The Power of Television Images in a Social Media Age: Linking Biobehavioral and Computational Approaches via the Second Screen

By
DHAVAN V. SHAH,
ALEX HANNA,
ERIK P. BUCY,
CHRIS WELLS,
and
VIDAL QUEVEDO

There is considerable controversy surrounding the study of presidential debates, particularly efforts to connect their content and impact. Research has long debated whether the citizenry reacts to what candidates say, how they say it, or simply how they appear. This study uses detailed coding of the first 2012 debate between Barack Obama and Mitt Romney to test the relative influence of the candidates' verbal persuasiveness and nonverbal features on viewers' "second screen" behavior—their use of computers, tablets, and mobile phones to enhance or extend the televised viewing experience. To examine these relationships, we merged two datasets: (1) a shot-by-shot content analysis coded for functional, tonal, and visual elements of both candidates' communication behavior during the debate; and (2) corresponding real-time measures, synched and lagged, of the volume and sentiment of Twitter expression about Obama and Romney. We find the candidates' facial expressions and physical gestures to be more consistent and robust predictors of the volume and valence of Twitter expression than candidates' persuasive strategies, verbal utterances, and voice tone during the debate.

Keywords: 2012 presidential debate; computational communication science; machine learning; nonverbal behaviors; political performance; sentiment analysis; Twitter

More than a half century after the first televised presidential debates between John F. Kennedy and Richard Nixon, broadcast debates remain central to U.S. political culture, albeit surrounded by questions about their

Dhavan V. Shah is the Louis A. & Mary E. Maier-Bascom Professor at the University of Wisconsin–Madison, where he is director of the Mass Communication Research Center. His work focuses on framing effects on social judgments, digital media influence on civic engagement, and the impact of health ICTs.

Alex Hanna is a doctoral candidate in the Department of Sociology at the University of Wisconsin–Madison. Alex is interested in social movements, media, and computational social science.

DOI: 10.1177/0002716215569220

electoral impact (Benoit 2013; Druckman 2003). Excepting Election Day itself, no events during a voting cycle compare to debates as moments of focused national attention and—in a social media age—public expression. In 2012, for example, more than 70 million Americans—the most in 32 years—watched the first debate between Barack Obama and Mitt Romney, with only the Super Bowl attracting more viewers (Carr 2012).[1] And during its 90 minutes, the debate generated 10 million posts on Twitter, making it "the most tweeted-about event in U.S. politics" up to that time (Sharp 2012, 1).

We offer these facts to make three points. First, debates constitute moments of considerable national attention—and via social media, public expression—among the electorate. Second, despite this, there remains considerable uncertainty about the nature of the public's response to these focal moments, that is, whether the citizenry reacts to what candidates say, how they say it, or simply how they appear (Benoit 2013; Cho et al. 2009; Zhu, Milavsky, and Biswas 1994). Third, research has not examined the strong, almost immediate, connection between televised debates and social media—linking "first" and "second" screens in real time—to examine how the volume and valence of posts are tied to what is heard and seen in those moments.

The conventional wisdom surrounding televised debates, beginning with the Kennedy-Nixon encounter, centers on the power of images and asserts that viewers are heavily "influenced by appearances, gestures, or other nonverbal behaviors" (Kraus 1996, 78). Druckman's (2003) test of either watching or listening to the 1960 debate (among subjects with no knowledge of its history) confirmed that viewing altered debate evaluations, primed a greater reliance on personality perceptions, and enhanced learning among nonsophisticates. These findings suggest that something beyond the functional features of persuasive discourse—attack (criticize, condemn), contrast (boast, tout, compare), respond (reply, defend, restore), and involve (share, relate, narrate)—drive these differences (Benoit and Harthcock 1999; Green and Brock 2000).

To examine the power of the visual in presidential debates, we combine computational and biobehavioral approaches. The latter begins with the assumption

---

Erik P. Bucy is the Marshall and Sharleen Formby Regents Professor of Strategic Communication in the College of Media and Communication at Texas Tech University. His research includes nonverbal aspects of political news and public opinion about the press. He is the editor of Politics and the Life Sciences, *an interdisciplinary journal.*

Chris Wells is an assistant professor in the School of Journalism and Mass Communication, codirector of the Social Media & Democracy and Civic Culture & Contentious Politics working groups both at the University of Wisconsin–Madison, and author of The Civic Organization and the Digital Citizen *(Oxford University Press 2015). His research explores citizenship and participation via emergent media.*

Vidal Quevedo is a doctoral candidate in the School of Journalism and Mass Communication at the University of Wisconsin–Madison. His research interests center on how social media are used by individuals and communities to interact and disseminate information.

NOTE: The authors would like to thank Zijian Harrison Gong and Riley Davis for their assistance with coding the debate and the Walter J. & Clara Charlotte Damm Fund of the Journal Foundation and Social Science Korea/Korea National Research Foundation for supporting this research.

that assessments of politicians in debates can depend as much, if not more, on their nonverbal behavior as on their verbal message (see Grabe and Bucy 2009). We thus assess the influence of functional elements alongside voice tone, facial expressions, and physical gestures by both candidates during the first 2012 debate, coding for these elements at the level of the individual camera shot (ranging from 12 to 30 seconds).

