Bad News or Mad News? Sentiment Scoring of Negativity, Fear, and Anger in News Content

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This article examines the prevalence and nature of negativity in news content. Using dictionary-based sentiment analysis, we examine roughly fifty-five thousand front-page news stories, comparing four different affect lexicons, one for general negativity, and three capturing different measures of fear and anger. We show that fear and anger are distinct measures that capture different sentiments. It may therefore be possible to separate out fear and anger in media content, as in psychology. We also find that negativity is more strongly related to anger than to fear for each measure. This result appears to be driven by a small number of foreign policy words in the anger dictionaries, rather than an indication that negativity in U.S. coverage reflects "anger." We highlight the importance of tailoring lexicons to domains to improve construct validity when conducting dictionary-based automation. Finally, we connect these results to existing work on the impact of emotion on political preferences and reasoning.

Keywords: negativity; dictionary-based sentiment analysis; discrete emotions

Negativity in news abounds. The prevalence of negativity is a regular feature not just in academic accounts of news content, but it is a subject of news itself. There has accordingly been a great deal of research on the prevalence and consequences of negativity in news content, both in the United States and elsewhere. Many scholars have raised concerns about the

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potentially detrimental impact of negativity, cynicism, and incivility in political discourse and electoral politics (Cappella and Jamieson 1997; Lichter and Noyes 1996; Sabato 1991). Indeed, the body of literature on negativity in political communication is expansive (e.g., Blumler and Gurevitch 1995; Lang and Lang 1968; Patterson 1994; Robinson and Sheehan 1983; Lengauer 2007; Soroka 2006, 2012, 2014a, 2014b; Trussler and Soroka 2014).

That said, there has been far less consideration of different kinds of negativity. "Bad" news typically refers to the occurrence of negative events. But what makes an event negative, and how is that negativity conveyed? Negativity may reflect the incidence of bad events, disapproval of policies, dislike of political candidates, or emotionality (the presence of emotion); and negative emotion may be conveyed as anger about a policy, fear or sadness in response to an event, or as general incivility. Clearly, there is much more to negativity than valence or polarity. Several authors have explored aspects of negativity relevant to political news, such as confrontation (Lengauer, Esser, and Berganza 2011), failure (Kepplinger 1998; see also 2011), and outrage (Sobieraj and Berry 2011) in political discourse. Soroka (2014a) makes the following distinction: "There are characteristics that are qualitatively negative, such as fear, or anger, and there are characteristics that are quantitatively negative, such as a monetary value that is lower than we expected, or a proposal that shifts policy away from our preferred level" (p. 29). For instance, a news story may be negative because unemployment is getting worse (quantitative negativity) or because a journalist or source is expressing disappointment or anger about the unemployment rate (qualitative negativity). Measures of negativity tend to reflect the former, or some combination of the two. They do little to distinguish between various types of "qualitative" negativity—essentially, the different negative emotions. Research on negativity biases in information processing has focused largely on our tendency to react more strongly to information that has negative rather than positive consequences. But we may also react quite differently to information conveying specific negative emotions, such as fear or anger. In that case, the emotional composition of the news becomes very important for media effects research. This is the core idea of the work that follows.

What kind of emotional appeals are being made, by whom, and across which news outlets? Do certain emotions frame particular topics? How are the affective elements of a text perceived and processed? To what extent, and in what manner, do these elements influence attitudes, opinions, and behaviors? We regard each of these as important and as-yet-unanswered questions. This article thus explores the possibility of capturing emotion in political news content, using large corpora that span considerable lengths of time. We use dictionary-based automated content analysis designed to capture trends in negativity, anger, and fear to analyze

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more than a decade of U.S. news content. We compare three different measures of fear and anger and compare those results to a previously validated measure of general negativity. We regard this as a first step toward a broader validation of fear and anger lexicons for political news. The end result is, we hope, a strong case for further, large-scale study of discrete emotions in news content.

Emotion in Politics and in Political News

Emotions are important for both political psychology and political communication. Work on emotion and reason has a long lineage, dating back to ancient Greek philosophers concerned with the role of emotion in political life (for discussions, see Elster 1999; Tarnopolsky 2010; Soroka 2014a). Damasio's (1994) account of two cases of frontal-lobe injuries has been particularly influential for those interested in the connection between emotion and reason. The centrality of emotions for rational thought is supported by work in psychology that links the ability to react to emotions to a range of outcomes, including life success (e.g., Goleman 2005), memory (e.g., Cahill 1996), and reasoning and decision making (e.g., Forgas 1995).

