Article

Communication Research
2018, Vol. 45(7) 1078–1098

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/0093650217725870
journals.sagepub.com/home/crx
SAGE

Negativity and Positivity Biases in Economic News Coverage: Traditional Versus Social Media

Stuart Soroka[1], Mark Daku[2], Dan Hiaeshutter-Rice[1], Lauren Guggenheim[1], and Josh Pasek[1]

Abstract
Past work suggests that the priorities for information propagation in social media may be markedly different from the priorities for news selection in traditional media outlets. We explore this possibility here, focusing on the tone of both newspaper and Twitter content following changes in the U.S. unemployment rate, from 2008 to 2014. Results strongly support the expectation that while the tone of newspaper content exhibits stronger reactions to negative information, the tone of Twitter content reacts more strongly to positive economic shifts.

Keywords
economic news, newspaper content, social media, Twitter, negativity bias

A growing body of work identifies systematic biases in economic news coverage. For instance, recent work suggests that U.S. media have a tendency to focus on changes in, rather than levels of, economic indicators (Soroka, Stecula, & Wlezien, 2015). Economic news coverage also intensifies when the economy is bad (e.g., Doms & Morin, 2004; Lamla & Lein, 2014; Shah, Watts, Domke, Fan, & Fibison, 1999). This reflects a more general tendency for media to focus on "problems" that extend well beyond the economic domain (see, e.g., Altheide, 1997; Bennett, 1997). Related to this is the tendency for media coverage to highlight negative rather than positive information (e.g., Fridkin

[1]University of Michigan, Ann Arbor, USA
[2]Texas Christian University, Fort Worth, USA

Corresponding Author:
Stuart Soroka, Department of Communication Studies, University of Michigan, 5370 North Quad, 105 South State Street, Ann Arbor, MI 48109-1285, USA.
Email: ssoroka@umich.edu

& Kenney, 2004; Niven, 2000; Soroka, 2014). These biases are of real significance, not just because of what they can tell us about the nature of news selection and newsmaking, but because news content can alter economic perceptions and behavior (e.g., Blood & Phillips, 1995, 1997; Boomgaarden, Van Spanje, Vliegenthart, & De Vreese, 2011; Carroll, 2003; De Boef & Kellstedt, 2004; Glynn, Huge, & Hoffman, 2008; Goidel, Procopio, Terrell, & Wu, 2010; Hollanders & Vliegenthart, 2011). In short, economic news coverage can be systematically different from economic reality, and those differences can have important real-world implications.

The news landscape is changing, however, and there are reasons to think these changes alter the nature of the economic news that is distributed and consumed. An increasing proportion of news consumers are getting information online, filtered through social media (e.g., Barthel, Shearer, Gottfried, & Mitchell, 2015; Pew Research Center, 2012). Some view this trend as leading to the collapse of media "gatekeeping"; others see it as involving additional layers of information filtering and selection. Either way, the shifting nature of news sources may have an impact on the types, and tone, of the information that reaches news consumers. It follows that the mediated economic "reality" to which citizens respond, both economically and politically, may be systematically different when it is being channeled through social rather than just traditional media.

Moreover, social media content is not just about the re-distribution of news stories: Certain types of news stories will be more (re-)circulated than others, and just as importantly, in the context of social media, information about our daily lives also becomes a part of users' daily "news" stream. What we learn about the economy from social media may be fundamentally different from what we learn about the economy from traditional news sources alone.

We suspect that the same is true for a much broader body of news content (i.e., not just economic news). But economic news is an attractive first step: Not only is it relatively frequent in both traditional and social media, there is a large literature testifying to its economic and political significance (cited above), and readily available quantitative measures of the economy with which to compare the content of different media. We accordingly explore economic information in traditional and social media below, comparing how the tone of information about employment differs between newspaper articles and posts on Twitter. This is to our knowledge the first direct comparison of dynamics in the tone of economic information across traditional and social media. We accomplish it by drawing on time series of monthly changes in (a) the unemployment rate, (b) employment coverage in the *New York Times* and *Washington Post*, and (c) millions of employment-related tweets from 2008 to 2014. Building on past models of asymmetric responses to information, and relying on the large-scale automated coding of sentiment using Lexicoder, we explore the possibility that upward and downward changes in the unemployment rate produce rather different reactions between social and traditional media.

Building on existing theories of gatekeeping and newsmaking in traditional news media, and on impression management and self-presentation in social media, we expect that the negativity bias so readily evident in traditional news content about the economy will not be evident in tweets about the economy. Indeed, even as traditional media content exhibits a negativity bias in its reactions to economic change, Twitter content may exhibit a positivity bias. This shift may produce significant differences in what we believe about the state of the economy. We first review the relevant literature below, and then turn to data analysis. Results, confirming these expectations, are discussed as they relate to the nature of social media and to economic and political considerations, both in the present and in the future.

"Newsmaking" in Traditional Media

Both the changing nature of traditional newsmaking and the increasing prevalence of social media are likely to shift the kinds of economic information that we receive. Media "gatekeeping" offers one lens through which to consider this possibility, particularly where traditional newsmaking is concerned. The gatekeeping literature is vast, a testament to the power of a relatively simple idea: When faced with limited newspaper space, and nearly unlimited options for possible news stories, editors and journalists must make decisions about what is newsworthy. Early gatekeeping work focused on the impact of personal decisions made by individual editors (e.g., White, 1950); subsequent work has emphasized the ways in which information filtering is driven by systematic tendencies in media organizations, journalistic practices, and human decision-making (for recent reviews, see, e.g., Shoemaker & Vos, 2009; Soroka, 2012). In sum, the gatekeeping literature has made clear that, in a media environment with constraints on space or time, personal biases, subjective decisions, and a wide range of institutional and sociological practices play a large role in what information finds its way into media content.

One of the most frequently identified tendencies in traditional media—and the focus of our analyses below—is the emphasis on negative information. A considerable number of analysts take the negativity bias as a hallmark trait of traditional news outlets (e.g., Fridkin & Kenney, 2004; Niven, 2000; Patterson, 1994; Soroka, 2014). This tendency is likely a function of multiple gatekeeping-related factors, including journalistic values (e.g., Gans, 1979), market incentives (e.g., Bennett, 2004), and cognitive biases (Stocking & Gross, 1989). The consequences are readily evident in work on negativity in economic news coverage (e.g., Soroka, 2006)—work that shows, ceteris paribus, that a given upward shift in the economy produces systematically less news coverage than an equal downward shift. (Also see recent accounts that seek to directly link the burgeoning literatures on negativity and gatekeeping, e.g., Shoemaker, 1996; Soroka, 2012, 2014.)

Of course, the nature of traditional media gatekeeping has almost certainly changed in the digital era. Sources and mediums for news content have proliferated, and ready access to multiple sources is facilitated by computers and cell phones. Recent work argues that these changes likely decrease the impact of some forms of media gatekeeping (e.g., Bennett & Iyengar, 2008; Chaffee & Metzger, 2001; Williams & Delli Carpini, 2000, 2004; Xu & Feng, 2014). The impact of any individual gatekeeper on consumers' news streams is reduced when news comes from multiple sources, for instance, and as news moves online, the pressures of limited page counts or broadcast lengths become less relevant (Bruns, 2011.)

