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Capturing Curiosity: Using Internet Search Trends to Measure Public Attentiveness

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While scholars have made great strides in formulating theories and measuring public attention, "most important problem" and media-based indicators are less than ideal measures. In order to address this shortcoming, this article borrows from health-care epidemiology to measure public attention based on Internet search trends. In doing so, it reviews the innovative ways in which scientists have used search activity to track the spread of infectious disease, discusses the ease and flexibility with which search data can be gathered, and then subjects a Google-based search measure to a series of validity tests. In particular, the analysis subjects the proposed measure to a battery of visual and statistical tests for convergent validity by comparing it with the most commonly used media-based measure of public attention—issue coverage in the New York Times. Across a range of policy issues (health care, global warming, and terrorism), the proposed measure demonstrates convergent validity. The article concludes by posing a series of important questions that the new measure will allow researchers to address.

KEY WORDS: mass politics, agenda setting, public attention, salience, measurement, Internet search trends

Introduction

For more than a century, political scientists have invested time and energy into systematically studying the dynamic interplay between political systems and society. All of the subfields—ranging from political theory and American politics to applied public policy and public administration—share a common history in questioning the responsiveness of democratic institutions to the wants and needs of the general public. A fundamentally important element in this interaction is public attention—the scarce resources that people are willing to devote toward thinking about a political issue. Within the confines of bounded rationality, finite resources, and circumscribed time, what issues do members of the mass public regard as particularly important and worthy of cognitive deliberation?

In the article that follows, I briefly review the progress that scholars have made in operationalizing and measuring public attention over time. Ultimately, I conclude that current indicators do not match our theories about how public attention "cycles" in modern society. In particular, our theories often assume that public attention is dynamic, episodic, and ephemeral; by contrast, the measures we often employ, such

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as "most important problem" (MIP) surveys, lack the precision, regularity, and temporal frequency necessary to abide by this assumption. Likewise, measuring shifts in media coverage may provide a useful proxy for public attention, but conflating these two variables limits our ability to test important hypotheses concerning the relationship between citizen attentiveness and the mass communications.

Noting these weaknesses, I borrow from public health epidemiology to propose a new indicator of public attention based on trends in Internet search activity. In doing so, I review the innovative ways in which epidemiologists have used Internet search activity to track the spread of infectious disease, discuss the public availability of data, address potential problems with this sort of measure, and then conclude with a number of avenues for future study. The innovative measure suggested in this article will serve as a springboard for future research that allows political scientists to refine and test theories of public attention that have up until now been hindered by data deficiencies.

Measuring Public Attention: Where We Are and Where We Want to Be

Public attention, though related, is not the same as public opinion. Drawing from Newig (2004), public attention denotes the scarce resources—time and other—that citizens willingly dedicate toward thinking about a publicly debated issue (p. 153).[1] As such, public attention is generally measured in terms of relative intensity (resource employment per time unit) or as a ratio (resource employment dedicated to one issue as compared with another issue competing for attention). By contrast, public opinion relates to individual value judgments and/or predispositions. Accordingly, public opinion is measured in terms of individual or aggregate attitudes. A heuristic way to distinguish between the two is as follows: public opinion is "what people think," whereas public attention is "what people think about" (Newig, 2004).

Distinguishing between public attention and public opinion is necessary because there are times when the two variables are discernibly different. For instance, an individual might have exceptionally strong opinions about anthropogenic global warming, but after having formed these attitudes, they need not spend any time thinking about the issue. Rather than erroneously assuming perfect correspondence between potentially distinct concepts, the relationship between attention and opinion is an empirical question subject to verification. More importantly, public opinion—because it reflects the recollection of deeply seeded values and belief systems within a larger population—is generally found to be relatively stable in the absence of a radical external shock (Page & Shapiro, 1992).[2] By comparison, public attention is thought to change rather quickly, mapping the ebbs and flows of political reality without requiring changes in public belief structures or value systems (Newig, 2004, p. 154). As such, conflating the two necessarily restricts our ability to test the dynamic propositions projected by our theoretical understanding of how public attentiveness to political problems effects, shapes, and/or constrains governmental behavior.

Moving on to measurement, public attention has been quantitatively operationalized in two broadly defined ways: nationwide MIP polls and media coverage. Though a number of different approaches can be identified under the "nationwide poll" umbrella, the most commonly used approach aggregates a series of cross-sectional polls that ask citizens to identify what they consider the MIP facing the nation (or some variant of that question). Raw numbers from these polls are then aggregated, normalized, and displayed as relative proportions—one issue as compared with the other issues competing for importance.[3] Well-documented in volumes of previous research, the problems associated with the MIP measure of public attention range from methodological issues concerning the sparseness and inconsistency with which the polls are administered (Henry & Gordon, 2001), the generally limited number of predetermined macro issues that respondents are forced to choose from (McCombs & Zhu, 1995; Newig, 2004), to more theoretical questions about construct validity and reliability (Wlezien, 2005). Most importantly, these issues have forced researchers into using a measure of public attention that does not line up with our understanding of how the world works. In particular, the static nature of MIP responses—which can be attributed to any one or more of the aforementioned problems—does not allow us to test the dynamic and ephemeral propositions that have been floating around in the literature since Anthony Downs' seminal work in 1972, which argued that "American public attention rarely remains sharply focused upon any one domestic issue for very long—even if it involves a continuing problem of crucial importance to society" (p. 40). If indeed this is the case, measuring public attention by way of static MIP polls is problematic.

Limited by the weaknesses associated with the MIP measure, researchers have migrated toward more dynamic and accessible measures of public attention, such as media coverage. Though some controversy exists concerning the recursive theoretical link between media coverage and public attention, a virtual consensus has emerged among scholars that there is a strong relationship between public and media attentiveness.[4] Recognizing this high correlation, scholars have agreed that media coverage (at the very least) serves as an instrumental proxy for public attention. As with the MIP measure, a number of different approaches can be identified under the "media coverage" umbrella, but the most commonly used approach involves tracking and indexing newspaper coverage of particular issues. Given that the majority of questions require research over relatively lengthy periods of time, most researchers refrain from reading and coding every story within their frame of analysis. Rather, scholars generally employ theoretically guided key word searches of extensive online archives such as the *New York Times Index* or *Readers' Guide* to identify the number of articles dedicated to a particular issue within a finite unit of time (see, for example, Baumgartner & Jones, 1993). The number of articles are then standardized and displayed as relative proportions—where the number of articles dedicated to a particular topic is divided by the total number of articles published within a comparable timeframe.[5]

The well-documented advantages of using the media coverage-based approach to measure public attention start with its low cost (in contrast to polling and interviewing) and its flexibility. As compared with MIP polls, which are inconsistently available at relatively rare intervals (quarterly or yearly), researchers can construct media coverage measures for virtually any timescale of interest, be it daily, weekly, or yearly. Likewise, because of the arduous efforts of newspaper archivists, data on media coverage enable researchers to conduct long-range studies of issues across generations and multiple issue cycles. Related to this accessibility and flexibility, measuring public attention by way of media coverage accounts for the primary weakness of the MIP measures—that they are not dynamic enough to support our episodic and ephemeral understanding of how issues attention changes over time. Moreover, media coverage as a measure of public attention allows scholars to track the dynamic rise and fall of specific (rather than broad-spectrum) issues covered by MIP polls.