There are similar findings in political psychology. Conover and Feldman (1986) find that people may well forget the details in a given media story, but their emotional reaction to that story can be enduring; affective judgments, above and beyond cognitive ones, are also systematically related to presidential assessments. Work on "affective intelligence" suggests that individuals process information more thoroughly when they are anxious than when they are enthusiastic (Marcus, Neuman, and MacKuen 2000; Marcus and MacKuen 1993). And there are now numerous information processing theories and models based on the affect-cognition interaction, for example, selective attention and exposure (Sears and Freedman 1967), affective primacy (Zajonc 1980), and motivated reasoning (Lodge and Taber 2000, 2013), to name a few. (Also see related work by Abelson et al. 1982; Brader 2005; Just, Crigler, and Neuman 1996; Kinder 1978; McDermott 2004; Neuman 2007; Ottati, Steenbergen, and Riggle 1992; Redlawsk 2006; Rudolph, Gangl, and Stevens 2000; Way and Masters 1996.)

There are thus good reasons to believe that affect and emotion are central to political reasoning. It follows that affect and emotion ought to be an important consideration for the way we understand the primary source of citizens' information about the political world, namely, news content. Our particular interest here is in the difference between fear and anger, two especially relevant dimensions of general negativity. Research suggests that fear and anger can have quite different consequences where political attitudes and behavior are concerned. Physiological research finds quite different patterns of response for the two emotions (e.g., Sinha 1996); the two also produce different degrees of risk perception, and distinct responses on a range of political attitudes (e.g., Druckman and McDermott 2008; Huddy et al. 2005; Lerner and Keltner 2001; Lerner et al. 2003; Miller et al. 2009; Spanovic et al. 2010; Valentino et al. 2011). Anger tends to decrease risk perceptions and is mobilizing; fear tends to increase risk perceptions and is immobilizing. Politically, this can be quite consequential. For instance, post–9/11, Huddy, Feldman, and Cassese (2007) found that anxious respondents were less likely to support the Iraq war, whereas angry respondents were more likely to support the war. The fact that most existing media-focused research considers negativity, without distinguishing between fear and anger, is thus problematic for those interested in media effects on political attitudes and behavior.

Sentiment Analysis for Political Communication

The analysis of large datasets is becoming an increasingly important research method in today's digital information environment. Big data holds the promise of large-scale comparisons of the nature of news coverage and political talk across news outlets, social media platforms, by specific actors, and across particular regions or countries. Moreover, big data analysis allows researchers to capture the media signal (and eventually, media effects) over the medium to long term.

There are substantive advantages to analyzing political communication over time. Most media effects research focuses on relatively short time spans: lab- and survey-based experiments look at effects taking place over somewhere between several milliseconds and 30 minutes; analyses of media content and aggregate-level public opinion model effects over days, weeks, or perhaps a few months. But there are a number of communication theories that anticipate effects over much longer time periods. For example, cultivation theory focuses on "the relationships between institutional processes, message systems, and the public assumptions, images, and policies that they cultivate" (Gerbner 1970, 71). Thus far, analyses of media content have been limited in their ability to capture a lifetime of media content. This need no longer be the case. Recent work by Druckman and colleagues on framing and counterframing effects over time also points to the advantages of taking longer time periods into account when thinking about media effects (Druckman et al. 2010; Chong and Druckman 2010, 2013). The study of negativity (and negative emotion) in news content might also benefit from the long-term perspective that new data sources are able to offer. There is an existing body of work tracking changes in the tone of election-period advertising over time (e.g., Geer 2008; Cappella and Jamieson 1997). This work makes the argument that negativity in ads has increased steadily over the postwar period. One common assumption is that the same is true for news content more generally, but there is as yet no evidence to support this conjecture. And the possibility that there have been shifts in the prevalence of negative emotions in news content is, as we have noted, almost wholly ignored.

How is sentiment assessed? An answer to this question requires us to consider both the mechanics of measurement, and what exactly sentiment is. We begin with the latter. Sentiment is a broad construct comprising attitudes, opinions, and emotions, where (1) attitudes refer to positive or negative evaluations, (2) opinions refer to judgments and beliefs, and (3) emotions refer to feelings. (There will be relationships between theses, of course—attitudes themselves are underscored by opinions and/or emotions, for example.) The aim of sentiment analysis is thus to detect attitudes, opinions, and/or emotions in a text. These different dimensions of sentiment require somewhat different methods, and may well afford a different set of inferences. Sentiment analysis can be applied to first person texts to make inferences about the attitudes, opinions, or affective state of a speaker. It can also be used to analyze news content, to map the affective composition of a text.