There is however no sign that changing technologies have altered the emphasis on negative content by traditional news organizations. Indeed, negative news content seems to be especially prevalent in the current media environment, and this is evident in work exploring negativity biases in recent news coverage, cited above. Our first hypothesis is thus straightforward:

> **Hypothesis 1:** The tone of traditional news content will exhibit a negativity bias in its reaction to changes in the economy.

"Newsmaking" in Social Media

Biases in traditional newsmaking may be replicated or augmented by social media; social media may also facilitate the distribution of rather different kinds of information and reflect rather different information-seeking priorities. Consider first changes in the distribution of traditional news content. Social media are increasingly a source for this information: A report from the Media Insight Project (2014) suggests that over 40% of Americans get some news through social media. There are growing numbers of Americans on Facebook, Twitter, and other sites; those users are increasingly getting at least some of their news through these platforms and these trends seem poised to continue (see, e.g., Duggan, Ellison, Lampe, Lenhart, & Madden, 2015). It follows that differences between the priorities of traditional newsmakers and social media users are increasingly significant for the distribution of "news."

There are reasons to expect that a shift from "editorial gatekeeping" to "social gatekeeping" alters not only the amount of content that can be disseminated (Jang & Pasek, 2015), but also the types of information that are likely to be distributed. A large body of work on journalistic norms highlights tendencies in news production by journalists and editors. Bennett's work, focusing in particular on the development of a clear storyline, and "indexing" content to existing power structures, has been particularly influential (see, e.g., Bennett, 1997, 2003) The charge that commercial priorities lead newsmakers toward eye-grabbing, negative and sensationalistic content is evident in Bennett's work as well but indeed is widespread and well-established throughout the field (see, e.g., Hallin, 2000).

In contrast, information propagation through social media is driven by rather different considerations. Individuals curate their social media presence to present an appealing identity; this is the focus of a growing body of work on "impression management" and "self-presentation" in social media. (The literature is vast, but see, e.g., Bullingham & Vasconcelos, 2013; Jung, Song, & Vorderer, 2012; Seidman, 2013; Toubia & Stephen, 2013; Walther, 1996, 2007; S. Zhao, Grasmuck, & Martin, 2008.) We would characterize the general thrust of this rich literature as follows: The commentary, photos, videos, and news stories that find their way into a social media user's stream often reflect a carefully cultivated, intentional, and controlled self-presentation. This comes alongside an active consideration of who one's social media audience is (see especially boyd, 2007; Litt, 2012; Litt & Hargittai, 2016; Marwick & boyd, 2011) and quite often the desire to appeal to that audience.

In sum, the rather different processes that characterize information distribution in social versus traditional media should produce a systematic difference between (a) the complexion of news stories generated by journalism professionals and (b) the complexion of the information shared by social media users. This is true not just because the news that is deemed important by editors will not necessarily be similar to the news distributed by users of social media. It is also the case that social media "news" includes but is by no means exclusively composed of traditional news stories. Social media blend traditional news with personal stories and commentary—a social connection's new (or lost) job becomes part of what we know about the state of the economy. Thus, we should be careful not to characterize social media as just another mechanism through which to receive a subset of traditional news content. It quite clearly is not, and the Twitter content we explore here no doubt reflects this diverse body of information that is social media-distributed economic "news."

There is of course a nascent body of work focused both on differences between traditional and social-media-circulated news content (see, e.g., Bastos, Raimundo, & Travitzki, 2013; Guggenheim, Jang, Bae, & Neuman, 2015; Kwon, Oh, Agrawal, & Rao, 2012; Molyneux, 2015; W. X. Zhao et al., 2011), and on what makes a given piece of information "go viral." Indeed, some of this work points to the possibility that social media may reflect a positivity rather than a negativity bias. Berger and Milkman's (2012) study of email-forwarding of *New York Times* articles reveals a number of correlates of virality, for instance, including emotionality, especially for positively valenced content. Evidence of a positivity bias in social media also is found in recent work looking at Twitter (e.g., Schultz, Utz, & Göritz, 2011).

This prior work focuses primarily on the sharing of news content; our analysis below focuses on the content of social media more broadly. Even so, our expectations are informed by the existing literature on virality:

> **Hypothesis 2:** The tone of social media content will exhibit a positivity bias in its reaction to changes in the economy.

Method

Our tests rely on a time-series data set of the unemployment rate, sentiment-scored newspaper coverage of employment/unemployment, and sentiment-scored Twitter content associated with the word "jobs." We compare data from these three sources to determine how closely they trend together and to assess how positive and negative economic shocks influence employment discussion in both newspapers and on Twitter. We focus on data from January 2008 to September 2014 inclusive.[1] Unemployment rate data were collected from the Federal Reserve Bank of St. Louis; we used the adjusted civilian unemployment rate (*unrate*), which, over the period of study, ranges from 4.9 to 10.0 (M = 7.9, SD = 1.4). Our data on newspaper and Twitter content are described in detail below.

Newspaper Stories

Our initial database of news stories includes all economic news stories in the *New York Times* and *Washington Post* from 1980 to 2015. It is based on an earlier corpus of economic news first collected for (Soroka, 2006), then updated for (Soroka, 2012), and finally updated here to include content through September 2014. The stories were obtained from the Lexis-Nexis database, using a subject search designed to identify all stories dealing with major macroeconomic issues.[2] Results were manually examined by the authors to confirm that each focused only on the domestic economy (that is, not on the economy of other countries); irrelevant stories were dropped. Any story of fewer than 100 words also was excluded, since these are typically short notes rather than actual newspaper articles. Economic coverage also tends to include stories that are just long lists of reported economic figures and indicators, so these too were omitted, and since our final analysis is focused on unemployment in particular, the analysis below relies only on articles that mention unemployment. (See the discussion of our measurement of sentiment.) The resulting number of articles used to generate our measure of news tone over the 80-month period is 7,203. There are of course more articles in the early years of the Great Recession than more recently; the number of newspaper articles by year is included in Online Appendix Table 1.

Twitter Data

This article focuses on data from Twitter, acknowledging that it is of course just one social media service, and one that may differ from others in some important ways. We focus on Twitter because (a) we believe that Twitter trends will be indicative of general patterns, (b) Twitter data are readily available, and (c) it is sufficiently common to share economic news on Twitter, enabling systematic analysis. We nevertheless consider differences that might be expected across social media platforms in the concluding discussion.

All U.S.-based employment-related tweets during the period of study were gathered by searching for the keyword "jobs" using the Topsy service.[3] Topsy was a firm that allowed subscribers to access all tweets from Twitter associated with a particular Boolean search term; the service has since been purchased by Apple Inc. and is no longer available to the public. Because Twitter had an agreement with Topsy to provide full "firehose" access (i.e., every single tweet was archived), it was possible to search and categorize all tweets, rather than the nonrandom subset available through the Twitter API or the limited systematic sample available through "gardenhose" access tools (gardenhose access provides a 10% systematic random sample). We used "jobs" as our search term, rather than "employment" for two key reasons. First, "employment" is used far less than "jobs" in the 140-character Twitter environment. This is evidenced in past work, but is confirmed in our own data. As a robustness check, we gathered separate corpuses using either "jobs" or "employment." The monthly average number of words in tweets including "jobs" (with irrelevant tweets removed, as described above) over the time period was 10,552,020; the monthly average number of words in tweets including “employment” was 444,889. The “jobs” corpus is roughly 23 times larger than the “employment” corpus. More importantly, past work suggests that “jobs” tweets correspond most closely with economic sentiment, a leading predictor of economic trends (O’Connor, Balasubramanyan, Routledge, & Smith, 2010).[4] We return to “employment” tweets as a robustness check below; for the time being, we focus on “jobs” tweets. Over our time period, there were just over 52 million relevant tweets, where the number over time varies as a consequence both of the salience of economic issues, and—moreover—the increasing number of Twitter users. The total number of tweets analyzed by year is included in Online Appendix Table 1.