We then relate these shot-by-shot differences in functional, tonal, and visual features to the volume and valence of expression on Twitter concerning Obama and Romney during both synchronous and lagged time periods. We acquired these indicators of online political expression by harvesting 10 percent of Twitter content (the Twitter "garden hose") and culling it for keyword mentions of the candidates and sentiment scoring of these posts. In doing so, we examine which specific features of the candidates' debate performance relate to responsiveness on the "second screen."

Literature Review

This research extends a long line of work examining visual portrayals and candidate nonverbal behavior (e.g., Hellweg and Phillips 1981; Tiemens et al. 1985) that runs parallel to studies on rhetorical strategies employed by candidates during modern presidential debates (see Benoit 2013; Jamieson and Birdsell 1990). Before reviewing these nonverbal factors, we first consider historical changes in debate presentation and performance that increasingly highlight contentiousness and incivility in such settings.

Debates and the "second screen"

Within U.S. electoral history, regular debates between presidential candidates are a relatively new phenomenon that parallels the rise of television. As television changed, so too did forms of debate. The 1960 debates were shown in black and white from a limited number of camera perspectives and fixed shot angles (Kraus 1996). By the 2000s, a dozen channels were broadcasting presidential debates, including CNN and Fox News, with more camera angles, moving shots, and split-screen presentations allowing viewers to continuously monitor the reactions of one candidate while the other was speaking (Cho et al. 2009).

Media changes have also altered the national conversation that occurs around debates. The largest change involves the many millions of debate viewers who are communicating with family, friends, and other social connections via networked digital media in real-time, typically through a "second screen" that is used to enhance a viewing experience (Tsekleves et al. 2007). Given that online networks often tend toward homophily and consensus (Conover et al. 2011), online exchanges may support or even amplify the long-standing finding that debate viewing "largely reinforces existing predispositions rather than substantially changing previously held images of candidates, issue orientations, or voting intentions" (Sigelman and Sigelman 1984, 624; Abramowitz 1978).

Similarly, social media use around the debate may reinforce what Wald and Lupfer (1978) observed—that debates increase cynicism and reduced trust. They attributed this to the tendency of debates to focus "primarily [on] a criticism of present and proposed government policy" (p. 351). Yet these and most other analyses fail to consider the tonal and visual elements of candidate behavior that also contribute, if not outperform, the influence of candidate statements. Mutz and Reeves (2005; see also Mutz 2007) consider this possibility in the context of televised conflicts among pundits. They find that heightening contention in tone and visual style, while keeping content constant, impacts viewer evaluations. In the contemporary environment, online interactions via "second screens" may amplify these effects.

Presentation and performance

Production practices work alongside candidate performances to heighten the sense of conflict when observing televised contention (Alexander 2010; Davis 1999; Zettl 1990). Mutz (2007) explicitly argues for the interplay of presentation and performance. Supporting the view that visual and tonal features shape responses beyond verbal strategies, she observes that the effect of televised incivility—that is, being disrespectful, interruptive, and inattentive—is amplified when presentation choices, such as close-up camera shots, highlight conflict. In a similar vein, the split screen format of recent presidential debates has allowed "viewers to constantly monitor the words, gestures, and reactions of each candidate, [heightening the] perception of conflict in much the same manner as close-up camera shots" (Cho et al. 2009, 245).

Underscoring the importance of effective nonverbal communication in politics, the first debate of 2012 was notable precisely because of the demeanor, engagement, and gaze of the candidates. As commentators like Jeffrey Alexander (2012) noted, "political performances are also about eyes and energy, about looking and being looked at, about seeming eager and interested and caring," and the candidates in the first debate varied considerably in their effectiveness. Thus, expressive variation during a debate not only takes the form of rhetorical maneuvers—attacks (e.g., criticism, condemnation), contrasts (e.g., comparison, promotion), responses (e.g., replies, defenses), and shared narratives (e.g., examples, involvement), for example (Benoit and Harthcock 1999; Green and Brock 2000)—but also continuous fluctuation in voice tone, facial expressions, and physical gestures.

Voice tone. Voice tone is a paralinguistic cue present in all spoken communication. It imparts the emotion of the speaker, potentially moderating the meaning of what is said and shaping audience reactions (Hall 1980). Tone also signals social intent, whether to communicate disapproval or threat, in the case of an angry tone, or reassurance, as in the case of a friendly one. As Laplante and Ambady (2003) find, tone of voice shapes judges' ratings of politeness or impoliteness. Longitudinal studies of presidential election coverage have found that challengers and debate losers tend to be more aggressive in tone than incumbents and front-runners (Bucy and Grabe 2008; Grabe and Bucy 2009), consistent with their tendency to attack (Benoit 2013).

Expressions and gestures. Even more consequential than tone of voice is the quality of the candidates' facial expressions. The face, more than any other expressive feature, serves as the primary channel of emotional communication, conveying affective states and behavioral intentions to observers. Two primary categories of displays derived from studies of primate ethology, a branch of behavioral biology, and identified in studies of nonverbal political communication are happiness/reassurance and anger/threat (Sullivan and Masters 1988). Happiness/reassurance displays facilitate a hedonic or friendly mode of social interaction, lowering the probability of an aggressive or agonistic encounter. Anger/threat displays, on the other hand, are associated with hostile encounters and attempts at unseating the leader (Bucy and Grabe 2008). Although reassurance is more commonly associated with effective leadership, in competitive contexts, partisans also respond positively to anger/threat (Masters et al. 1986).