Unfortunately, the advantages of media coverage-based measures are purchased at a rather steep theoretical cost, which further distances the measure of public attention from its rather distinct conceptualization, and analytically combines theoretically separate concepts—the media and the public. In addition to problems associated with content validity, using media coverage as a proxy for public attention constrains our ability to test important empirical hypotheses about the relationship between the two variables. For instance, research remains inconclusive regarding questions on which variable precedes and which variable follows—media coverage or public attention (Soroka, 2002). Likewise, if we hope to someday respond to important questions concerning the resonation of particular stories/issues within the public, it is necessary to distinguish between the two concepts.

The primary purpose of this discussion is not to discount the tremendous progress that researchers have made in terms of formulating theories and measures about public attention. Rather, it is to remind the reader that both the MIP and media-based indicators are less than ideal measures of public attention and that choosing either of the two (or both) forces scholars into making costly trade-offs—MIP measures are infrequent, static, and too broad, whereas media coverage is a proxy that separates the measure from the concept and prohibits our ability to test important propositions about how mass communication and the public interact in the political system. The deficiencies of these measures could be eliminated if researchers had direct access to rolling surveys that tap into citizens' thought processes and information-seeking behavior. Unfortunately, such data do not exist. However, the vast amount of real-time information contained on the Internet might serve as a close approximation. Thus, in the remainder of this article, I propose a new indicator of public attention based on trends in Internet search activity, which attempts to address the aforementioned shortcomings. In addition to being both dynamic and flexible, the behavioral processes that underlie the search-based measure more closely align with how the discipline has defined public attention. Despite the obvious fact that individuals approach information seeking on the Web with a wide array of distinct motives, two factors remain constant. First, search behavior is necessarily motivated by some degree of thought about a particular issue. Second, searching for something on the Web requires that individuals invest some degree of time and energy in pursuit of their interest. When considering the definition of public attention—the scarce resources that citizens are willing to spend thinking about a public issue—aggregate search behavior appears to be a valid approximation. After all, if a citizen is willing to invest scarce time and energy into searching the Web for information about a public issue, it can be safely assumed that he or she is interested in and attentive to that public issue.

Infodemiology: Search Trends in Public Epidemiology

In addition to the transmission of enormous amounts of information, data related to Internet utilization is a tremendous resource that scientists are beginning to use in order to better understand how the natural and social world works. Beginning with the seminal work of Gunther Eysenbach (2002), health-care "infoepidemiologists"—which study the "distribution and determinants of information in an electronic medium . . . to inform health and public policy" (Eysenbach, 2009)—remain at the forefront of this development.[6] Though research on infodemiology is quickly proliferating, most applications of Internet data can be divided into one of two categories, supply- or demand-based studies (Eysenbach, 2009).

Supply-based applications analyze what is being *published* on the Internet (e.g., on Twitter, Facebook, Web pages, blogs, or other social media sites) in order to track what individuals within a population are posting over time. The basic idea behind supply-based research is that monitoring published information on mediums such as Twitter for symptom-specific information will help to identify trends in the spread of infectious disease (Eysenbach, 2009). Likewise, tracking the availability, popularity, and quality of health-related information has been instrumental in the detection and spread of misinformation across vulnerable populations (Eysenbach, 2009).

Complementing supply-based studies, research on the demand side—which analyzes the information that individuals are looking for on the Internet—has been predominantly used and proven quite effective in tracking the spread of diseases such as influenza (Eysenbach, 2006; Ginsberg et al., 2009; Hulth, Rydevik, & Linde, 2009; Polgreen, Chen, Pennock, & Nelson, 2008) and listeriosis (Wilson & Brownstein, 2009). The basic theory underlying demand-based research is that tracking Internet search activity (e.g., key words related to symptoms, diseases, or treatments) should help health-care officials more quickly detect and attempt to treat/contain the spread of disease across populations. For example, researchers have demonstrated that the relative frequency of certain queries helps to "accurately estimate the current level of weekly influenza activity in each region of the United States, with a reporting lag of about one day" (Ginsberg et al., 2009).

While the incorporation of both approaches into the study of social behavior are beneficial, demand-based "infoveillance"—defined as the "automated and continuous analysis of unstructured, free text information available on the Internet" (Eysenbach, 2009)—offers distinct advantages when addressing questions related to public attention. Evidencing this point, demand-based approaches are already yielding results in other fields of research. For example, econometricians have investigated the way in which particular search trends predict economic fluctuations such as monthly unemployment rates and consumer behavior related to automotive and home sales (for research in applied econometrics, see Askitas & Zimmermann, 2009; Choi & Varian, 2009a, 2009b; D'Amuri, 2009; D'Amuri & Marcucci, 2009; Suhoy, 2009). In addition to revealing strong correlations between key word searches and unemployment/behavior, this research is the first of its kind to link Internet usage with changes in individual and social behavior. Though not directly related, this suggests the utility and appropriateness of search-based infoveillance methods for measuring trends in social behavior and more specifically, public attention.

Public Attention and Search-Based Infoveillance: Google Trends

As has been argued, the use of demand-based infoveillance is a promising direction for future research on the relationship of public attention to political issues. However, before moving forward to test this proposition, it is necessary to briefly discuss the selection and availability of data. Continuing in the tradition of recent social science research (Askitas & Zimmermann, 2009; Ginsberg et al., 2009), tracking Google search trends as an indicator of public attentiveness appears to be an appropriate starting point. In addition to building upon previous research, examining Google as opposed to trends in other search engines (such as Yahoo or Bing) is merited based on the fact that Google is currently the most widely used engine in the world.

Though estimates are sure to differ, analysts agree that Google dominates the search engine market. For example, according to Netmarketshare (2010), Google currently accounts for 85.75 percent of the global search engine market. Within the United States, Hitwise (2010) estimated that Google owns 70.17 percent of the search engine marked. As illustrated in Figure 1, the next closest competitor is Yahoo, which accounts for about 5.38 percent of global searches and 15.15 percent of search traffic within the United States.

Given these dramatic differences in popularity, using Google as a tool to track public attentiveness is certainly a reasonable place to begin. The aptness of this choice is reinforced by the ease with which data can be collected by way of *Google Trends* or

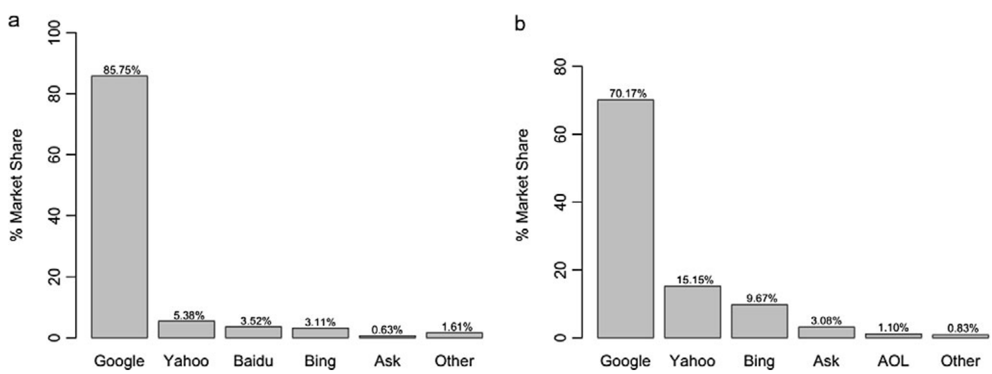

Figure 1. Internet Search Engine Market Share: (a) Global, *Source*: Netmarketshare (2010); (b) United States, *Source*: Hitwise (2010).