These dimensions are often blurred or collapsed in computer science and market research, where the majority of sentiment analysis has taken place (e.g., Pang and Lee 2008; Liu 2012). Despite adopting a broad definition of sentiment, the vast majority of sentiment analysis measures valence (positive/negative) (e.g., Pang, Lee, and Vaithyanathan 2002). Analysis of textual polarity is particularly useful for attitude research (like/dislike, good/bad, support/disapprove); it nicely captures "emotionality" (the presence or absence of emotion) (Cho et al. 2003); and it is the standard approach to assess the "tone" (positive/negative) of news coverage, a summary measure of affective content that comprises all three dimensions of sentiment (e.g., Soroka 2006, 2012). "Opinion mining" refers to the extraction of opinions (subjectivity) from a text (Kushal, Lawrence, and Pennock 2003). It is often used interchangeably with sentiment analysis, although in the literature, opinion mining refers to the measurement of opinions and/or attitudes, and tends to ignore emotions.

Generally speaking, much less research has been conducted on specific emotions that inform and reflect attitudes and opinions. Is a review negative because a product is disliked, or because the product does not work? Is an event negative because it is sad, or scary? Several studies have automated the coding of fear and anger using dictionary-based analysis on large corpora, for online support groups (Alpers et al. 2005), text messages on 9/11 (Back, Küfner, and Egloff 2011), and political tweets (Tumasjan et al. 2010). Interrater validation has focused largely on valence; however, efforts to validate discrete emotion measures are infrequent, and results are mixed. Studies are finding low to moderate positive correlations between manually annotated data and dictionary scores. Reliability and validity tend to vary across different emotions and corpora, for humans and machines.

Those conducting machine learning approaches to sentiment analysis also struggle to validate measures. Supervised approaches require manually annotated data to train classifiers for coding. As above, the reliability of human annotations varies across emotions. For instance, for both annotations for emotions in blogs (Aman and Szpakowicz 2007) and for news headlines (Strapparava and Mihalcea 2008), fear was more reliably coded than anger. Strapparava and Mihalcea (2008) compared measures of anger, disgust, fear, joy, sadness, and surprise generated using a sentiment dictionary (WordNet Affect), expert coded headlines, and user-annotated blogs. Training on blogs proved best for measures of anger and joy; and annotated headlines best captured fear and surprise. For all emotions, dictionaries had exceptional precision, but very low recall, suggesting that the method can be accurate, but that current lexicons are lacking scope.

Machine learning systems worked in the opposite manner, exhibiting greater coverage but more error.

Dictionary-Based Coding of Fear and Anger

Is it possible to capture affect and emotion using dictionary-based automated content analysis? We believe that it is. We have already developed a dictionary-based system for capturing positive and negative affect in news content (Young and Soroka 2012).[1] The Lexicoder Sentiment Dictionary (LSD) is a comprehensive affect lexicon constructed and tailored for political news; it consists of 4,567 positive and negative words and phrases. The dictionary has been validated against manually coded data and in predictive models. It was also compared to, and outperformed, nine other valence dictionaries (including those in this study). The LSD is being used in a growing number of studies (e.g., Soroka 2012, 2014a; Balmas 2014; Fournier et al. 2013; Giasson 2012). Our goal here is to build on this existing research.

Dictionary-based coding is a simple and powerful analytic approach to text analysis. Dictionary construction is quite laborious, but once a dictionary is established, the dictionary-based coding is easy to implement, computationally straightforward, and transparent. Dictionary-based coding relies on a simple frequency count of keywords in a text from a predefined dictionary. It does not require extensive coding to train classifiers, and it is reliable.