Sentiment Coding

The reliability of dictionary-based automated measures of sentiment depends on the quality of the dictionary of positive and negative words. Since the 1960s, scholars have been developing lexicons in which words are classified as positive or negative. There are numerous machine-readable dictionaries available for research (e.g., Hart, 1984; Mergenthaler, 1996; Pennebaker, Francis, & Booth, 2001; Whissell, 1989). There also is a vast literature by computational linguists interested in developing sentiment lexicons (e.g., Subasic & Huettner, 2001). The one used here, the *Lexicoder Sentiment Dictionary* (LSD), was developed to address some of these shortcomings. The LSD is the product of manually sorting and merging hundreds of affect and emotion categories from three of the largest and most widely used lexical resources for automated content analyses: *Roget’s Thesaurus* (Roget, 1911), the General Inquirer (GI, Stone, Dunphy, Smith, & Ogilvie, 1966), and the Regression and Imagery Dictionary (RID, Martindale, 1990).

The LSD has already been described in some detail elsewhere (Young & Soroka, 2012). For the current purposes, suffice it to say that the final dictionary includes 6,016 words scored for positive or negative tone alongside the preprocessing of over 1,500 words. The LSD produces counts of positive words and negative words; we use those to produce a measure of net tone using the following very simple formula: ((# positive words – # negative words) / total # words) × 100. The measure thus captures both the direction and magnitude of tone.[5] This measure has been shown in past work to correlate strongly with economic trends, and to slightly outperform similar sentiment dictionaries in this regard (e.g., Soroka et al., 2015). It also has been tested against eight other sentiment dictionaries as well as human coders across four topics: foreign affairs, crime, the environment, and—most importantly for our purposes—the economy (Young & Soroka, 2012).

Note that our newspaper data are not exclusively about employment—they capture a wide range of macroeconomic topics. Because our focus here is on employment specifically, we use a hierarchical dictionary search to capture the tone only in sentences that include topic keywords related to employment (employ*, unemploy*, jobs, and jobless), and capture tone *just* for the sentences in which these employment-related terms occur. We thus capture the tone of all mentions of employment, across a broad range of macroeconomic articles. We aggregate articles by day for processing, and then calculate a daily count of the number of positive and negative words using the LSD (where word counts, too, are based only on employment-related sentences), and a daily net tone measure as described above.

We then average over months to generate monthly data. That said, we do not use calendar month, but rather what might be called “reporting months.” The National Bureau of Labor Statistics typically releases Current Employment Statistics (CES) on the third Friday after the conclusion of the reference week, that is, the week which includes the 12th of the month. This is usually the first Friday of the (following) month. Our expectation is that media can respond to unemployment data only after those data are released, and so our monthly aggregations start with the first Friday of the month, and continue to the first Friday of the following month, so they correspond perfectly to Bureau of Labor Statistics reporting periods. Note that this is *not* because we expect a good amount of content to be driven by the CES reports themselves, and there indeed is no evidence in our data that reporting spikes at these times. To the extent that media content responds to unemployment rates, however, it can do so only after data are publicly released.

The net tone measure for Twitter content is produced in exactly the same way: We aggregate tweets by day, calculate the number of positive and negative words, generate a daily net tone measure, and then average that tone over “reporting months.” The newspaper and Twitter data are thus directly comparable. Trends in both series are illustrated alongside monthly changes in the unemployment rate in Figure 1.

Net Tone for newspaper content ranges from –.95 to .87 (M = .27, SD = .37). Net Tone for Twitter content ranges from .02 to 1.68 (M = .98, SD = .41). There is a rough correspondence between trends in unemployment change and trends in both media series. Unemployment is particularly high at the beginning of the time period; at the same time, tone in media is comparatively low. Media tone then improves over 2009 and 2010, just as unemployment is moving downward. The basic bivariate correlation between the two series in the bottom panel of Figure 1 is .29, and both newspaper and Twitter sentiment are correlated with the unemployment change data in the top panel of Figure 1, at –.33 and –.25, respectively (where all correlations are significant at $p <$ .01). What is perhaps more important—and foreshadowing of results below—is the tendency for tone in Twitter to be more positive than tone in newspaper content. The Twitter (dashed) line in the bottom panel of Figure 1 is steadily above the newspaper (solid) line.

Already, then, there are hints that Twitter content may not reflect the same degree of negativity as traditional news content. Whether the two respond differently to changes in the unemployment rate is another matter, however, and the subject of the section that follows.

Results

We report here some simple models exploring the impact of the unemployment rate on the tone of newspaper and Twitter content. Following recent work, we use error correction models (ECMs) to capture the relationship between the two series. One

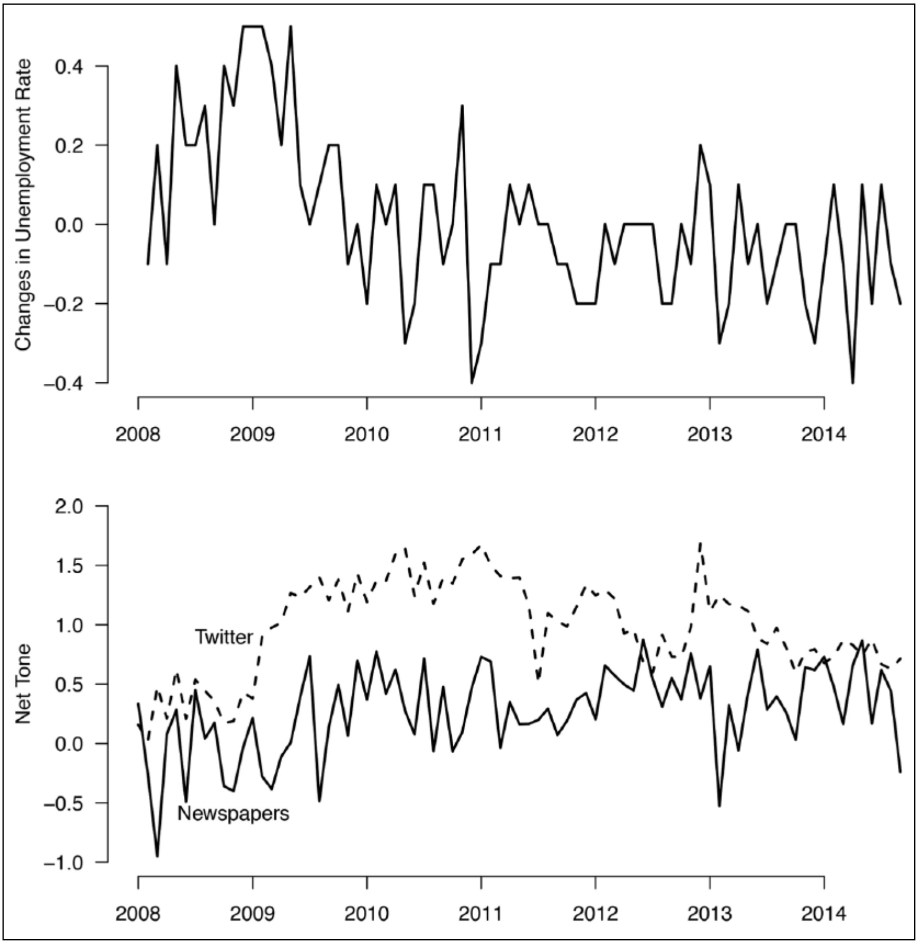

Figure 1. Tone in newspaper and Twitter content, 2008-2015.