Google Insights for Search—both of which allow users to track how often a particular term is invoked as compared with the total number of searches done on Google across specific regions, categories, and time frames (beginning in 2004).[7] Such a tool does not exist yet for competing search engines.

When using Google Insights, users are prompted to enter up to five search terms or key words (e.g., "economy," "Iraq," "health care," "energy," "federal deficit"). After deciding upon the key words to search, users can filter by region (if searching within the United States, users can also filter by state and metropolitan area), time frame, and category. After the search terms are entered and the appropriate filter is activated, the Google service generates results that are normalized,[8] scaled,[9] and illustrated on an automatically generated line graph. To derive these results, the program analyzes a sample of Web searches to determine how many searches have been done for the terms the user has entered, relative to the total number of searches done on Google for that term over time. These estimates indicate the likelihood that a random user searches for a particular search term from a certain location at a certain time.[10] In addition to displaying the likelihood that a random user would search for that particular key word within a specified location and time, Google provides data on "Top Searches" (terms that have the highest level of interest and are related to the search term, category, or country/territory as indicated) and "Rising Searches" (which refers to searches that have experienced significant growth in a given time period with respect to the preceding time period). For example, searching the term "Nuclear Weapons" (entered on November 26, 2009) yields Top Searches such as "nuclear weapons Iran," "nuclear war," and Rising Searches of "Obama nuclear weapons," "nuclear weapons wiki," and "nuclear weapons Iran."[11] Perhaps most useful of all, the data from search queries can then be downloaded as a *comma-separated values* file for purposes of additional analysis. Demonstrating this process, the analytical portion of this article is based on separate queries for three different terms: "health care," "global warming," and "terrorism." The filter was set to estimate search volume within the United States between January 4, 2004 and November 22, 2009.

Assessing Validity: Cross-Validation and Improvement

When assessing the development of any new measure, researchers should pay careful attention to validity—the extent to which the measure accurately indicates the specific concept that the analyst is attempting to measure. Unfortunately, social scientists generally deal with measures rather than "true" concepts because the behavior of interest cannot be directly observed; as such, testing for validity can be quite challenging. For example, examining the validity of search-based infoveillance requires that we test it against the real value of public attention, which cannot be observed. As such, we are forced into indirectly assessing validity in a number of different ways, most often by way of face and construct examination.

With regard to face validity, a researcher examines the degree to which the measure looks like it is accurately reflecting what it is designed to measure. For instance, if it looks like a particular measure closely approximates a specific concept,

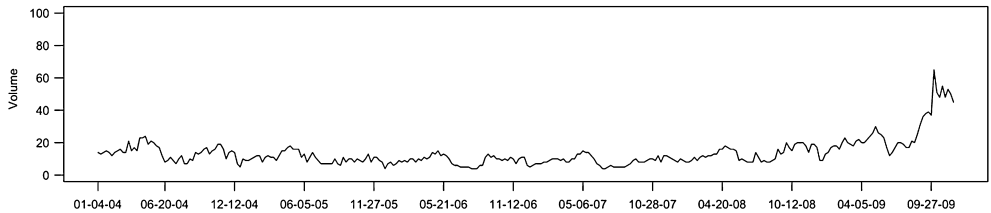

Figure 2. Google Search Trends for Afghanistan War (January 2004–November 2009).

then it may be considered to have face validity. Likewise, if logic tells you that a particular variable should act in a certain way, and the measure is behaving in a way consistent with those expectations, the measure is said to have face validity. Relating this to search-based measures of public attention, if we assume that how and when people search for information on public issues accurately reflects patterns of individual attention, then it is reasonable and appropriate to aggregate these behaviors in order to estimate public attentiveness.

Both theory and logic dictate that public attention to particular issues is ephemeral but correlated with governmental and media attention; as such, we would expect search-based measures of public attention to behave in a similar way. This is exactly what we see when measuring attention to issues such as the war in Afghanistan. As illustrated in Figure 2, the volume of "Afghanistan War" searches is relatively low but sporadic until the time frame of August 2009 through October 2009 when the number of queries nearly tripled, suggesting an intensification of public attention in response to governmental consideration of an additional surge and the media coverage of that debate.[12] Again, this pattern of attention is precisely what we would expect given a cursory knowledge of current events and citizen attentiveness. Accordingly, search-based measures of public attention appear to have achieved face validity. However, face validity is only one of a number of ways to test how accurately a new measure represents the intended concept. A more rigorous analysis involves testing convergent validity, which is the extent to which the new measure correlates or converges with theoretically similar concepts or previously specified operationalizations.

To test for convergent validity, a search-based measure of public attention and a media coverage measure were constructed and compared. Google Insights for Search was used to create a search volume index based on week-by-week data on the number of "health care," "global warming," and "terrorism" searches between January 4, 2004 and November 28, 2009 (308 weeks). Descriptive statistics for the search volume index are displayed in Table 1. Next, a media volume index was created based on the number of stories yielded from key word searches of "health care," "global warming," and "terrorism" in the *New York Times* article archive in each of the aforementioned weeks.[13] To facilitate comparison across weeks and issues, the media volume index was then scaled by dividing the number of stories in each week by the number of articles in the peak week and then multiplying by 100. Descriptive statistics for the media volume index are listed in Table 1. The test for

Table 1. Descriptive Statistics: *New York Times* Coverage of and Google Search Trends for Health Care, Global Warming, and Terrorism

	Min	Max	Mean	Standard Deviation
New York Times coverage				
Health care	17	100	36.95	13.49
Global warming	2	100	36.73	20.73
Terrorism	6	100	34.21	18.80
Google search trends				
Health care	19	100	34.83	8.56
Global warming	6	100	33.01	18.60
Terrorism	14	100	41.91	20.26

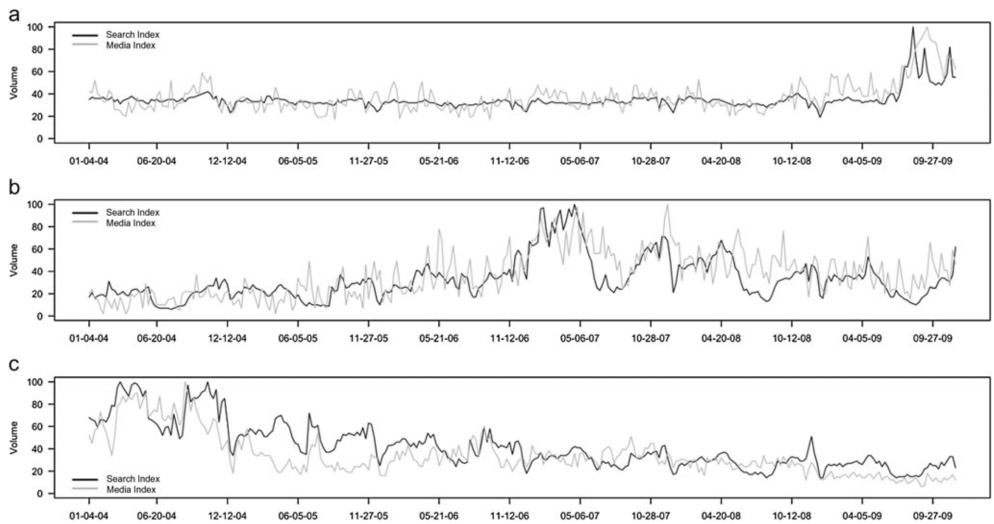

Figure 3. Time Series Plots *New York Times* Coverage to Google Search Volume: (a) Health Care; (b) Global Warming; (c) Terrorism.

convergent validity expects that these two variables will be similar to one another; theory suggests that they will be positively and significantly related.[14]

To test these propositions, three methods were used. First, as displayed in Figure 3, a time-series plot of the two indices was constructed in order to visually examine the relationship between the *New York Times* measure and the search-based measure in the three different policy areas. In all three plots, the trends clearly track one another. For instance, in Figure 3a both health care indices experienced relative dips in and around the month of December each year, and relatively large spikes around July of 2009. Likewise, in Figure 3b the indices that measure attentiveness to global warming are convergent in that they rise significantly around November of 2006 and begin to fall around May or June 2007. The same is true of the terrorism measures, which are compared in Figure 3c. For example, at the early end of the terrorism scales (around January 2004), attentiveness begins to climb; in April 2004, the attention tapers off only to rise again in August of 2004.

