.67, which is positive and statistically significant ($p < 0.001$). Again, this finding supports our contention that the search-based measure of public attention is useful for predicting election outcomes.

Conclusion

At the beginning of this article, we briefly discussed the story of Scott Brown. Upon winning, observers pointed to a number of variables that might help to explain his success, including structural variables and low approval rating for the Democrat-controlled Congress. While structural variables still explain a substantial amount of Senate election results, the impact of public attention should not be ignored. Indeed, a valid and concurrent measure of public attention can be useful for gauging the state of an election, especially when analyzed in conjunction with structural variables.

Brown's story is consistent with our argument in this article. A quick look at Figure 2 supports this notion. At the beginning of August, Coakley was clearly winning the battle for public attention. As the campaign wore on, her advantage began to slip and was ultimately surpassed by Brown in December 2009. A week before the election, public attention to his campaign peaked, which propelled him past Coakley in terms of cumulative attention. His public attention advantage helps to complete the narrative of his unlikely victory.

In the broader picture, the Google Insights measure of relative public attention shows the shifts in public attention as the campaign is waged and is consistent with how we would expect to see such a measure behave. The measure is significantly correlated with two-party vote share and remains statistically significant when controlling for a standard battery of explanatory variables. We also find evidence to support our hypotheses: the more attention that a candidate garners vis-à-vis his or her opponent. The higher the share of votes he or she will tend to get on Election Day, especially for open-seat elections.

This research opens numerous avenues for research. In being careful not to overstate the causal link between public attention and election outcomes, we advocate for a research agenda that focuses on the individual-level causal mechanisms that link these two phenomena. What motivates an individual to pay attention to a particular candidate? How does that behavior influence an individual's decision to vote, and who to vote for? Future research should look at macro-level variables that instigate shifts in relative attention throughout the campaign process. Next, researchers should closely examine the types of attention that campaigns receive, be it positive or negative. Is all attention good attention? Or, does attention coming from gaffes and/or scandals hurt rather than help a candidate's chance of winning? Finally, scholars should continue to refine existing measures and/or develop new measures of public attention. We believe that our measure is a useful proxy that will help researchers to better specify the relationship between attention and campaign outcomes, as well as other important relationships in American politics. While the search-based measure is imperfect, we hope that future research will bring about new measures that will help us to better understand the relationship between public attention and electoral outcomes. For now, this article represents an important first step in that direction.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix A: Measurement of Variables