advantage of ECMs is that they can be robust when dealing with cointegrated time series, but our use of ECMs is driven mainly by an interest in capturing a combination of short- and long-term effects of unemployment on media content.[6] The basic symmetric model is thus specified as follows,

$$\Delta \text{Media Tone}_t = \beta_1 \text{Media Tone}_{t-1} + \beta_2 \, \Delta\text{Unemp}_t + \beta_3 \text{Unemp}_{t-1} + \varepsilon_t,$$

where Media Tone is either drawn from newspapers, or Twitter; β_1 captures the autocorrelation in the dependent variable (i.e., the degree to which current changes in tone are affected by past levels of tone); β_2 captures the short-term influence of changes in unemployment on changes in tone; and β_3 captures the longer-term impact of lagged

Table 1. Symmetric and Asymmetric Models of Media Tone, 2008-2014.

	Symmetric		Asymmetric	
	Δ Newspaper $tone_t$	Δ Twitter tone	Δ Newspaper $tone_t$	Δ Twitter tone
Δ Unemployment $rate_t$	−0.464*	−0.016		
	(0.202)	(0.120)		
Upward Δ unemployment $rate_t$ (NEGATIVE)			−0.970**	0.275
			(0.328)	(0.191)
Downward Δ unemployment $rate_t$ (POSITIVE)			0.216	−0.418†
			(0.404)	(0.238)
Unemployment $rate_{t-1}$	0.046	0.123***	0.040	0.122***
	(0.028)	(0.028)	(0.028)	(0.027)
DV_{t-1}	−0.895***	−0.545***	−0.938***	−0.521***
	(0.115)	(0.102)	(0.116)	(0.101)
Constant	−0.120	−0.442**	0.034	−0.512**
	(0.226)	(0.154)	(0.236)	(0.155)
N	80	80	80	80
R^2	.445	.299	.471	.333

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

levels of unemployment. The asymmetric model then separates changes in unemployment into two variables, one that captures upward change in unemployment (and is equal to zero otherwise), and another, which captures downward change in unemployment (and is equal to zero otherwise). The resulting equation is as follows,

$$\Delta \text{Media Tone}_t = \beta_1 \text{Media Tone}_{t-1} + \beta_{2A}\,\Delta\,\text{Unemp}(\text{UP})_t + \beta_{2B}\,\Delta\,\text{Unemp}(\text{DN})_t + \beta_3 \text{Unemp}_{t-1} + \varepsilon_t,$$

where β_{2A} and β_{2B} capture the potentially different impact of upward and downward changes in unemployment.

Both symmetric and asymmetric models are included in Table 1. The first model shows results for changes in newspaper tone over the 80 months for which we have both newspaper and Twitter data. Results make clear the relationship between unemployment and our measure of media tone. The central coefficient here is for changes in the unemployment rate, and that coefficient (–.464) suggests that the short-term effect of unemployment on tone is negative, that is, as unemployment shifts upward, tone shifts downward. This is of course exactly as we should expect.

Do Twitter data show the same relationship with the unemployment rate? The second column of Table 1 shows results from the symmetric model, but using tone extracted from Twitter content.[7] The absence of a significant coefficient for changes in the unemployment rate suggests no short-term relationship between changes in unemployment and Twitter tone, although the coefficient for lagged levels does suggest a more long-term relationship between the series. We do not wish to place too much emphasis on these first two models, however, which assume symmetry in the impact of upward and downward changes in unemployment. We thus wait to consider short- versus long-term effects in the context of asymmetric models.

Do models allowing for asymmetry in the impact of upward versus downward change in unemployment produce different results? The third column of Table 1 shows an asymmetric model for newspaper tone. The coefficients are roughly as we would expect given previous work (cited above): Negative (upward) changes in the unemployment rate have a markedly larger coefficient than do positive (downward) changes (–.970 vs. .216). The former is significantly different from zero; the latter is not; and an F test of the difference in the coefficients is significant ($F = 3.74$, $p = .05$). These results clearly signal a negativity bias in short-term newspaper responses to changes in the unemployment rate. In this model, just as in the symmetric model, the impact of unemployment on media tone appears to be entirely concurrent: An insignificant coefficient for the lagged dependent variable suggests no additional long-run relationship.

Twitter content, the focus of the last column in Table 1, shows a rather different dynamic. The negative change coefficient here (.275) is incorrectly signed and statistically insignificant. The coefficient for positive (downward) change (–.418) is in contrast negatively signed and (weakly) statistically significant. Again, the two coefficients are statistically different from one another ($F = 3.78$, $p = .05$). Whereas newspapers lean in the direction of a negativity bias, then, Twitter content appears to lean in the direction of a positivity bias. Results are thus exactly as we would expect if Twitter content exhibited a rather different selection mechanism than did the news—one driven less by traditional standards of newsworthiness, and more by the concerns highlighted in the literature on impression management.

Note in column 3 of Table 1 that the coefficient for lagged levels of unemployment rate is insignificant for newspaper tone, and the rate of error correction (–.938) is very high. This suggests that the effect of unemployment on newspaper tone is immediate and short-lived. The final model for Twitter, in the last column of Table 1, suggests a somewhat different long-run dynamic: Lagged levels of unemployment are significantly associated with Twitter tone, and the positive sign on the coefficient suggests that even as unemployment is negatively related to tone in the short term, it is positively related to tone over the long term. This fits with trends in Figure 1, which shows especially positive tone in Twitter over the early years of the Great Recession. That Twitter remains relatively positive over a time period in which unemployment is particularly bad may fit well with our expectations, though our hypotheses are focused on the differential impact of positive and negative shifts over the short term. We are unsure whether this long-term effect would obtain in data over a longer period, and we have no expectations about the generalizability about this finding. Only time will tell, of course; in the meantime, we note, in line with past work (Soroka et al., 2015), that the short-term impact of unemployment far outweighs the long-term impact.[8]

Comparing the magnitude of short-term coefficients across models is difficult, since the variance in dependent variables is different. Table 2 thus presents some standardized results, expressing the impact of a one-standard-deviation shift in changes in

Table 2. Standardized Effects, Symmetric and Asymmetric Models of Media Tone.