Though useful, ocular testing of trends are notoriously deceiving. As such, two forms of statistical analysis were used to test for convergent validity. First, pairwise correlation analysis revealed statistically significant ($p < 0.001$) Pearson correlation coefficients, between each of the three comparisons. The correlation coefficients were 0.71, 0.69, and 0.76 for the health care, global warming, and terrorism indices (respectively). Each of these relationships is strongly positive and statistically significant, suggesting that the search-based measure of public attention corresponds rather well with the media-based measure that previous scholars have relied upon.

Though visual inspection and Pearson correlation analysis go a long way in demonstrating convergent validity, a more advanced and nuanced statistical procedure is necessary in order to provide additional information about the relationship between the two measures of public attentiveness. Accordingly, a series of vector autoregressive (VAR) models was constructed.[15] This modeling strategy—which follows Wood and Peake (1998), Soroka (2002), Green-Pedersen and Stubager (2010), and many others—is often applied when multiple time series variables are thought to affect one another in a theoretically imprecise way.[16]

In short form, VAR models are estimated by running a series of simultaneous or seemingly unrelated (SUR) ordinary least squares (OLS) regressions, where each of the endogenous variables is the dependent variable in one equation, with lags of itself and the other endogenous variables as the predictor variables. Because the set of equations is estimated simultaneously, the bias that would have been introduced if the regressions were run independently is removed. For the question at hand, equations (1) and (2) represent the relationship between search trends and media coverage:

$$m_t = \beta m_0 + \beta_1 m_{t-1} + \ldots + \beta_n m_{t-p} + \beta_n s_{t-1} + \ldots + \beta_n s_{t-p} + \varepsilon \tag{1}$$

$$s_t = \beta s_0 + \beta_1 s_{t-1} + \ldots + \beta_n s_{t-p} + \beta_n m_{t-1} + \ldots + \beta_n m_{t-p} + \varepsilon \tag{2}$$

where m_t is the number of *New York Times* articles that mention the key word (“health care,” “global warming,” or “terrorism”) during week t, s_t is the number of Google searches for that key word in week t, and p is the model-specific lag order. To determine the appropriate lag length for the three systems of equations being estimated, several models were constructed and compared according to final prediction error and Akaike’s information criterion. In all three models, the two tests converged on lag orders of 5, 7, and 3, for the health care, global warming, and terrorism models (respectively).

Having determined the appropriate lags, the three models were estimated. The sums of the lagged coefficients for each model are listed in Table 2. Note that the partial regression coefficients in each model exist only in relation to the simultaneous system that was mentioned earlier. Accordingly, the analytical import from this table is the direction of the relationship rather than statistical significance. As expected by the test for convergent validity, the VAR models suggest a positive relationship between the search index and the media index in all of the policy areas. Moving on to inference, hypothesis testing in VAR models is not based on conventional methods

Table 2. Vector Autoregressive (VAR) Estimates Comparing *New York Times* Coverage of Health Care, Global Warming, and Terrorism to Google Search Trends

Dependent Variable	Coefficient Block	Sum of Coefficients		
		Health Care	Global Warming	Terrorism
Media index	Media index	0.647	0.711	0.919
	Search index	0.516	0.263	0.030
	Constant	–4.792	2.238	1.343
	Adjusted R^2	0.697	0.630	0.855
Search index	Search index	0.774	0.884	0.893
	Media index	0.088	0.058	0.074
	Constant	4.695	1.887	1.799
	Adjusted R^2	0.742	0.871	0.891

Note: The health care VAR contains five lags, the global warming VAR contains seven lags, and the terrorism VAR contains three lags (weeks). There were 308 weekly observations.

Table 3. Granger Tests Comparing *New York Times* Coverage of Health Care, Global Warming, and Terrorism with Google Search Trends

Dependent Variable	Coefficient Block	Health Care		Global Warming		Terrorism	
		F-Statistic	p Value	F-Statistic	p Value	F-Statistic	p Value
Media index	Search index	*8.611*	*<0.001*	*3.991*	*<0.001*	*3.545*	*0.015*
Search index	Media index	1.665	0.143	*4.121*	*<0.001*	*4.518*	*0.004*

Note: The Health Care vector autoregressive (VAR) contains five lags, the Global Warming VAR contains seven lags, and the Terrorism VAR contains three lags (weeks). There were 308 weekly observations. Statistically significant F-tests ($p > 0.05$) are listed in italics.

such as statistical significance, the magnitude of individual coefficients, or the overall fit of the model. Rather, the relationships between the variables within a system are analyzed by assessing the joint statistical significance of the coefficients on single variables or on blocks of endogenous variables (Freeman, Williams, & Lin, 1989). Granger causality tests, which rely on a series of nested F-tests, are specifically designed for this purpose. Given two trends, say x and y, they enable a researcher to determine if x "Granger causes" y, if y "Granger causes" x, or if both trends change simultaneously. Table 3 reports Granger tests that compare the search index with the media index for each of the three policy models.[17]

As indicated by the multiple italic values in Table 3, the media-based measure of public attention is indeed closely related to the search-based measure in the three issue areas. Across the range of issues, the search index Granger causes the media index. In others words, the block of search coefficients (which includes the coefficient at time t plus the coefficients' p lags) significantly improves upon our ability to explain or forecast *New York Times* coverage. Turning now to the dependent variable, we see that the media-based trend Granger causes the search index in the global warming and terrorism models, and nearly causes the search trend in the health care model.[18] Both specifications suggest that media-based measure of public attention is intimately related to the search-based measure in the three different issue areas.

In short, the Granger tests provide additional evidence that the media and search-based measures track or "converge upon" one another. Thus, vector autoregression, correlation analysis, and visual inspection all suggest that the aforementioned propositions were correct. The search volume measure and the media coverage measure are indeed similar to one another. As theory maintains, the two are positively and significantly associated. In all, the two measures do converge, which furthers confidence in the search-based measure of public attention. This finding backed by theory, logic, face validity, and the ease and flexibility with which this search data can be gathered suggests that future research should incorporate this measure of public attention into empirical models about how the political world works.

Caveat Emptor: Potential Problems Associated with the Search-Based Measure

Before moving on to discuss the implications of this article and directions for future research, it is necessary to briefly consider a caveat and a few limitations associated with using search-based infoveillance as a measure of public attentiveness. First, though this article focuses exclusively on Google, researchers should remember that *Google Insights* is merely a tool that provides data about relatively recent Internet search trends. In the future, it is likely that another search engine or tool will emerge that will make data collection more comprehensive and representative. If and when this happens, search-based infoveillance as method of measuring public attentiveness is expected to remain valid even if Google ceases to exist. In other words, it is necessary to remember that individual search behavior is the primary unit of analysis, not Google Search trends *per se*.