There are limitations to this approach, of course. For instance, a manually generated set of words cannot possibly reflect all of the lexical ambiguity in natural language. To mitigate this problem, we have developed an extensive preprocessing system based on the contextual and domain-specific use of dictionary terms in political news. This process standardizes language and punctuation and facilitates basic word sense disambiguation for more than fifteen hundred frequently occurring words. We disambiguate homonyms and multiple word senses, and correct truncation errors; we also account for basic negation patterns. Many entries were added or adjusted using keyword-in-context (KWIC) analysis. Some KWIC-adds reflect our truncation decisions, for example, "discrimina*," "garbl*," "disab*," "cloudi*"; others include domain-specific expressions, for example, "black mark," "can of worms," "holier than thou," "hot headed," "off the rails," "play god," "rock bottom"; and some include word sense disambiguation, for example "cool" was removed and replaced with "cool head," "cool reception," "play it cool," and "supercool." Preprocessing and tailoring to domain reduces both noise and bias in the measure. For the analysis below, all text was preprocessed using the Lexicoder preprocessing scripts in TextWrangler, a robust and freely available Mac-based text editor.[2] The frequency of positive and negative words was generated using the Lexicoder software and a measure of net tone was calculated as follows: (#positive words – #negative words)/total words.

Dictionaries may be particularly well suited to code emotion. Humans are able to react to a text, but the linguistic presence of fear and anger in a text is rather abstract and particularly difficult for humans to reliably code. A theoretically driven lexicon is able to provide a consistent measure that can be validated by other means. Although there are numerous affect lexicons available, only a handful include discrete emotion categories, and not all of these include fear and anger in particular. Although these categories are often internally consistent, external validation is a work in progress. Different lexicons operationalize emotion in different ways and these measures are rarely compared. Evidence of the convergent and discriminant validity of negativity, fear, and anger measures provides a starting point for a broader validation of automated measures of discrete emotions.

Here we used the three existing affect dictionaries with discrete emotion categories: Linguistic Inquiry and Word Count (LIWC; Pennebaker, Francis, and Booth 2001), the Regressive Imagery Dictionary (RID; Martindale 1975), and the General Inquirer (GI; Stone et al. 1966). LIWC was constructed for use in psychology. It draws on a wide range of written and spoken text. Individual words were classified into sixty-two affective and cognitive categories by expert judges. Validation efforts focus on only a handful of those categories. The RID employs a theoretically and empirically driven schema to measure primordial (associative) versus conceptual thinking. Validity and reliability (Martindale 1975) studies found more primordial content in fantasy genres and folktales, historic texts, and among youth. The RID contains forty-three categories for a range of cognitive and affective processes. Few efforts have been made to validate the composite categories. The GI is a widely used lexicon for political communication research. It was constructed by merging several psychological and political dictionaries. The GI contains 182 social and psychological dimensions. Past research has found the GI to be overly broad and nondiscriminating (Young and Soroka 2012).

To construct fear and anger measures, we used pre-existing categories when they were available and constructed them from conceptually related categories when they were not. From LIWC we used the existing categories *anxiety* and *anger* (n = 273). The RID contains the category *anxiety*, but not *anger*, and the GI contains neither. To identify conceptually related categories, we searched for the presence of related core entries, such as anxiety, fear, and scared; or anger, hate, and aggression.[3] From these results we constructed a list of fear- and anger-related words. From RID we used an existing category labeled *anxiety* and identified the category *aggression* as conceptually related to anger (n = 271). From GI, our search identified the categories *pain* and *weak* as containing fear-related words; and the categories *hostile* and *vice* as containing anger-related words (n = 1,358). A small number of words appeared in both categories and these were removed, so the measures are mutually exclusive. The fear lexicons include words such as, “grieve,” “timid,” and “fearful”; and anger words include “arrogant,” “disparage”, and “attack.” Fear and anger measures were standardized by dividing the frequency of words in each list by the total number of words in an article.

Data and Analysis

Our analysis here is necessarily brief and introductory in scope, but we see our results as an important first step in what we hope will be a serious consideration

TABLE 1
Bivariate Correlations; Measures of Negativity, Fear, and Anger

	LSD Negative	GI Anger	GI Fear	LIWC Anger	LIWC Fear	RID Anger
GI anger	.56					
GI fear	.23	.10				
LIWC anger	.59	.28	.05			
LIWC fear	.30	.15	.16	.12		
RID anger	.42	.23	.06	.30	.02	
RID fear	.08	.03	.06	–.03	.06	.00

NOTE: N = 53,358. All correlations are significant at $p < .01$, except the correlation between anger and fear in the RID.

of dictionary-based automated coding of discrete emotion in news content. We test-run these dictionaries using a set of roughly fifty-five thousand front-page stories from the *New York Times* and the *Washington Post*; that is, all front-page stories from 2000 through 2013 available through Lexis-Nexis.