	Δ Newspaper tone$_t$	Δ Twitter tone
Symmetric model		
Δ Unemployment rate$_t$	−.21	(−.01)
Asymmetric model		
Upward Δ unemployment rate$_t$ (NEGATIVE)	−.44	(.24)
Downward Δ unemployment rate$_t$ (POSITIVE)	(.10)	−.37

Note. Insignificant effects are in parentheses. Based on models in Table 1.

unemployment in standard deviations of either changes in newspaper tone or changes in Twitter tone.[9] Insignificant effects are in parentheses; recall that, as with the coefficients for changes in unemployment above, we expect the direction of effects to be negative. Results for the symmetric model suggest that a one-standard-deviation change in unemployment is associated with an –.21 standard-unit shift in newspaper. The impact is markedly larger (or, alternatively, insignificant) when upward and downward changes are separated, however. Here, we see a –.44-unit shift in newspaper tone in response to negative (upward) change in unemployment; and in Twitter, a nearly identical –.37-unit shift in tone in response to positive (downward) change. The asymmetry in Twitter is nearly the mirror image of the asymmetry in news content.

Table 2 captures what we regard as rather stark differences in the short-term reactions of news content and Twitter to changes in unemployment. This is not the only way in which Twitter differs from news content, however: While an insignificant coefficient on the lagged dependent variable for news content (in Table 1) suggests no long-term impact, a significant coefficient for lagged tone in Twitter suggests that unemployment rates produce long-term shifts in the equilibrium of Twitter net tone.[10] The implied long-term effect of unemployment is captured by dividing the coefficient for lagged unemployment (.122) by the coefficient for the lagged dependent variable (–.521).[11] The resulting long-term effect of a one-point increase in unemployment is a shift in net tone of –.234. It thus appears as though there is a long-term impact of unemployment on Twitter, but not on news content. This makes good sense. News content tends to highlight short-term change. Tweets should capture ongoing experiences of the user with (un)employment, however, and these are reflected in a combination of both short- and long-term effects.

That the short-term effects of the unemployment rate on Twitter appear to be a mirror image of what we have seen for news content is, we believe, particularly important. Recall that this is not just a function of individuals selecting different news content than editors and journalists, however. It is at least partly a consequence of the fact that Twitter is not just about re-distributing news—it includes a good deal of information from users' daily lives. At the same time, our Twitter content includes tweets sent out by journalists and newspapers. (In this way, our Twitter and newspaper samples are not totally independent, but partially overlapping.) All of this content contributes to the measure of Twitter sentiment used above.

Whether this is an advantage or disadvantage of our analysis is a matter of perspective. We suggest that the distinction between "news" content and other information in social media is increasingly blurred and that we should regard all economic information in a Twitter stream as being part of a body of economic information that citizens use to assess current circumstances. Insofar as this is true, it makes sense to analyze tweets as a whole, and compare the information distributed by journalists in traditional news outlets to the information—all of it—distributed by Twitter users.

It may nevertheless be useful, as a diagnostic exercise, to explore subsets of tweets, mainly to confirm that our results are not driven by forwarded news content, or forwarded job ads, or indeed re-tweeted links to either. Thankfully, it is relatively easy to focus on some relevant subsets of tweets in our database. Online Appendix Table 3 shows results from a series of analyses focused on two subsets of tweets: with and without retweets, and with and without hyperlinks. (Online Appendix Table 1 also shows the proportion of tweets with each, by year. Overall, roughly 15% of the tweets in our database are retweets, and roughly 58% of all tweets in our database link to some kind of online content, typically news stories or job ads.) Results there confirm that the dynamics revealed in Table 2 are not overturned by subsetting our data. Indeed, to the extent that results differ, it appears as though some subsets of Twitter content may actually respond to negative shifts in unemployment by becoming more *positive* in tone. In sum, our results strongly suggest that the sentiment of economic information in Twitter responds rather differently to economic change than does the sentiment of economic information in traditional news.

Would results be fundamentally different if we were to focus on tweets using terms other than "jobs"? As noted above, we collected a parallel corpus of tweets using "employment," so this is relatively easily tested. We calculate the tone of coverage in the same way; the "jobs" and "employment" Twitter tone measures are correlated at .56 ($p < .01$). Online Appendix Table 4 includes a replication of Table 1 models using the "employment" measure. We find hints of a positivity bias: a correctly signed coefficient for positive (downward) changes in unemployment, and an incorrectly-signed coefficient for negative (upward) changes. Neither coefficient is statistically significant, however—We suspect partly because of the comparatively small number of "employment" tweets, and a correspondingly noisy "net tone" measure. Regardless, it is clear that results are not overturned by focusing on a different search term.

Discussion

Existing work suggests that the considerations governing information selection in social media are markedly different from those governing news selection in traditional news outlets. We have explored that possibility here, focusing on the response of both newspapers and Twitter content to shifts in the U.S. unemployment rate. Results powerfully support our expectations: While newspapers exhibit a negativity bias in their responses to changing unemployment rates, Twitter exhibits a positivity bias.

This fact could have important consequences, as an increasing number of Americans receive an increasing proportion of their news via social media. To the extent that we receive our information about the economic world around us via social media rather than newspapers, we may experience an information stream that is rather more positive. Economic and political behavior may shift accordingly. Imagine a public that rewards or penalizes politicians for the economy based on rather different social or traditional media-driven perceptions of economic circumstances; or shifts consumption behavior based on different prospective economic expectations.) Of course, we may also adjust our news-seeking habits in light of differences across mediums—we may seek out some kinds of information (i.e., negative content) in newspapers and other kinds (i.e., positive content) in social media. Put differently, the results observed above may not be a consequence of each medium operating independently, but rather in parallel. News providers may also shift the way in which news is produced, in reaction to readers' social media behavior. There is, we suspect, an evolving, reciprocal relationship between information consumers and information producers (and of course a blurring of the line between the two).[12] Our results cannot speak directly to these dynamics. For the time being, all we can say is that information about employment is systematically more positive in social media than in traditional news sources. How this plays out in the future is as yet unclear.

It is worth noting that our comparison focuses on the content of news and the content of tweets; it does not explore the content of the information—news and otherwise—that is linked to Twitter content. Our view of Twitter-circulated information about employment is thus driven entirely by what users write, either independently or in relation to online content. An alternative exploration might focus on the actual content being linked in Tweets. Our expectation is that the tone of tweeted content will differ from a broader body of traditional news content in the same ways that we have observed here: Articles that are more positive will be circulated more in social media. This would certainly be in line with existing work on virality, cited above.

We can nevertheless confirm that a positivity bias is equally clear in social media content that is not directly about news content. We believe that it is of some significance that a positivity bias is found above for all Twitter content, including Twitter content that is not clearly focused on news articles. What we learn through social media about the economy comes through a combination of traditional news sources and personal commentary. And all of that information tends to present a rather more positive perspective of the economy than does traditional news.