Second, as with the case of media-based measures, one must be highly systematic in determining which key words to use as indicators of public attention. For example, when looking for information about health-care policy, it is unlikely that a single key word will capture all or even most of the Internet search activity. Rather, there are a wide variety of words or phrases that people might search. For example, some might type in "health care reform," whereas others might type in "socialized medicine," "death panels," or even "public option." Though not insurmountable, deciding upon proper key words from which to create an attentiveness index is an obstacle that researchers will have to carefully consider. As with all scholarly endeavors, researchers using these tactics will have to be highly transparent about what they have done—including the exact words or phrases used to create measures as well as when the data was collected.

A third limitation associated with search-based measures is simply the fact that we do not know why a person is looking into a particular issue. Is it because they have a particular interest in that issue? Is it because they are researching it for a school project? Or is it because they are worried about or unhappy with the current state of affairs? In a more basic sense, in contrast to the media-based measurement—where it is possible to code whether or not an article is eliciting positive or negative public attention—we are unable to assess the direction (good or bad) in which the population is leaning. Perhaps this limitation could be rectified if researchers were able to distill and code a list of key words that suggest a particular connotation. Sticking with the health-care example, are people searching for negative terms such as "socialized medicine" and "death panels" or positive terms such as "health care reform" or "universal health care?"

An additional caveat that is necessary to understand before wholesale acceptance of the search-based measure is one of reliability. To estimate the volume of particular search terms, Google makes use of an algorithm derived to indicate the likelihood that a random user would query a particular search term from a certain location at a certain time.[19] Fortunately, they provide the user with the uncertainty (standard error) associated with this likelihood. Unfortunately, though their Web site has a lot of useful information about their product, they do not publish the algorithm they use nor do they reveal the threshold that they use to determine whether or not to collect data on a particular term. For example, it would be acceptable but less than ideal to say that a key word such as "nuclear abolition" fell below *x* number of searchers and was therefore not recorded; without knowing what that cutoff point is we get no sense of how popular a relatively "rare" key word is. Does rare mean less than 1,000,000, less than 1,000, or less than 100? In terms of assessing public attention, this information would be quite helpful.

A potentially more serious drawback associated with the search-based measure of public attention is the fact that the data only go back to January 2004. This is particularly problematic given that many of the theories related to public attention and the political system revolve around longer term changes in the policy process or cyclical patterns of attentiveness that recycle or repeat over lengthy periods of time. In this regard, five to six years worth of data is useful but limits our ability to study and draw inferential conclusions about the relationship between long-term change in the political system and public attention. As such, if one is interested in answering macro sorts of questions, using media coverage as a proxy for public attention may be the only option.

The most immediate problem that must be addressed when using search-based infoveillance as an indicator of public attention is that of representativeness. In particular, two questions must be addressed in order to ensure that the search measure is not systematically biased in favor of a particular group in society. First, it is commonly understood that access to the Internet is not equally distributed across the population. Likewise, among those with access to the Internet, it cannot be assumed that all groups within the population are equally as likely to use Google as their preferred search engine. In response to the first concern, the results of a Pew Research survey on Internet usage are listed in Table 4.

As indicated, 77 percent of all adults (18+) are considered Internet users. In terms of overrepresentation, it is no surprise that young, white, highly educated, wealthy people are the most likely to use the Internet. By contrast, we should be concerned that minorities, the elderly, the relatively poor, and uneducated are systematically underrepresented in the search-based measure, suggesting a potentially biased sample. Also, we should keep in mind that the survey results presented in Table 4 do not account for the number of children using the Internet—which is potentially a large part of the Google search sample. In response to the second concern, researchers have yet to conduct a survey capable of determining proportions of the population most likely to use Google as their preferred search engine. Until questions

Table 4. Demographics of Internet Users

	Use of the Internet (%)
Total adults	(77)
Men	78
Women	76
Race/ethnicity	
White, Non-Hispanic	(80)
Black, Non-Hispanic	72
Hispanic (English-speaking)	61
Age	
18–29	(93)
30–49	83
50–64	77
65+	43
Household income	
Less than $30,000/year	(62)
$30,000–$49,000	83
$50,000–$74,000	93
$75,000+	95
Educational attainment	
Less than high school	(37)
High school	72
Some college	87
College+	94
Community type	
Urban	(73)
Suburban	75
Rural	71

Note: This is a modified version of a table presented by the Pew Research Center based on a September 2009 survey. $N = 2{,}353$; margin of error is $\pm 2\%$. Available at: http://www.pewinternet.org/Static-Pages/Trend-Data/Whos-Online.aspx.

related to sample bias are resolved, analysts using Google to construct their search-based measures of public attention should approach inference and generalization with caution.

Conclusions and Directions for Future Research

Public attention, defined as the scarce resources (time and other) that citizens willingly dedicate toward thinking about a publicly debated issue, is an essential but sometimes overlooked variable when trying to understand the relationship between citizens and their government in a democratic system. As Jones (1994) noted, "democratic governments are more responsive to changes in attentiveness to problems than they are to the particular distribution of opinion on a problem" (p. 125). Noting this importance, political scientists have made great progress in theoretically explaining and empirically measuring public attention. However, because of data limitations, current measures have become increasingly divorced from our theories about how public attention "cycles" in modern society. In particular, our theories explicitly assume and/or argue that issue attention is dynamic, episodic, and ephemeral; by contrast, the measures we often employ, such as MIP surveys, lack the precision and regularity necessary to abide by this assumption. Likewise, measuring shifts in media coverage may provide a useful proxy for public attention, but conflating these two variables limits our ability to test important hypotheses concerning the relationship between citizen attentiveness and mass communications. This research draws upon these weaknesses to propose a more dynamic and theoretically meaningful indicator of public attention—separate from media coverage—based on trends in Internet search activity.

In doing so, I explained the measure, how it can be employed, and then tested face and convergent validity in a number of ways. Related to face validity, visually inspecting search trends for key words such as "Afghanistan War" comports with logic and our theoretical expectations about when attentiveness should go up and when it should fall. Likewise, I tested for convergent validity by way of comparing media (*New York Times*) coverage of "health care," "global warming," and "terrorism" with the number searches for these three phrases between January 2004 and November 2009. In accord with my expectations, the time-series graph, correlation analysis, and vector autoregression all suggest that the two measures are highly related, demonstrating that the search-based measure converges upon but does not replicate the previously used media coverage measure. However, as with all measures, face and convergent validity are not sufficient for establishing construct validity. Moreover, as social scientists well know, a measurement is only useful to the extent that it explains what it purports to explain within a model designed to simplify a complex social and political reality. As such, there remain a number of promising avenues for future research.

One such direction for future research involves using this measure to further develop and test a number of current and undeveloped theories related to public attention and political systems. In particular, researchers should start by reexamining the recursive relationship between public attention and media coverage. Does media coverage generally lead or follow public attention? The results of my statistical analysis suggest that public attentiveness to some variables (such as health care) might precede media coverage, whereas attentiveness to other issues (such as terrorism or global warming) appears to parallel or even lag media coverage. A systematic comparison of issues coupled with better specified models promises to go a long way in sorting out the messy relationship between media and public attentiveness.