Similar to voice tone, trailing candidates and debate losers are shown more often in political news coverage as exhibiting anger/threat and making defiant gestures, including finger pointing or wagging, making a fist, or shaking their head in disagreement (Grabe and Bucy 2009). Debate winners, by contrast, are more likely to be shown engaging in affinity behaviors that imply bonding, compassion, or friendship. While less nuanced than facial expressions, gestures usually work in tandem with expressions and are thought to amplify their effect. The capacity of nonverbal displays to have political influence depends on at least two qualities of candidates, political status and expressive ability, as well as the context in which the displays occur.

In close elections where much is at stake, leader displays are likely to take on added significance. High-status leaders are said to have an "attention-binding" quality that draws continued observance by other members of the social group (whether journalists, party activists, or interested voters). Indeed, Sullivan and Masters (1993) have characterized facial displays as leadership behavior. Thus, in cases where the incumbent performs particularly poorly or commits a violation of nonverbal expectations (see Burgoon and Hale 1988), such as acting in an inappropriate or unexpected manner, we would expect a higher volume of attention to and communication in response to these actions, as well as an outpouring of negatively valenced reactions.

Hypotheses and Research Questions

In this study, we measure communication behavior in response to an actual presidential debate, as it was occurring, by tracking the volume and sentiment of realtime public expression on Twitter. By measuring actual responses from users of a popular social network, this approach benefits from a high degree of ecological validity. Although Twitter users are not necessarily representative of the population, they are nonetheless quite diverse, and their voluminous real-time comments allow us to trace, in a highly granular fashion, the connections between the first and second screens that characterize the television viewing experience in a social media age.

We expect that the tonal and visual elements of the candidates' debate performance will shape reactions on social media above and beyond the verbal strategies candidates use in an effort to score political points, win favor with the public, and (inadvertently) create quotable moments. In light of these considerations, we predict that:

Hypothesis 1 (H1): Nonverbal elements of candidate behavior, specifically voice tone, facial expressions, and gestures, will explain differences in the *volume* of online expression directed at each candidate above and beyond what is accounted for by verbal elements.

H2: Nonverbal elements of candidate behavior, specifically voice tone, facial expressions, and gestures, will explain differences in the *sentiment* of online expression directed at each candidate above and beyond what is accounted for by verbal elements.

Given the novel nature of this analysis, we pose two general research questions regarding the relative influence of tonal and visual factors on the volume and valence of expression, as well the role of specific tonal qualities, facial expressions, and gestures. Accordingly, we ask:

Research Question 1 (RQ1): Which tonal qualities, facial expressions, and gestures explain differences in the *volume* of online candidate expression when accounting for verbal elements?

RQ2: Which tonal qualities, facial expressions, and gestures explain differences in the *sentiment* of online candidate expression when accounting for verbal elements?

Methods

To examine these relationships, we merged two datasets: (1) a shot-by-shot content analysis of the first presidential debate between Barack Obama and Mitt Romney that coded for functional, tonal, and visual elements; and (2) corresponding measures of the volume of name mentions of Obama and Romney on Twitter and the sentiment scoring of this expression.

Debate coding

For the verbal, tonal, and visual content analysis, C-SPAN's televised coverage of the first debate was used. This feed showed both candidates in split-screen format, using a medium shot from the waist up, for the duration of the debate, enabling coding of all nonverbal responses. Given that other broadcasters drew on the same nine camera feeds, but were free to use whichever images they chose, it is notable that all the major news outlets—ABC, CBS, NBC, CNN, and Fox News—favored split-screen shots. As Sam Feist, CNN's Washington bureau chief stated, "We want to give our viewers the opportunity to see both candidates as frequently as possible. In a presidential debate, the image of the candidate who is listening is frequently as interesting as the candidate who is talking" (Peters 2012, A11). To standardize analysis across comparable units, the visual, tonal, and verbal aspects of the debate were coded at the level of the individual camera shot. In cases where shots exceeded 30 seconds, they were divided into 30-second increments. For the 90-minute debate, this resulted in 177 codable segments ranging from 5 seconds to 30 seconds.

Coding of the debate proceeded in two stages. In the first stage of the analysis, the candidates' statements were coded for their primary rhetorical function and "memes"—a reproducible unit of culture that is widely shared (Dawkins 1976). In the second stage, the candidates' nonverbal behavior was coded for tonal and visual elements, along with debate memes.

Rhetorical functions. Major rhetorical functions identified in individual debate segments included *attacks* on the opponent, *contrast statements* that highlighted differences between the speaker and his opponent, direct *responses* to statements (typically attacks) made by the opponent, and *personal narratives* from the candidate's own experience (see Benoit and Harthcock [1999]; Green and Brock [2000] for details on these categories).[2]

Memes. We identified five memes in the first debate, including Romney's promise to cut funding for public television, even though he declared, "I love Big Bird"; and Obama's statement to moderator Jim Lehrer, "I had five seconds before you interrupted me." Because memes are memorable debate encounters based on the utterances of the candidates, they were included with the verbal elements. Via digital media, memes reproduce almost immediately as highly quotable sound bites that are discussed by pundits in postdebate analyses and rebroadcast in news reports.