Even though we rely entirely on Twitter above, we recognize that it is not necessarily representative of all social media. Exploring the extent to which our findings are generalizable to other social media is another area for future work. We expect, based both on the affordances of existing social media and on past work on self-presentation in social media, that results will not be fundamentally different on other social media. Even so, recent work points to some differences in the motivations behind Facebook and Twitter use, and these may matter for the kinds of economic information distributed through the different social networks. (The literature is growing quickly, but see, e.g., Choi & Bazarova, 2015; Davenport, Bergman, Bergman, &

Fearrington, 2014; Panek, Nardis, & Konrath, 2013.) Our “imagined audiences” in different social media environments may similarly matter for the kinds of economic information we choose to share (see especially boyd, 2007; Litt, 2012; Litt & Hargittai, 2016; Marwick & boyd, 2011). As a consequence, shifts in the tone of economic information will depend both on how much information we receive from social versus traditional media, and the peculiarities of specific social media, both current and forthcoming.[13] Recognizing this possibility makes even small changes to the affordances of social media of real importance, both economically and politically. Exploring the ways in which social media might shift our views of the economy is thus an important avenue for future research.

Finally, note that we cannot yet speak to whether the dynamics identified here are equally evident across a wide range of topics; we know only about content related to employment. As noted above, there are advantages to focusing on a domain in which there is a reasonable measure of “reality,” in this case, the unemployment rate. Comparisons across media may be straightforward, but comparing each to the real world is typically more complex. This makes the extension of these results to other domains difficult, but certainly not impossible. What might be the result of extending these analyses? The research on virality and impression management that informs our analyses would seem to apply across a wide range of domains, so there are good reasons to expect our results to be generalizable. That said, there may be interesting differences in information-seeking and (re-)distribution across issues. Thus far, we simply do not know.

In the meantime, our analyses highlight one important way in which the tone of economic information circulated through social media differs from what tends to be distributed by traditional news outlets. We have found evidence that traditional media reflect a negativity bias in their reporting of employment, but the information distributed through social media reflects a positivity bias. Do social media users have different perceptions of the economy as a consequence? Is it possible that aggregate-level trends in political support and/or economic confidence shift as a result of the tone of information in one medium or another? We cannot yet answer these questions, but the analysis above highlights their significance for future work.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Notes

1. These start and end dates are the product of data availability. Although Twitter data are available for roughly a year before this, there were sufficiently few tweets before January

2008 that monthly aggregations for 2007 are unreliable. Our data end in 2014 due to the end of the service from which we archived tweets, discussed further below.

2. The search was designed based on an exhaustive list of Lexis-Nexis subject categories. The final search—described in (Soroka, 2006) and replicated here—captured stories for which any of the following terms were listing as "Relevancy: Major Terms only": under (a) "Economic Conditions": Deflation, Economic Decline, Economic Depression, Economic Growth, and Economic Recovery, Inflation and Recession; under (b) "Economic Indicators": Average Earnings, Consumer Credit, Consumer Prices, Consumer Spending, Employment Rates, Existing Home Sales, Money Supply, New Home Sales, Productivity, Retail Trade Figures, Unemployment Rates, Wholesale Prices.
3. Topsy claimed to remove spam from their tweets and allowed us to select Twitter users tweeting in English in the United States. It is not clear exactly how these categories were determined, but these filters were used because they allowed us to match the tweets to the country of examination and to run English-language sentiment analysis tools.
4. We do make some adjustments above and beyond what O'Connor, Balasubramanyan, Routledge, and Smith (2010) suggest is necessary: we drop all tweets about Steve Jobs and all tweets with sexual references that include the word "jobs."
5. There are of course other dictionaries that may work just as well for our purposes here, though comparisons of results using the LSD and other dictionaries reveal either minor differences in the final outcome, or a slight advantage for the LSD, even for some dictionaries focused on economic news content (Soroka, Stecula, & Wlezien, 2015; Wlezien, Soroka, & Stecula, in press; Young & Soroka, 2012). Even so, see Barberá, Boydstun, Linn, McMahon, and Nagler (2016) for a useful comparison of dictionary to machine learning approaches to estimating tone, as well as a consideration of the differences between corpuses extracted using full-text versus subject searches. Note also that our analyses will miss positive and negative words that are part of longer hashtags (e.g., #badeconomy) but will catch words in single-word hashtags (e.g., #bad).
6. For tests of integration, see Online Appendix Table 2, which shows results from Augmented Dickey-Fuller tests using a single lag, with all variables in levels and then changes. (Using up to three lags does not change the findings reported.) The tests suggest that all variables are stationary in changes; in levels, only for the unemployment rate do we fail to reject the null hypothesis. There is some debate in the literature about whether an error correction model (ECM) is robust to a situation in which there is one integrated independent variable, and also whether we have the right specification at all if the left-hand side of the model is stationary while the right-hand side is not. Our own inclination is to treat unemployment as though it is stationary, even though tests using the data in our relatively shortly sample period suggest otherwise. (Unemployment is stationary over the long term, after all.) That said, the critical results from our models are not fundamentally different when we use a model that excludes lagged levels of unemployment.
7. Note that our model assumes that Twitter tone is led by the unemployment rate, but we recognize that Twitter content may well precede changes in the unemployment rate as well. It may be that tweets reflect the hiring and firing that produces change in unemployment in the next month, after all. Indeed, tests of Granger causality, using both variables in levels, and including a single lag, suggest bidirectional causality. We do not explore this further here, though note that model that more fully explore asymmetric, bidirectional effects may be worth pursuing in future work.
8. Short-term effects in the ECM are captured by the coefficients for changes in unemployment. Estimating the long-term effect requires dividing the coefficient for lagged levels

of unemployment by the coefficient for the lagged dependent variable. In the asymmetric model for newspapers, that long-term effect is .042, and is statistically insignificant; in the same model for Twitter, it is .234 ($p < .05$), roughly half the size of the short-term effect. For further details on short- versus long-term effects in ECMs, see Pickup (2015).

9. One standard deviation in our unemployment change variable is .21; in newspaper tone, it is.44; and in Twitter tone, it is .24.
10. The fact that both unemployment and Twitter tone are integrated is thus of some significance here—It is because these series are long-memoried that there is the potential for a long-term impact.
11. We draw here on similar interpretations in Soroka, Stecula and Wlezien (2015).
12. Relatedly, it could be the case that the content (and impact) social media is contingent on the nature of the media system into which it is introduced. It could be the case that a negatively oriented U.S. media leads to positively oriented reaction in social media; in another system, social media may serve a rather different purpose.
13. Even small changes in affordances may matter. Consider just one recent change: If we post information at least in part with the possibilities for feedback in mind, then the shift toward more detailed reactions on Facebook may matter to the sentiment of information we distribute.

Supplemental Material

Supplemental material is available for this article online.

References

Altheide, D. L. (1997). The news media, the problem frame, and the production of fear. *Sociological Quarterly the Sociological Quarterly*, *38*, 647-668. doi:10.1111/j.1533-8525.1997.tb00758.x

Barberá, P., Boydstun, A., Linn, S., McMahon, R., & Nagler, J. (2016, September). *Methodological challenges in estimating tone: Application to news coverage of the U.S. economy*. Paper presented at the Annual meeting of the American Political Science Association, Philadelphia, PA.

Barthel, M., Shearer, E., Gottfried, J., & Mitchell, A. (2015). *The evolving role of news on Twitter and Facebook*. Retrieved from http://www.journalism.org/2015/07/14/the-evolving-role-of-news-on-twitter-and-facebook/

Bastos, M. T., Raimundo, R. L., & Travitzki, R. (2013). Gatekeeping Twitter: Message diffusion in political hashtags. *Media, Culture & Society*, *35*, 260-270. doi:10.1177/0163443712467594

Bennett, W. L. (1997). Cracking the news code: Some rules that journalists live by. In *Do the media govern*?, Iyengar, S., & Reeves, R., eds., Thousand Oaks CA: Sage. (pp. 103-117).