Table 1 shows correlations among the various measures of negativity, fear, and anger. All correlations are statistically significant and in the expected direction. But the magnitude of correlations varies a good deal. LSD negativity is more strongly related to anger than to fear in each of the three other dictionaries. The strongest correlation is between the LIWC and RID measures of anger. And as a general rule, the measures of anger are more strongly related to each other; and the same is true for measures of fear. Even so, bivariate correlations make clear that the four dictionaries are capturing somewhat different things.

Table 2 offers a factor analysis of the measures of fear and anger. The idea here is to make clear(er) the connection between fear measures on one hand and anger measures on the other. There quite clearly is a difference between the two, and we take this as an early indication that, just as it is possible to separate out fear and anger in psychophysiology and political psychology, it is possible to separate out fear and anger in media content. The factor analysis also points to one possible way of combining the information from multiple dictionaries. In short, rather than rely on a single measure of fear or anger, we can use factor loadings to capture the underlying fear and anger dimensions, essentially, the common variance in fear and anger coding across the three dictionaries. We take advantage of this possibility in Figure 1.

Figure 1 plots annual averages for each measure of negativity, fear, and anger. More precisely, the figure shows, in the top left panel, predicted values of the LSD negativity measure, based on an ANOVA, where year is the only independent variable. (All panels show margins of error for each estimate.) The process is repeated for all separate measures of anger and fear, and then for the factor loadings for each of anger and fear. The figure illustrates what we already know from Tables 1 and 2: there are real differences among negativity, fear, and anger; and

TABLE 2
Factor Analysis, Fear and Anger across Dictionaries

	Factor	
	1	2
GI anger	**0.64**	0.05
LIWC anger	**0.76**	0.22
RID anger	**0.72**	0.07
GI fear	0.11	**0.66**
LIWC fear	0.09	**0.67**
RID fear	0.07	**0.50**
Eigenvalue	1.54	1.22

NOTE: N = 53,358. Based on a principal components factor analysis with orthogonal rotation.

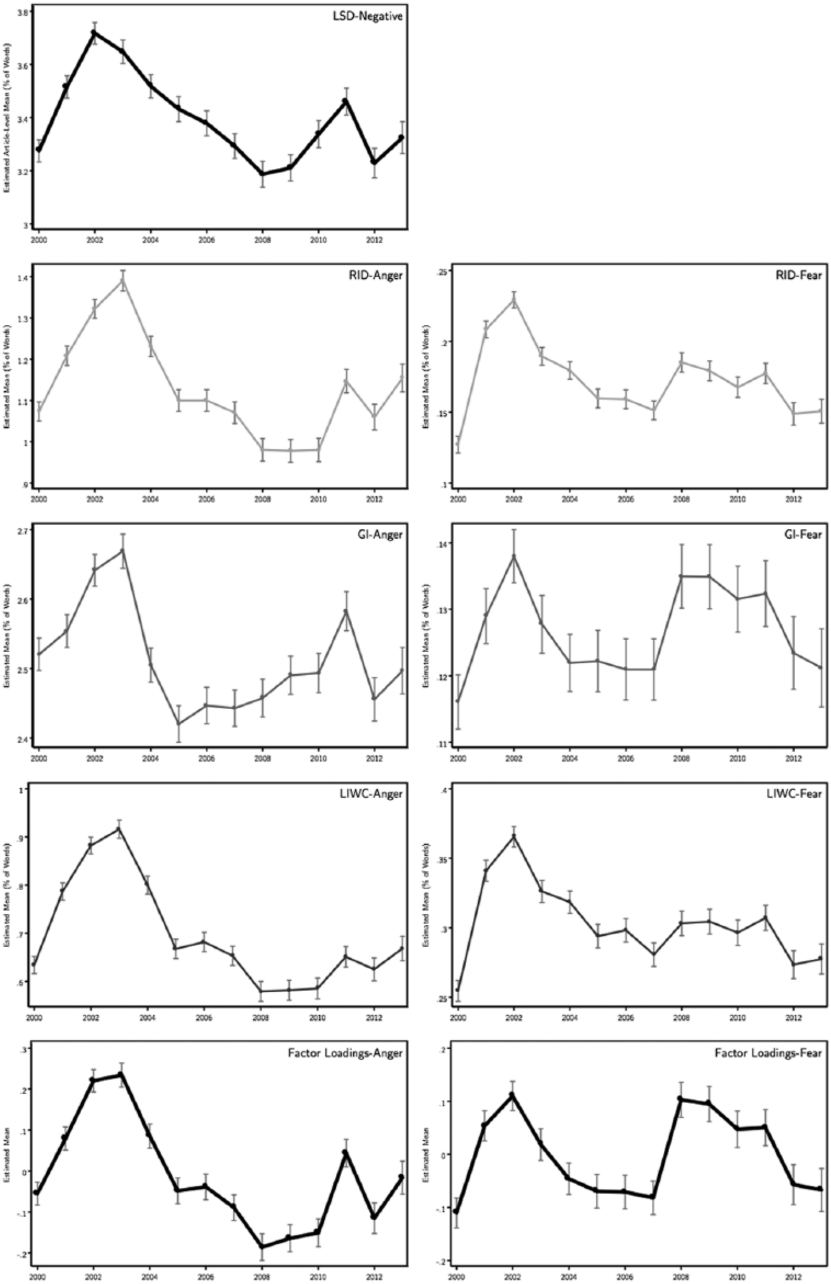
the separate measures of fear and anger, though they are based on rather different sets of words, produce relatively similar results.