Tonal elements. In any persuasive encounter, a large part of nonverbal influence stems not just from semantic content but also from voice tone and variability (Bucy and Grabe 2008). We coded for presence or absence of two emotion/intention pairs that play a central role in political competition: anger/threat and happiness/reassurance. These categories reflect the felt emotion and presumed behavioral intention of the communicator (Way and Masters 1996).

Anger/threat was operationalized as statements in which the candidate's tone had a menacing or hostile feel; where the candidate used confrontational verbal tactics to challenge his rival; where the candidate revealed a desire to do political battle, or took exception to and forcefully rebutted a claim by his opponent; or where the overall tone of a segment could be characterized as enraged, feisty, bold, or aggressive.

Happiness/reassurance was operationalized as statements in which the candidate's tone had an optimistic or cheerful feeling; where the candidate's voice was upbeat, positive, and conveyed an affiliative intent; where the candidate offered hopeful predictions about what will happen to the country if elected; or where the tone suggested an attempt at bonding or reinforcing a sense of goodwill with potential supporters.

Visual elements. Next, we coded aspects of the candidates' nonverbal behavior, particularly facial expressions and body language. Consistent with voice tone, we coded for the presence of anger/threat and happiness/reassurance in facial expressions. We also documented the occurrence of gestures that signaled affinity (bonding) or defiance (aggression).

Consistent with the biobehavioral approach to nonverbal communication (see Masters et al. 1986), facial expressions that contained one or more of the following key elements were classified as anger/threat displays: lowered eyebrows, a staring gaze, the visibility of lower teeth, lowered mouth corners (frowning), facial rigidity that showed little to no movement, lips pressed firmly together, or an overall expression that was negative or hostile.

Similarly, happiness/reassurance displays were operationalized using very specific behavioral criteria as expressions containing one or more of the following elements: a smile with relaxed mouth position, the visibility of upper or both rows of teeth, nodding up and down, a combination of brief eye contact to avoid staring, open or just slightly closed eyes, "Crow's feet" wrinkles around the eyes, or an overall expression that was welcoming.

Gestures were coded as body language that signaled affinity or defiance (see Grabe and Bucy 2009). Affinity gestures consisted of hand, body, or facial movements that suggest a friendly relationship or attempt at bonding between the candidate and the audience, opponent, or moderator. Examples include waving or giving a "thumbs-up"; winking or nodding knowingly to the camera, moderator, or other candidate; or using an open palm when referencing the audience or opponent (rather than a closed fist or pointed finger).

Defiance gestures consisted of hand, body, or facial movements that suggest a threatening or antagonistic relationship between the candidate and his opponent. Examples include finger pointing, wagging, or shaking; raising a fist; shaking's one's head in disagreement; negative expressions accompanied by prolonged stares; or other behaviors signaling aggression.

Intercoder reliability. For each verbal, tonal, and visual variable, a trained coder documented the presence or absence of each defined category for each shot or 30-second segment. Each element was coded 1 if present and 0 if absent for all 177 codable segments.

For the verbal elements, a second coder assessed each of the 177 retained segments, agreeing on all but 38 of the 1,770 individual codings, for Krippendorff's alphas ranging from .89 for Obama's use of contrast to 1.00 for Romney's use of response. Instances of disagreement were discussed between coders until a consensus was achieved. For the tonal and visual variables, 11 percent of the debate footage, or twenty segments, was assessed by a second coder. Tonal variables had a high level of agreement. Krippendorff's alpha for Obama and Romney's anger/threat and happiness/reassurance voice tone was .93 and 1.00, respectively. Affinity and defiance gestures had perfect agreement. For facial expressions, again of anger/threat and happiness/reassurance, there was .95 agreement, which dropped to alpha scores of .83 and .78 when adjusted with Krippendorff—still an acceptable level of agreement.

Each coded shot of the debate was the unit of observation and analysis, with the volume and sentiment of expression on Twitter normed by the length of the unit, so that differences were not due to differences in the timing of the shots.

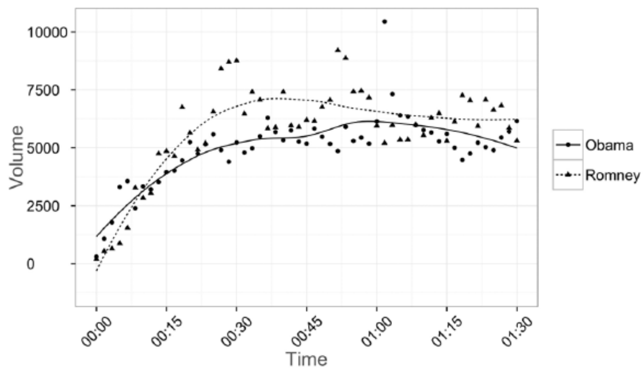
Twitter harvesting

For this study, we archived the Twitter garden hose as a sample of social media activity through its Streaming API.[3] Twitter describes the garden hose as a continuous 10 percent sample of the 300 to 500 million global tweets per day. Tweet information includes a variety of different fields, including user information, tweet time, geolocation (if available), and platform used to post the tweet.[4] From this archive, we drew posts around a 50-day window before the election, from September 19, 2012, to November 8, 2012, that included "Obama," "Romney," "Biden," or "Paul Ryan" (not case-sensitive). We then focused on the tweets on October 10, 2012, that referenced Obama or Romney in the body text. For each tweet, we coded for whether it mentioned only Obama or only Romney based on usage of their last names, which was the basis for the volume measures.