Bennett, W. L. (2003). *News, the politics of illusion*. New York, NY: Longman.

Bennett, W. L. (2004). Gatekeeping and press-government relations: A multigated model of news construction. In L. L. Kaid (Ed.), *Handbook of political communication research* (pp. 283-313). Mahwah, NJ: Lawrence Erlbaum. doi:10.4324/9781410610584.

Bennett, W. L., & Iyengar, S. (2008). A new era of minimal effects? The changing foundations of political communication. *Journal of Communication*, *58*, 707-731. doi:10.1111/j.1460-2466.2008.00410.x

Berger, J., & Milkman, K. L. (2012). What makes online content viral? *Journal of Marketing Research*, *49*, 192-205. doi:10.2139/ssrn.1528077

Blood, D. J., & Phillips, P. C. (1995). Recession headline news, consumer sentiment, the state of the economy and presidential popularity: A time series analysis 1989-1993. *International Journal of Public Opinion Research*, *7*, 2-22. doi:10.1093/ijpor/7.1.2

Blood, D. J., & Phillips, P. C. (1997). Economic headline news on the agenda: New approaches to understanding causes and effects. In M. Mccombs, D. L. Shaw & D. Weaver (Eds.), *Communication and democracy: Exploring the intellectual frontiers in agenda-setting theory* (pp. 97-113). Mahwah, NJ: Lawrence Erlbaum.

Boomgaarden, H. G., Van Spanje, J., Vliegenthart, R., & De Vreese, C. H. (2011). Covering the crisis: Media coverage of the economic crisis and citizens' economic expectations. *Acta Politica*, *46*, 353-379. doi:10.1057/ap.2011.18

boyd, d. (2007). Why youth (heart) social network sites: The role of networked publics in teenage social life. In *Macarthur foundation series on digital learning—Youth, identity, and digital media volume*, Buckingham, D., ed. Cambridge, MA: MIT Press. (pp. 119-142).

Bruns, A. (2011). Gatekeeping, gatewatching, real-time feedback: New challenges for journalism. *Brazilian Journalism Research Journal*, *7*, 117-136. doi:10.25200/BJR.v7n2.2011.355

Bullingham, L., & Vasconcelos, A. C. (2013). "The presentation of self in the online world": Goffman and the study of online identities. *Journal of Information Science*, *39*, 101-112. doi:10.1177/0165551512470051

Carroll, C. D. (2003). Macroeconomic expectations of households and professional forecasters. *The Quarterly Journal of Economics*, *118*, 269-298. doi:10.1162/00335530360535207

Chaffee, S. H., & Metzger, M. J. (2001). The end of mass communication? *Mass Communication and Society*, *4*, 365-379. doi:10.1207/s15327825mcs0404_3

Choi, Y. H., & Bazarova, N. N. (2015). Self-disclosure characteristics and motivations in social media: Extending the functional model to multiple social network sites. *Human Communication Research*, *41*, 480-500. doi:10.1111/jcom.12106

Davenport, S. W., Bergman, S. M., Bergman, J. Z., & Fearrington, M. E. (2014). Twitter versus Facebook: Exploring the role of narcissism in the motives and usage of different social media platforms. *Computers in Human Behavior*, *32*, 212-220. doi:10.1016/j.chb.2013.12.011

De Boef, S., & Kellstedt, P. M. (2004). The political (and economic) origins of consumer confidence. *American Journal of Political Science*, *48*, 633-649. doi:10.1111/j.0092-5853.2004.00092.x

Doms, M. E., & Morin, N. J. (2004). *Consumer sentiment, the economy, and the news media* (FRB of San Francisco Working paper). doi:10.2139/ssrn.602763

Duggan, M., Ellison, N. B., Lampe, C., Lenhart, A., & Madden, M. (2015). *Social media update 2014*. Pew Research Center.

Fridkin, K. L., & Kenney, P. J. (2004). Do negative messages work? The impact of negativity on citizens' evaluations of candidates. *American Politics Research*, *32*, 570-605. doi:10.1177/1532673x03260834

Gans, H. J. (1979). *Deciding what's news: A study of CBS Evening News, NBC Nightly News, Newsweek, and Time*. New York, NY: Pantheon Books.

Glynn, C., Huge, M., & Hoffman, L. (2008). *Did the media help inflate the housing bubble? Media coverage of real estate markets in times of change*. Paper presented at the Annual meeting of the Association for Education in Journalism and Mass Communication, Marriott Downtown, Chicago, IL, August 2008.

Goidel, K., Procopio, S., Terrell, D., & Wu, H. D. (2010). Sources of economic news and economic expectations. *American Politics Research, 38*, 759-777. Advance online publication. doi:10.1177/1532673x09355671

Guggenheim, L., Jang, S. M., Bae, S. Y., & Neuman, W. R. (2015). The dynamics of issue frame competition in traditional and social media. *The ANNALS of the American Academy of Political and Social Science*, *659*, 207-224. doi:10.1177/0002716215570549

Hallin, D. C. (2000). Commercialism and professionalism in the American news media. *Mass Media and Society*, *3*, 243-262.

Hart, R. P. (1984). *Verbal style and the presidency: A computer-based analysis*. Orlando, FL: Academic Press.

Hollanders, D., & Vliegenthart, R. (2011). The influence of negative newspaper coverage on consumer confidence: The Dutch case. *Journal of Economic Psychology*, *32*, 367-373. doi:10.2139/ssrn.1430287

Jang, S. M., & Pasek, J. (2015). Assessing the carrying capacity of Twitter and online news. *Mass Communication and Society*, *18*, 577-598. doi:10.1080/15205436.2015.1035397

Jung, Y., Song, H., & Vorderer, P. (2012). Why do people post and read personal messages in public? The motivation of using personal blogs and its effects on users' loneliness, belonging, and well-being. *Computers in Human Behavior*, *28*, 1626-1633. doi:10.1016/j.chb.2012.04.001

Kwon, K. H., Oh, O., Agrawal, M., & Rao, H. R. (2012). Audience gatekeeping in the Twitter service: An investigation of tweets about the 2009 Gaza conflict. *AIS Transactions on Human-Computer Interaction*, *4*, 212-229.

Lamla, M. J., & Lein, S. M. (2014). *The role of media for consumers' inflation expectation formation*. *Journal of Economic Behavior and Organization*, 106, 62-77.

Litt, E. (2012). Knock, knock. Who's there? The imagined audience. *Journal of Broadcasting & Electronic Media*, *56*, 330-345. doi:10.1080/08838151.2012.705195

Litt, E., & Hargittai, E. (2016). The imagined audience on social network sites. *Social Media & Society*, *2*,. doi:10.1177/2056305116633482

Martindale, C. (1990). *The clockwork muse: The predictability of artistic change*. New York, NY: Basic Books.