Moving on to theories of agenda setting, a second puzzle that this measure will help to analyze is that of issue attention cycles; do issues "suddenly leap into prominence, remain there for a short time, and then—though still largely unresolved—gradually fade from the center of public attention" as Downs (1972) has suggested? Is public attention really zero-sum as Zhu (1992) suggested? In other words, do issues compete in an attention forum where the rise of one issue necessitates the fall of another issue? Continuing with questions related to agenda setting, Cobb and Elder (1971) suggested that there are two different types of agendas, the systemic and the institutional. Broadly speaking, public attention characterizes the systemic agenda. Using the search-based measure as an outcome variable, future research projects should start to explain when and why some issues become important to the public whereas others do not. Likewise, as Jones and Baumgartner (2005) argued, large-scale changes within the systemic agenda can push issues onto the institutional agenda, sometimes disrupting policy monopolies and ultimately causing punctuated policy change. In order to investigate this phenomenon, students could use the search-based measure of public attention to predict changes in the institutional agenda, such as the number of congressional hearings, court cases, or content of a political leader's public addresses.

Proceeding beyond agenda setting, search-based measures of public attention, which can be broken down by city and state, will be useful to state policy and diffusion scholars looking to improve the theoretical connection between the adoption, innovation, or reinvention of a particular policy in one state that is thought to be driven by the political pressure created by a neighboring state's policy (Berry & Berry, 1990; Glick & Hays, 1991; Lamothe, 2005; Walker, 1969). Does the number of searches (attention) rise in a particular state when a neighboring state adopts a new policy? For example, does public attention to a particular policy in Oklahoma become intensified after Texas adopts or reinvents that particular policy?

Related to democratic theory more broadly, scholars "often gauge the quality of democratic government by the responsiveness of public policymakers to the preferences of the mass public" (Erikson, Wright, & McIver, 1993, p. 1). In this regard, the quality of democracy in a given polity is directly related to the influence of public opinion on public policy. Though research has made great progress in detailing the subtleties of this relationship, much work remains. In particular, though scholars have reached a virtual consensus regarding the interactive relationship between issue salience and the impact of public opinion, the noted theoretical significance of salience has not led to a comparable level of importance in academic research (Burstein, 2003). Assessing public attentiveness by way of search trends provides instant access to massive amounts of information, all of which can be used to create broad and flexible measures of issue salience. Accordingly, this measure will assist public opinion scholars in their attempts to link political preferences and beliefs with policy outcomes. Is public opinion more influential when the public is highly attentive?

Moving outside of the public policy domain to American politics and voting behavior, the new measure will help to answer a number of interesting questions. At the most basic level, how well do Google search trends predict electoral outcomes? If public attention to a particular issue is extraordinarily intense, might this suggest that turnout in that geographic region would be higher? Moreover, if a particular candidate's name or campaign rhetoric is being searched more than his or her opponent, might this increase his or her chances of winning an election? Lastly, in terms of campaign strategy, consultants and researchers can use search trends and attention as a way to gauge the public's interest in a particular message. For instance, does a week of targeted campaign advertisement within a particular region increase the search activity associated with that rhetoric or slogan?

All and all, this article is just the tip of the iceberg. Public attentiveness to political issues is an important topic that researchers have wrestled with for decades. My hope is that search-based infoveillance—in tandem with the continued use of MIP polls and media coverage—will serve as a tool that will help political scientists in the unending quest to develop, systematically test, and refine theories related to individuals and their political systems. While there are certainly limitations and challenges associated with the purposed measure, I submit that the potential gains realized by seriously considering this new and innovative way to capture the public's political curiosity make it a worthy scholarly endeavor.

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Notes

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1. Defined in this way, public attention often mirrors the conceptually encompassing idea of *salience*. Generally speaking, the public can be expected to pay attention to issues of high importance. For more on issue salience and mass politics, see Burstein (1995, 2003).
2. Historically, there is some debate within the literature on the stability and coherence of public opinion. *Traditionalists*, mirroring the work of Lippmann (1922), Converse (1964), and Zaller (1992), are generally skeptical of the cognitive capacities of the general public, arguing that the public opinion is volatile and lacks a coherent structure. By contrast, *revisionists*, such as Page and Shapiro (1992), Sniderman, Brody, and Tetlock (1991), and Herron and Jenkins-Smith (2006), argue that the public is capable of formulating coherent beliefs that are organized according to rational heuristics and are therefore relatively stable and responsive to political phenomena.
3. Gallup's Most Important Problem Survey is the most commonly used survey in the United States. For more on this measure, refer to Wlezien (2005), Smith (1980, 1985). For examples of how this measure has been used, please reference Jones and Baumgartner (2005), McCombs and Zhu (1995), and Peters and Hogwood (1985). Many other countries also employ a similar measure of public attention; for example, see Sheafer and Weimann (2005).
4. For excellent reviews of this controversy, see Dearing and Rogers (1996), Soroka (2002), and McCombs (2004).
5. There remains some debate concerning the most appropriate outlet from which coverage should be tracked. For the most part, because of a high correlation with other measures and theoretically based arguments about who sets the media agenda, most scholars simply use the *New York Times* to construct their measures. For example, please see Baumgartner and Jones (1993), Epstein and Segal (2000), and Newig (2004). However, increasingly popular measures include the number of minutes devoted to each issue on television news programs, which can be accessed by way of searching the *Vanderbilt Television News Abstracts*. For instance, see Iyengar, Peters, and Kinder (1982), Wood and Peake (1998), and Boykoff (2008).
6. Infodemiology appears to have gone "mainstream" with a recent publication on Google Flutrends in *Nature* (Ginsberg et al., 2009). However, research of this variety can be traced back to Eysenbach (2002, 2003), and Eysenbach and Kohler (2002). Likewise, other recent studies have pushed the field forward. For instance, see Cooper, Mallon, Leadbetter, Pollack, and Peipins (2005); Polgreen et al. (2008); Brownstein, Freifeld, and Madoff (2009); Hulth et al. (2009); and Wilson and Brownstein (2009).
7. Google Trends (http://www.google.com/trends) and Google Insights (http://www.google.com/insights/search/) use the same data, but Insights provides users with more advanced features. As such, the remainder of the discussion will focus on Google Insights.
8. Results from Google Insights for Search are *normalized* (or weighted) according to regional populations. Doing so enables users to meaningfully compare trends in search popularity across geographic regions (i.e., city, state, or country). If the data were not normalized, regions with a higher population

would show a higher search volume simply because there are more people and therefore more searchers. For the purposes of this article, which does not compare trends across regions, the practice of normalization is irrelevant. However, if one is interested in learning more about how and why Google does this, refer to its help page: http://www.google.com/support/insights/bin/bin/answer.py?answer=87284&topic=13975.