We conducted a sentiment analysis using a supervised machine learning method. To generate a training set, we randomly sampled 1,000 tweets, 500 mentioning Romney and 500 mentioning Obama. Two coders then coded these tweets for three possible sentiment values: positive, negative, or neutral. After coding separately, coders met to resolve any disagreements. We found that most tweets had either a positive or negative value. In the final training set we used only the 869 tweets that were coded as positive or negative, or numerically 1 and −1, respectively. We then randomly separated the training set into training and validation sets, 80 percent going into the former and 20 percent into the latter. Last, we trained a support vector machine classifier with a linear kernel using the Python scikit-learn library. The classifier obtained an F1-score of 0.77, which is well within acceptable levels of accuracy (Yang and Liu 1999).

To align Twitter activity to archived video material of the debate, we identified four points where we knew there was high Twitter volume: Romney's quip, "I love Big Bird"; moderator Jim Lehrer "Let's not" reply to Romney; Obama's "I had five seconds" remark; and Romney's self-correction when he referred to low-income children as "poor kids." Assuming a small gap between broadcast and Twitter reaction, we then used the first mention of these sound bites as the measure of the lag. We found a consistent gap between the debate clock on the C-SPAN feed and the UTC (Coordinated Universal Time) timestamp on the Twitter posts. Accordingly, we synchronized our Twitter data to the debate feed.

FIGURE 1
Volume per Minute by Candidate, with LOESS Regression Smoothed Average



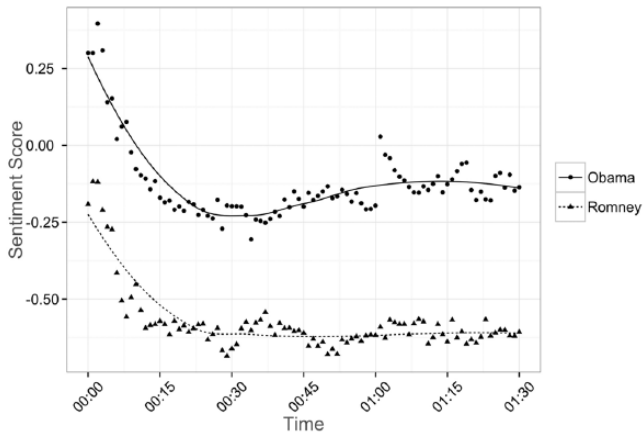
For each shot, we next generated a synchronous volume metric and average sentiment score for both candidates, along with three lagged versions of these variables, at 15, 30, and 45 seconds. These lagged values account for any delayed reaction by Twitter users and observe the robustness of effects. This resulted in the generation of sixteen variables matched or lagged to the start-stop times on the debate clock (volume for Obama and Romney synchronous, volume for Obama at 15-, 30-, and 45-second lags, sentiment for Obama and Romney synchronous and sentiment for Obama and Romney at 15-, 30-, and 45-second lags).

Figure 1 shows the volume per minute by candidate, while Figure 2 shows the average sentiment per minute by candidate. The lines on each graph represent LOESS regression (local regression) smoothed averages for the candidates over their data points, which provide the minute-by-minute averages. The plots in Figure 1 are comparable to Twitter's own graph of total debate volume not distinguished by candidate.[5] The highest volume points for Romney occur across the 00:30 and 00:50 minute marks, which included Romney's "Big Bird" comment and his sparring with Lehrer over rules and topics. The highest volume moment for Obama is at the 01:01 mark—his "I had five seconds before you interrupted me" comment. The sentiment plots reveal that Twitter favored Obama over Romney, a result that held throughout the debate, albeit with considerable variation over time. Notably, both candidates averaged sentiment scores below 0, indicating generally negative expression.

Analysis

Before testing our hypotheses, we thought it important to verify that the debates were indeed moments of national attention and expression. To do so, we charted the volume of keyword references to Obama, Romney, Biden, and Ryan during the 50-day window of our archive draw. The results are presented in Figure 3,

FIGURE 2
Sentiment per Minute by Candidate, with LOESS Regression Smoothed Average



and clearly indicate that the debates were high intensity moments during the campaign, with the first debate between Barack Obama and Mitt Romney being the highest volume moment other than Election Day.

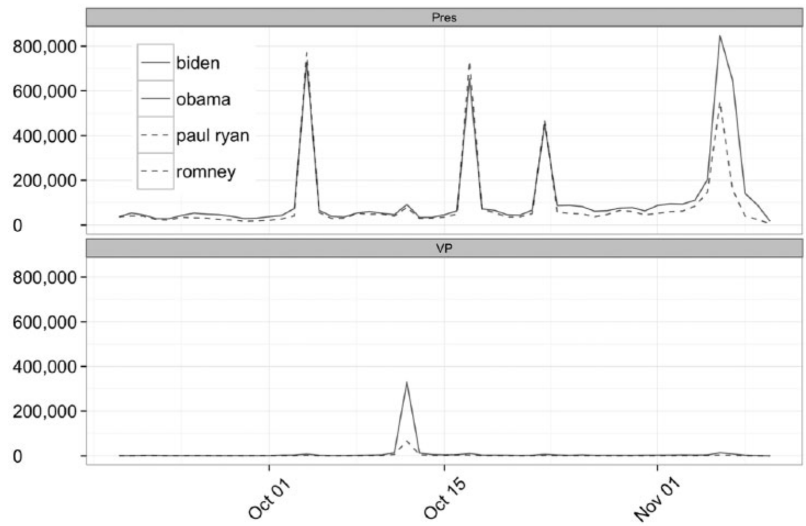
Next, we conducted hierarchical multiple regression analyses on the normalized volume measures (ratio of number of posts to seconds in the shot) and average sentiment scores (the mean value of scores across seconds in the shot) of the tweets mentioning Obama or Romney. As noted above, these analyses were run with four different versions of the dependent variables: at the moment of the shot, and at 15, 30, and 45 seconds after the shot.