Marwick, A. E., & boyd, d. (2011). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society*, *13*, 114-133. doi:10.1177/1461444810365313

The Media Insight Project. (2014). *The personal news cycle*. Retrieved from http://www.apnorc.org/PDFs/Media%20Insight/News%20Cycle/The_Media_Insight_Project_The_Personal_News_Cycle_Final.pdf

Mergenthaler, E. (1996). Emotion-abstraction patterns in verbatim protocols: A new way of describing psychotherapeutic processes. *Journal of Consulting and Clinical Psychology*, *64*, 1306-1315. doi:10.1037//0022-006x.64.6.1306

Molyneux, L. (2015). What journalists retweet: Opinion, humor, and brand development on Twitter. *Journalism*, *16*, 920-935. doi:10.1177/1464884914550135

Niven, D. (2000). The other side of optimism: High expectations and the rejection of status quo politics. *Political Behavior*, *22*, 71-88. doi:10.1023/A:1006642501693

O'Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*, *11*, 1-2.

Panek, E. T., Nardis, Y., & Konrath, S. (2013). Mirror or megaphone? How relationships between narcissism and social networking site use differ on Facebook and Twitter. *Computers in Human Behavior*, *29*, 2004-2012. doi:10.1016/j.chb.2013.04.012

Patterson, T. E. (1994). *Out of order*. New York, NY: Vintage Books.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). *Linguistic Inquiry and Word Count: LIWC 2001*. Mahwah, NJ: Lawrence Erlbaum.

Pew Research Center. (2012). *Trends in news consumption: 1991-2012: In changing news landscape, even television is vulnerable*. Retrieved from www.people-press.org/files/legacy-pdf/2012%20News%20Consumption%20Report.pdf

Pickup, M. (2015). *Introduction to time series analysis*. Thousand Oaks, CA: SAGE.

Roget, P. M. (1911). *Roget's thesaurus of English words and phrases*. USA: Thomas Y. Crowell.

Schultz, F., Utz, S., & Göritz, A. (2011). Is the medium the message? Perceptions of and reactions to crisis communication via Twitter, blogs and traditional media. *Public Relations Review*, *37*, 20-27. doi:10.1016/j.pubrev.2010.12.001

Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and Individual Differences*, *54*, 402-407. doi:10.1016/j.paid.2012.10.009

Shah, D. V., Watts, M. D., Domke, D., Fan, D. P., & Fibison, M. (1999). News coverage, economic cues, and the public's presidential preferences, 1984-1996. *The Journal of Politics*, *61*, 914-943. doi:10.2307/2647548

Shoemaker, P. J. (1996). Hardwired for news: Using biological and cultural evolution to explain the surveillance function. *Journal of Communication*, *46*, 32-47. doi:10.1111/j.1460-2466.1996.tb01487.x

Shoemaker, P. J., & Vos, T. (2009). *Gatekeeping theory*. New York, NY: Routledge.

Soroka, S. N. (2006). Good news and bad news: Asymmetric responses to economic information. *Journal of Politics*, *68*, 372-385. doi:10.1111/j.1468-2508.2006.00413.x

Soroka, S. N. (2012). The gatekeeping function: Distributions of information in media and the real world. *Journal of Politics*, *74*, 514-528. doi:10.1017/s002238161100171x

Soroka, S. N. (2014). *Negativity in democratic politics: Causes and consequences*. Cambridge, UK: Cambridge University Press.

Soroka, S. N., Stecula, D. A., & Wlezien, C. (2015). It's (change in) the (future) economy, stupid: Economic indicators, the media, and public opinion. *American Journal of Political Science*, *59*, 457-474. doi:10.1111/ajps.12145

Stocking, S. H., & Gross, P. H. (1989). *How do journalists think? A proposal for the study of cognitive bias in newsmaking*. Bloomington: ERIC Clearinghouse on Reading and Communication Skills, Smith Research Center, Indiana University.

Stone, P. J., Dunphy, D. C., Smith, M. S., & Ogilvie, D. M. (1966). *The general inquirer: A computer approach to content analysis*. Cambridge, MA: MIT Press.

Subasic, P., & Huettner, A. (2001). Affect analysis of text using fuzzy semantic typing. *IEEE Transactions on Fuzzy Systems*, *9*, 483-496. doi:10.1109/91.940962

Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to Twitter? *Marketing Science*, *32*, 368-392. doi:10.1287/mksc.2013.0773

Walther, J. B. (1996). Computer-mediated communication impersonal, interpersonal, and hyperpersonal interaction. *Communication Research*, *23*, 3-43. doi:10.1177/009365096023001001

Walther, J. B. (2007). Selective self-presentation in computer-mediated communication: Hyperpersonal dimensions of technology, language, and cognition. *Computers in Human Behavior*, *23*, 2538-2557. doi:10.1016/j.chb.2006.05.002

Whissell, C. M. (1989). The dictionary of affect in language. In R. Plutchik & H. Kellerman (Eds.), *Emotion: Theory, research, and experience* (pp. 113-131). New York, NY: Academic Press.

White, D. M. (1950). The gate keeper: A case study in the selection of news. *Journalism and Mass Communication Quarterly*, *27*, 383. doi:10.1177/107769905002700403

Williams, B. A., & Delli Carpini, M. X. (2000). Unchained reaction: The collapse of media gatekeeping and the Clinton–Lewinsky scandal. *Journalism*, *1*, 61-85. doi:10.1177/146488490000100113

Williams, B. A., & Delli Carpini, M. X. (2004). Monica and Bill all the time and everywhere: The collapse of gatekeeping and agenda setting in the new media environment. *American Behavioral Scientist*, *47*, 1208-1230. doi:10.1177/0002764203262344

Wlezien, C., Soroka, S., & Stecula, D. (in press). A cross-national analysis of the causes and consequences of economic news. *Social Science Quarterly*.

Xu, W. W., & Feng, M. (2014). Talking to the broadcasters on Twitter: Networked gatekeeping in Twitter conversations with journalists. *Journal of Broadcasting & Electronic Media*, *58*, 420-437. doi:10.1080/08838151.2014.935853

Young, L., & Soroka, S. (2012). Affective news: The automated coding of sentiment in political texts. *Political Communication*, *29*, 205-231. doi:10.1080/10584609.2012.671234

Zhao, S., Grasmuck, S., & Martin, J. (2008). Identity construction on Facebook: Digital empowerment in anchored relationships. *Computers in Human Behavior*, *24*, 1816-1836. doi:10.1016/j.chb.2008.02.012

Zhao, W. X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., & Li, X. (2011). Comparing Twitter and traditional media using topic models. In P. Clough et al. (Eds.), *Advances in information retrieval* (pp. 338-349). Berlin, Germany: Springer. doi:10.1007/978-3-642-20161-5_34

Author Biographies

Stuart Soroka (PhD, University of British Columbia, 2000) is the Michael W. Traugott Collegiate Professor of Communication Studies and Political Science, and Faculty Associate at the Center of Political Studies, Institute for Social Research, University of Michigan.

Mark Daku (PhD, McGill University, 2015) is an assistant professor in the Department of Political Science, Texas Christian University.

Dan Hiaeshutter-Rice is a graduate student in the Department of Communication Studies, University of Michigan.

Lauren Guggenheim (PhD, University of Michigan 2012) is a senior researcher at the Center of Political Studies, Institute for Social Research, University of Michigan.

Josh Pasek (PhD, Stanford 2011) is an assistant professor in the Department of Communication Studies, University of Michigan.