9. Results from Google Insights for Search are placed on a scale from 0 to 100 by dividing the total search volume at each point in time by the highest value within that same time frame (http://www.google.com/support/insights/bin/answer.py?hl=en&answer=87282).
10. Note that the numbers provided by Google are not estimates of absolute search volume. Instead, the data is scaled (from 0–100) to the average search traffic for the key word during a given time period. For example, if the term "global warming" is entered, the estimated search volume will be scaled to the average of all search traffic for "global warming" in the given time frame. Researchers interested in using Google Insights for search should keep this in mind when interpreting its results. For more on this, refer to: http://www.google.com/support/insights/bin/answer.py?hl=en&answer=92768.
11. More information on Top Searches and Rising Searches can be obtained at http://www.google.com/support/insights//bin/answer.py?hl=en-US&answer=99742 and http://www.google.com/support/insights//bin/answer.py?hl=en-US&answer=94793, respectively.
12. In September of 2009, a controversial report was released to the public by General Stanley McChrystal calling for thirty thousand to forty thousand more troops in Afghanistan; this report, which was highly covered in the media, prompted a public debate about the future of the war.
13. *New York Times*—as opposed to an alternative media indicator—was used for two reasons. First, the *New York Times* habitually functions as an agenda setter for other media outlets, including television and the Internet (see McCombs, 2005). Accordingly, trends in *New York Times* coverage are likely to parallel trends in other sources. Second, this is the most common practice in previous research on public attention (see especially Baumgartner & Jones, 1993 and Jones & Baumgartner, 2005).
14. For more information about measurement and validity in the social sciences, see Adcock and Collier (2001). For a sample of previous research in political science that relies upon statistical methods to test for construct validity, refer to Berry, Ringquist, Fording, and Hanson (1998); Brace, Langer, and Hall (2000); Alvarez, Cheibub, Limongi, and Przeworski (1996); Baumgartner and Walker (1990); Bollen (1980); Cheibub, Przeworski, Limongi, and Alvarez (1996); and Hill, Hanna, and Shafqat (1997).
15. Technically, the two measures of public attentiveness are count variables, but as Greene (2002), Sprecher and DeRouen (2005), and Reuvent and Thompson (2002) noted, count models with a large variance approximate traditional linear models that comprise VAR equations. To verify linear approximation, simple linear estimates were compared with Poisson models. Although there the standard errors associated with the partial regression coefficients were slightly different, the magnitude, significance, and direction of relationships remained consistent across specifications.
16. For more on vector autoregression, see Brandt and Williams (2006), Freeman et al. (1989), or Sims (1980).
17. In general, Granger causality assumes that the variables being compared are stationary and/or cointegrated. In terms of this research, Phillips–Ouliaris tests confirm that the search and media trends are cointegrated. Given the high correlations that are noted earlier, this should come as no surprise. For more on this, see Lütkepohl (2005).
18. In that the purpose of this analysis was to compare a media-based measure of public attention to the search-based measure, Granger causality is the appropriate test. If one wishes to supplement this analysis by way of forecasting, simulated impulse response and moving average analysis is suggested in addition to an analysis of the decomposed forecast error variance.
19. To read more about how Google derives search data, refer to http://www.google.com/support/insights/bin/answer.py?hl=en&answer=92768.

References

Adcock, Robert, and David Collier. 2001. "Measurement Validity: A Shared Standard for Qualitative and Quantitative Research." *American Political Science Review* 95: 529–46.

Alvarez, Mike, José Cheibub, Fernando Limongi, and Adam Przeworski. 1996. "Classifying Political Regimes." *Studies in Comparative International Development* 31: 3–36.

Askitas, Nikolaos, and Klaus Zimmermann. 2009. "Google Econometrics and Unemployment Forecasting." *Applied Economics Quarterly* 55: 107–20.

Baumgartner, Frank R., and Bryan D. Jones. 1993. *Agendas and Instability in American Politics*. Chicago: University Of Chicago Press.

Baumgartner, Frank R., and Jack L. Walker. 1990. "Response to Smith's 'Trends in Voluntary Group Membership: Comments on Baumgartner and Walker': Measurement Validity and the Continuity of Results in Survey Research." *American Journal of Political Science* 34: 662–70.

Berry, Frances Stokes, and William D. Berry. 1990. "State Lottery Adoptions as Policy Innovations: An Event History Analysis." *American Political Science Review* 84: 395–415.

Berry, William D., Evan J. Ringquist, Richard C. Fording, and Russell L. Hanson. 1998. "Measuring Citizen and Government Ideology in the American States, 1960–93." *American Journal of Political Science* 42: 327–48.

Bollen, Kenneth A. 1980. "Issues in the Comparative Measurement of Political Democracy." *American Sociological Review* 45: 370–90.

Boykoff, Maxwell. 2008. "Lost in Translation? United States Television News Coverage of Anthropogenic Climate Change, 1995–2004." *Climatic Change* 86: 1–11.

Brace, Paul, Laura Langer, and Melinda Gann Hall. 2000. "Measuring the Preferences of State Supreme Court Judges." *Journal of Politics* 62: 387–413.

Brandt, Patrick T., and John Taylor Williams. 2006. *Multiple Time Series Models*. Thousand Oaks, CA: Sage Publications.

Brownstein, John, Clark Freifeld, and Lawrence Madoff. 2009. "Digital Disease Detection—Harnessing the Web for Public Health Surveillance." *New England Journal of Medicine* 360: 2153–37.

Burstein, Paul. 1995. "Directing Electoral Appeals Away from the Center: Issue Position and Issue Salience." *Political Research Quarterly* 48: 479–505.

———. 2003. "The Impact of Public Opinion on Public Policy: A Review and an Agenda." *Political Research Quarterly* 56: 29–40.

Cheibub, José, Adam Przeworski, Fernando Limongi, and Mike Alvarez. 1996. "What Makes Democracies Endure?" *Journal of Democracy* 7: 39–55.

Choi, Hyunyoung, and Hal Varian. 2009a. *Predicting the Present with Google Trends* [Online]. http://www.google.com/googleblogs/pdfs/google_predicting_the_present. Accessed October 2, 2010.

———. 2009b. *Predicting Initial Claims for Unemployment Benefits* [Online]. http://research.google.com/archive/papers/initialclaimsUS.pdf. Accessed October 2, 2010.

Cobb, Roger W., and Charles D. Elder. 1971. "The Politics of Agenda-Building: An Alternative Perspective for Modern Democratic Theory." *Journal of Politics* 33: 892–915.

Converse, Phillip E. 1964. "The Nature of Belief Systems in Mass Publics." In *Ideology and Discontent*, ed. David E. Apter. New York: Free Press, 206–61.

Cooper, Crystale Purvis, Kenneth P. Mallon, Steven Leadbetter, Lori A. Pollack, and Lucy A. Peipins. 2005. "Cancer Internet Search Activity on a Major Search Engine, United States 2001–2003." *Journal of Medical Internet Research* 7: e36.

D'Amuri, Francesco. 2009. *Predicting Unemployment in Short Samples with Internet Job Search Query Data* [Online]. http://ideas.repec.org/p/pra/mprapa/18403.html. Accessed November 2, 2010.

D'Amuri, Francesco, and Juri Marcucci. 2009. *"Google It!" Forecasting the US Unemployment Rate with a Google Job Search Index* [Online]. http://ideas.repec.org/p/pra/mprapa/18248.html. Accessed November 2, 2010.

Dearing, James W., and Everett M. Rogers. 1996. *Agenda-Setting*. Thousand Oaks, CA: Sage Publications.

Downs, Anthony. 1972. "Up and Down with Ecology: The Issue Attention Cycle." *Public Interest* 28: 38–50.

Epstein, Lee, and Jeffrey A. Segal. 2000. "Measuring Issue Salience." *American Journal of Political Science* 44: 66–83.

Erikson, Robert S., Gerald C. Wright, and John P. McIver. 1993. *Statehouse Democracy: Public Opinion and Policy in the American States*. New York: Cambridge University Press.

Eysenbach, Gunther. 2002. "Infodemiology: The Epidemiology of (Mis) Information." *American Journal of Medicine* 113: 763–35.