The independent variables were grouped in three blocks that were sequentially added to each regression: verbal, tonal, and visual. The first block consisted of persuasive variables (attack, contrast, response, and narrative) for both Obama and Romney, and variables indicating whether either candidate sparked a meme during the segment. The second block added variables assessing the tone of voice of each candidate (anger/threat, happiness/reassurance). The final visual block added variables coding facial expressions (anger/threat, happiness/reassurance), affinity and defiance gestures by either candidate during the shot.

Results

The results of the ordinary least squares (OLS) regression analyses present a clear picture of the factors that shaped the volume and valence of responses on Twitter. Beginning with the volume of Obama mentions, the results are highly consistent across the synched, 15- 30-, and 45-second lag models (see Table 1). The verbal factors account for a small amount of variance in the volume of Obama mentions, with F-change scores significant for all four of these tests. Comparatively, when

FIGURE 3
Volume of Name Mentions of Presidential and Vice Presidential Candidates on Twitter



the tonal block is added, the models' performance does not improve substantially, with F-change scores nonsignificant for all four tests. However, the addition of the visual block contributes significantly to the models' performance, with F-change scores significant for all four tests. These results provide strong support for Hypothesis 1, at least for Obama volume.

Examining the individual variables that predict Obama volume in at least three of the four models at $p < .10$, we find that Romney's attacks along with Obama's responses and use of narratives were linked to a greater volume of Obama mentions on Twitter. Notably, the single strongest predictor in the models is Obama's spawning of memes (e.g., "I had five seconds"), which was strongly and immediately tied to a higher volume of posts mentioning him. A similarly strong and immediate relationship was observed when Romney's facial expressions denoted anger or threat. On the other hand, both the use of a reassuring tone by Romney and gestures signaling affinity by Obama were related to a lower volume of Obama tweets.

Moving next to the volume of Romney mentions, the results are again readily interpretable across the synched, 15-, 30-, and 45-second lag models (see Table 2). The verbal factors account for little variance in the immediate volume of Romney mentions but begin to account for a significant amount of variance in the lagged models, with F-change tests achieving significance. Comparatively, the tonal block consistently adds to overall performance of the models, with F-change scores significant for all four tests. As with the pattern observed for Obama, the addition of the visual block contributes substantially and significantly to the models' performance, with large block variances and F-change highly significant for

TABLE 1
Synchronous and Lagged Models Predicting Normalized Volume of Obama Mentions

	Obama Volume Synch	Obama Volume 15 Sec.	Obama Volume 30 Sec.	Obama Volume 45 Sec.
Block 1: Verbal				
Obama Attack	–.02	–.02	.02	.03
Obama Response	.09	.14†	.20**	.24**
Obama Contrast	–.04	–.03	–.04	–.04
Obama Narrative	.10	.12†	.14*	.14*
Romney Attack	.13†	.14†	.15†	.14†
Romney Response	–.03	.00	.01	.02
Romney Contrast	.01	.01	.02	.00
Romney Narrative	.00	–.02	–.02	–.01
Obama Meme	.43***	.36***	.31***	.26***
Romney Meme	–.06	–.01	.02	.03
Block 2: Tonal				
Obama Tone—Angry/Threat	.09	.09	.09	.04
Obama Tone—Happy/Reassuring	.10	.10	.13	.16*
Romney Tone—Angry/Threat	–.04	–.09	–.08	–.02
Romney Tone—Happy/Reassuring	–.14*	–.14†	–.16*	–.17*
Block 3: Visual				
Obama Facial—Angry/Threat	.02	.00	–.02	–.01
Obama Facial—Happy/Reassuring	.11	.11	.11	.09
Romney Facial—Angry/Threat	.30***	.30***	.26***	.21**
Romney Facial—Happy/Reassuring	.10	.10	.12	.15*
Obama Affinity Gesture	–.17**	–.16*	–.17*	–.17*
Obama Defiance Gesture	.01	.06	.08	.08
Romney Affinity Gesture	.10	.11	.11	.09
Romney Defiance Gesture	–.07	–.04	–.03	–.04

Model Summary

Block	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$
Verbal	.23	***	.18	***	.17	***	.16	***
Verbal + Tonal	.24		.19		.18		.16	
Verbal + Tonal + Visual	.40	***	.36	***	.33	***	.29	***

NOTE: For OLS regressions, all entries are standardized beta coefficients from the final model. For model summary, entries are adj. R^2 upon block entry, with significance of the F-change.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

all four tests ($p < .001$). These results, in combination with those observed for Obama volume, provide strong support for Hypothesis 1.