The correlation between LSD negativity and anger (seen both in Table 2 and Figure 1) was unexpected. Does negativity in U.S. coverage reflect "anger"? The correlation is not an artifact of the number of words in a dictionary; anger lexicons contain more words than anxiety dictionaries, but the top twenty in each account for most variation in the measure. In fact, the top five most frequent words in LIWC and RID anger lexicons account for 80 and 40 percent of variation in those measures, respectively. Moreover, these top words all relate to foreign policy: "war," "attack," "fight," and "threat." Thus, anger measures appear to have a topic confound in the political domain—they are driven largely by several words relating to foreign policy. If anger is picking up foreign policy salience, the correlation with negativity may be due to the general negativity of foreign policy coverage, rather than being an indication that negative coverage reflects "anger."

What is important is that this correlation is not driven by anger (or topic) words in the LSD—as intended, this lexicon is driven by general negativity. The top five most frequent words in the LSD account for only 12 percent of its variance, and these words are much more general, including "problem," "hard," and "ill." (We note that GI top words suggest a lack of construct validity: anger includes "war," but also "time" and "run"; and fear includes "concern," but also the word "blue.") The LSD is not confounded by political topics because it was customized and tailored for political texts (Young and Soroka 2012). This discussion points to the importance of customizing dictionaries for specific domains, and the pitfalls of "off-the-shelf" usage. Disambiguating political topics and emotion words could greatly improve the construct validity of current emotion lexicons (especially anger) for use on political texts. Analyzing words in context and incorporating natural language frequencies are useful tools to do so.

Although we cannot provide adequate tests of validity here, and despite apparent weaknesses in existing measures of anger in particular, there are several hints

FIGURE 1
Negativity, Fear, and Anger over Time



that we are capturing something of substance. We see the strong relationship between measures of fear and anger as one indication that the various dictionaries are capturing something "real." We also note the increase in all measures following 9/11, and again during the Great Recession. It appears as though fear peaked in 2001, and anger peaked in 2003. We see this as a potentially interesting chain of emotions following 9/11. This is largely conjectural at this stage, of course. But as previous work suggests, quite different political responses to terrorism would be expected based on exposure to fear versus anger. Clearly, further work on the role of media in this particular domain is warranted.

Conclusion

It is important to distinguish between different negative emotions to better understand the attitudinal and behavioral consequences of negative news content. The results presented above suggest that fear and anger lexicons are able at least in part to capture these different emotions.

We argue that one advantage to the ready availability of large bodies of data (from multiple mediums and media sources) is that we are better able to capture media content and effects over the very long term. We also outline some of the tools required to do so and provide a preliminary analysis using more than a decade of front-page news stories. We take these results as illustrative of the capacity and potential for automated techniques to capture emotion in very large bodies of media data. We believe that this work points to new avenues for future research, then, with the potential to deepen our understanding of the effects of negativity, and emotion more generally, in news coverage.

Notes

1. The Lexicoder Sentiment Dictionary, software, and preprocessing scripts are freely available for academic use at lexicoder.com.

2. There are many PC-based text editors that could be used. However, the preprocessing scripts available with the Lexicoder software are currently formatted for Mac only. We intend to include integrated or cross-platform options for preprocessing in future versions of Lexicoder.

3. Alternately, we could have manually identified related categories based on their labels. We found this approach to be unreliable. While some labels could easily be identified (e.g., "attack"), others may have been overlooked (e.g., "weak").

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