———. 2003. "SARS and Population Health Technology." *Journal of Medical Internet Research* 5: e14.

———. 2006. "Infodemiology: Tracking Flu-Related Searches on the Web for Syndromic Surveillance." *AMIA Annual Symposium Proceedings* 2006: 244–48.

———. 2009. "Infodemiology and Infoveillance: Framework for an Emerging Set of Public Health Informatics Methods to Analyze Search, Communication and Publication Behavior on the Internet." *Journal of Medical Internet Research* 11: e11.

Eysenbach, Gunther, and Christian Kohler. 2002. "How Do Consumers Search for and Appraise Health Information on the World Wide Web? Qualitative Study Using Focus Groups, Usability Tests, and In-Depth Interviews." *BMJ* 324: 573–7.

Freeman, John R., John T. Williams, and Tse-Min Lin. 1989. "Vector Autoregression and the Study of Politics." *American Journal of Political Science* 33: 842–77.

Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant. 2009. "Detecting Influenza Epidemics Using Search Engine Query Data." *Nature* 457: 1012–14.

Glick, Henry R., and Scott P. Hays. 1991. "Innovation and Reinvention in State Policymaking: Theory and the Evolution of Living Will Laws." *Journal of Politics* 53: 835–50.

Greene, William H. 2002. *Econometric Analysis*. Princeton, NJ: Prentice Hall.

Green-Pedersen, Christoffer, and Rune Stubager. 2010. "The Political Conditionality of Mass Media Influence: When Do Parties Follow Mass Media Attention?" *British Journal of Political Science* 40: 663–77.

Henry, Gary, and Craig Gordon. 2001. "Tracking Issue Attention: Specifying the Dynamics of the Public Agenda." *Public Opinion Quarterly* 65: 157–77.

Herron, Kerry G., and Hank C. Jenkins-Smith. 2006. *Critical Masses and Critical Choices: Evolving Public Opinion on Nuclear Weapons, Terrorism, and Security*. Pittsburg, PA: University of Pittsburgh Press.

Hill, Kim Quaile, Stephen Hanna, and Sahar Shafqat. 1997. "The Liberal–Conservative Ideology of U.S. Senators: A New Measure." *American Journal of Political Science* 41: 1395–413.

Hitwise. 2010. *Top 20 Sites & Engines* [Online]. http://www.hitwise.com/us/datacenter/main/dashboard-10133.html. Accessed April 18, 2010.

Hulth, Anette, Gustaf Rydevik, and Annika Linde. 2009. "Web Queries as a Source for Syndromic Surveillance." *PLoS ONE* 4: e4378.

Iyengar, Shanto, Mark D. Peters, and Donald R. Kinder. 1982. "Experimental Demonstrations of the 'Not-So-Minimal' Consequences of Television News Programs." *American Political Science Review* 76: 848–58.

Jones, Bryan D. 1994. *Reconceiving Decision-Making in Democratic Politics: Attention, Choice, and Public Policy*. Chicago: University Of Chicago Press.

Jones, Bryan D., and Frank R. Baumgartner. 2005. *The Politics of Attention: How Government Prioritizes Problems*. Chicago: University Of Chicago Press.

Lamothe, Scott. 2005. "State Policy Adoption and Content: A Study of Drug Testing in the Workplace Legislation." *State and Local Government Review* 37: 25–39.

Lippmann, Walter. 1922. *Public Opinion*. New Brunswick, NJ: Macmillan Company.

Lütkepohl, Helmut. 2005. *New Introduction to Multiple Time Series Analysis*. New York: Springer.

McCombs, Maxwell. 2004. *Setting the Agenda: The Mass Media and Public Opinion*. Cambridge: Polity Press.

———. 2005. "The Agenda-Setting Function of the Press." In *The Institutions of American Democracy: The Press*, ed. Geneva Overholser, and Kathleen Hall Jamieson. New York: Oxford University Press, USA, 156–68.

McCombs, Maxwell, and Jian-Hua Zhu. 1995. "Capacity, Diversity, and Volatility of the Public Agenda." *Public Opinion Quarterly* 59: 495–525.

Netmarketshare. 2010. *Search Engine Market Share* [Online]. http://marketshare.hitslink.com/search-engine-market-share.aspx?qprid=4. Accessed April 18, 2010.

Newig, Jens. 2004. "Public Attention, Political Action: The Example of Environmental Regulation." *Rationality and Society* 16: 149–90.

Page, Benjamin I., and Robert Y. Shapiro. 1992. *The Rational Public: Fifty Years of Trends in Americans' Policy Preferences*. Chicago: University Of Chicago Press.

Peters, B. Guy, and Brian W. Hogwood. 1985. "In Search of the Issue-Attention Cycle." *Journal of Politics* 47: 238–53.

Polgreen, Philip M., Yiling Chen, David M. Pennock, and Forrest D. Nelson. 2008. "Using Internet Searches for Influenza Surveillance." *Clinical Infectious Diseases* 47: 1443–8.

Reuvent, Rafael, and William Thompson. 2002. "World Economic Growth, Northern Antagonism, and North–South Conflict." *Journal of Conflict Resolution* 46: 484–514.

Sheafer, Tamir, and Gabriel Weimann. 2005. "Agenda Building, Agenda Setting, Priming, Individual Voting Intentions, and the Aggregate Results: An Analysis of Four Israeli Elections." *Journal of Communication* 55: 347–65.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica* 48: 1–48.

Smith, Tom W. 1980. "America's Most Important Problem—A Trend Analysis, 1946–1976." *Public Opinion Quarterly* 44: 164–80.

———. 1985. "The Polls: America's Most Important Problems Part I: National and International." *Public Opinion Quarterly* 49: 264–74.

Sniderman, Paul M., Richard A. Brody, and Phillip E. Tetlock. 1991. *Reasoning and Choice: Explorations in Political Psychology*. New York: Cambridge University Press.

Soroka, Stuart N. 2002. "Issue Attributes and Agenda-Setting by Media, the Public, and Policymakers in Canada." *International Journal of Public Opinion Research* 14: 264–85.

Sprecher, Christopher, and Karl DeRouen Jr. 2005. "The Domestic Determinants of Foreign Policy Behavior in Middle Eastern Enduring Rivals." *Foreign Policy Analysis* 1: 121–41.

Suhoy, Tanya. 2009. *Query Indices and a 2008 Downturn: Israeli Data* [Online]. http://www.bankisrael.gov.il/deptdata/mehkar/papers/dp0906e.htm. Accessed September 2, 2010.

Walker, Jack L. 1969. "The Diffusion of Innovations among the American States." *American Political Science Review* 63: 880–99.

Wilson, Kumanan, and John S. Brownstein. 2009. "Early Detection of Disease Outbreaks Using the Internet." *Canadian Medical Association Journal* 180: 829–31.

Wlezien, Christopher. 2005. "On the Salience of Political Issues: The Problem with 'Most Important Problem'." *Electoral Studies* 24: 555–79.

Wood, B. Dan, and Jeffrey S. Peake. 1998. "The Dynamics of Foreign Policy Agenda Setting." *American Political Science Review* 92: 173–84.

Zaller, John R. 1992. *The Nature and Origins of Mass Opinion*. New York: Cambridge University Press.

Zhu, Jian-Hua. 1992. "Issue Competition and Attention Distraction: A Zero-Sum Theory of Agenda-Setting." *Journalism Quarterly* 69: 825–36.