TABLE 2
Synchronous and Lagged Models Predicting Normalized Volume of Romney Mentions

	Romney Volume Synch	Romney Volume 15 Sec.	Romney Volume 30 Sec.	Romney Volume 45 Sec.
Block 1: Verbal				
Obama Attack	–.11	–.11	–.08	–.04
Obama Response	.14†	.12†	.10	.07
Obama Contrast	–.03	–.03	–.02	.00
Obama Narrative	–.02	–.02	–.03	–.03
Romney Attack	–.07	–.08	–.08	–.09
Romney Response	–.13†	–.11	–.09	–.09
Romney Contrast	–.07	–.03	–.01	–.02
Romney Narrative	–.05	–.05	–.03	–.01
Obama Meme	–.07	–.06	–.06	–.06
Romney Meme	.05	.13*	.19***	.20***
Block 2: Tonal				
Obama Tone—Angry/Threat	–.07	–.06	–.03	–.01
Obama Tone—Happy/Reassuring	–.08	–.07	.00	.05
Romney Tone—Angry/Threat	.06	.06	.12	.23**
Romney Tone—Happy/Reassuring	.04	.08	.12	.13†
Block 3: Visual				
Obama Facial—Angry/Threat	.09	.09	.09	.10*
Obama Facial—Happy/Reassuring	.05	.07	.07	.09
Romney Facial—Angry/Threat	.46***	.44***	.44***	.41***
Romney Facial—Happy/Reassuring	.01	–.03	–.04	–.05
Obama Affinity Gesture	–.22***	–.24***	–.25***	–.27***
Obama Defiance Gesture	–.05	–.06	–.07	–.06
Romney Affinity Gesture	–.03	–.03	–.03	–.01
Romney Defiance Gesture	.05	.09	.11	.09

Model Summary

Block	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$
Verbal	.02		.06	*	.09	**	.08	**
Verbal + Tonal	.07	*	.12	**	.18	***	.22	***
Verbal + Tonal + Visual	.35	***	.40	***	.47	***	.49	***

NOTE: For OLS regressions, all entries are standardized beta coefficients from the final model. For model summary, entries are adj. R^2 upon block entry, with significance of the F-change.
$^{\dagger}p < .1$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Turning to the individual predictors that explain variation in Romney volume in at least three of the four models at $p < .10$, we find that Romney's spawning of memes (e.g., "I love Big Bird") was the only verbal variable linked to a greater volume of mentions. As was observed for the volume of Obama mentions, Romney's facial expressions of anger or threat increased the volume of his mentions, whereas Obama's affinity gestures were related to a lower volume of tweets. Notably, the single strongest predictor in the models is Romney's facial expressions, which accounted for nearly half of the variance explained across the synched and lagged tests.

For the sentiment analysis of posts mentioning Obama, we again ran the synched, 15-, 30-, and 45-second lag models (see Table 3). The verbal factors account for a small amount of variance in the sentiment of posts mentioning Obama, with F-change significant for the three lagged models. The tonal block contributes significantly in all four models based on F-change tests. The addition of the visual block contributes significantly to the models, especially the synched test, with F-change significant for three or four tests, and approaching significance in the forth. The results for the tonal and visual blocks provide support for Hypothesis 2.

Focusing on the individual variables that predict Obama sentiment in at least three of the four models at $p < .10$, Romney's efforts to contrast his record and positions against his opponent was linked to higher sentiment scores for Obama, as was the generation of memes by Obama. Nonverbal variables also contributed consistently to the models, particularly an angry or threatening tone and accompanying facial expressions by Obama, both of which were negatively related to sentiment. When Romney's facial expressions denoted anger or threat, this also corresponded to lower sentiment for Obama, whereas Romney's use of affinity gestures showed the inverse relation.

Concluding with the sentiment of Romney mentions, the results reveal an even starker pattern across the synched, 15-, 30-, and 45-second lag models (see Table 4). The verbal and tonal factors account for minimal variance in the sentiment scores for Romney, failing to achieve significance in any F-change tests. In sharp contrast, the addition of the visual block contributes substantially and significantly to the models' performance, with F-change significant for all four tests, and with the block accounting for a quarter to a third of the variance in sentiment toward Romney. These results, in combination with those observed for Obama sentiment, provide strong support for Hypothesis 2 concerning the tonal and visual elements.

Considering the individual predictors of Romney sentiment in at least three of the four models at $p < .10$, we find that when Obama responded to attacks by Romney or when Romney displayed angry or threatening facial expressions, Romney's sentiment scores decreased. Conversely, when Obama used affinity gestures, this nonverbal behavior coincided with positive sentiment for Romney. Although tonal variables did not consistently predict Twitter sentiment across a majority of models, a happy or reassuring tone by Obama corresponded to lower sentiment scores for Romney in the 30- and 45-second lag models. Notably, Obama's use of contrast rhetoric and Romney's generation of memes were also

TABLE 3
Synchronous and Lagged Models Predicting Sentiment of Obama Mentions

	Obama Sentiment Synch	Obama Sentiment 15 Sec.	Obama Sentiment 30 Sec.	Obama Sentiment 45 Sec.
Block 1: Verbal				
Obama Attack	.12	.13	.10	.03
Obama Response	–.02	–.02	.00	.02
Obama Contrast	.10	.11	.10	.08
Obama Narrative	.07	.08	.06	.05
Romney Attack	.13	.11	.16†	.08
Romney Response	.01	.04	.10	.08
Romney Contrast	.21**	.21**	.25***	.24**
Romney Narrative	.10	.10	.10	.11
Obama Meme	.15*	.23**	.22**	.17*
Romney Meme	–.05	–.09	–.07	–.01
Block 2: Tonal				
Obama Tone—Angry/Threat	–.17†	–.18*	–.18*	–.14
Obama Tone—Happy/Reassuring	.01	–.07	–.08	–.07
Romney Tone—Angry/Threat	–.08	–.12	–.22*	–.16
Romney Tone—Happy/Reassuring	.07	.10	.10	.13
Block 3: Visual				
Obama Facial—Angry/Threat	–.11	–.14†	–.14†	–.12†
Obama Facial—Happy/Reassuring	–.13†	–.09	–.09	–.14†
Romney Facial—Angry/Threat	–.13†	–.15*	–.14†	–.18*
Romney Facial—Happy/Reassuring	.12	.04	.07	.11
Obama Affinity Gesture	.17*	.01	.00	.05
Obama Defiance Gesture	–.11	–.06	–.05	.01
Romney Affinity Gesture	.19*	.16*	.15†	.20*
Romney Defiance Gesture	–.07	–.11	–.09	–.04

Model Summary

Block	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$
Verbal	.04		.08	**	.08	**	.05	*
Verbal + Tonal	.08	*	.15	**	.17	***	.14	**
Verbal + Tonal + Visual	.16	**	.19	*	.21	*	.20	*

NOTE: For OLS regressions, all entries are standardized beta coefficients from the final model. For model summary, entries are adj. R^2 upon block entry, with significance of the F-change.
†$p < .1$. *$p < .05$. **$p < .01$. ***$p < .001$.

TABLE 4
Synchronous and Lagged Models Predicting Sentiment of Romney Mentions

	Romney Sentiment Synch	Romney Sentiment 15 Sec.	Romney Sentiment 30 Sec.	Romney Sentiment 45 Sec.
Block 1: Verbal				
Obama Attack	–.13	–.10	–.08	–.15†
Obama Response	–.21**	–.19*	–.21*	–.21**
Obama Contrast	–.05	–.09	–.18*	–.21**
Obama Narrative	.04	.04	.00	–.03
Romney Attack	–.05	–.05	–.06	–.02
Romney Response	–.02	–.04	–.06	–.03
Romney Contrast	–.08	–.11	–.09	–.07
Romney Narrative	–.03	–.01	–.03	–.04
Obama Meme	.02	–.01	–.05	–.07
Romney Meme	–.08	–.10	–.13†	–.12†
Block 2: Tonal				
Obama Tone—Angry/Threat	.13	.10	.09	.09
Obama Tone—Happy/Reassuring	–.06	–.11	–.18*	–.14†
Romney Tone—Angry/Threat	–.02	.00	–.02	–.04
Romney Tone—Happy/Reassuring	–.05	–.07	–.09	–.08
Block 3: Visual				
Obama Facial—Angry/Threat	–.01	–.03	–.07	–.06
Obama Facial—Happy/Reassuring	–.04	–.04	–.05	–.05
Romney Facial—Angry/Threat	–.32***	–.38***	–.37***	–.31***
Romney Facial—Happy/Reassuring	–.17*	–.12	–.03	–.01
Obama Affinity Gesture	.34***	.30***	.31***	.33***
Obama Defiance Gesture	.07	.03	–.05	–.06
Romney Affinity Gesture	.03	.05	.04	.00
Romney Defiance Gesture	–.05	–.07	–.05	–.05

Model Summary

Block	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$	Adj. R^2	$F\Delta$
Verbal	–.01		.00		.01		.01	
Verbal + Tonal	.00		.00		.02		.01	
Verbal + Tonal + Visual	.29	***	.29	***	.28	***	.24	***

NOTE: For OLS regressions, all entries are standardized beta coefficients from the final model. For model summary, entries are adj. R^2 upon block entry, with significance of the F-change.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

linked to lower sentiment scores in these models. Still, the visual variables consistently accounted for the most explained variance in the models across the four tests.

Taken as a whole, these results indicate that the candidates' nonverbal communication mattered mightily in terms of the volume and valence of expression on Twitter. Visual aspects of the candidates' performance, namely, nonverbal expressions and gestures, were particularly important for shaping expression via social media. Overall, these results provide strong support for Hypotheses 1 and 2. In terms of individual predictors, we observe that responses by Obama and his generation of memes were consistent predictors across multiple models, as were attacks by Romney and his generation of memes. Yet the power of these verbal predictors was generally dwarfed by the role of nonverbal factors, especially anger/threat displays by Romney and affinity gestures by Obama, which contributed significantly across twenty-nine of thirty-two tests.

Discussion

Consistent with theoretical expectations and previous experimental findings, the nonverbal behavior of candidates is at least as consequential in driving social media responses as is what the candidates actually say during debates (Zhu, Milavsky, and Biswas 1994; Benoit 2013; Cho et al. 2009). Our results show that the consequences of debate performance and presentation can be observed in the volume and valence of expression about the candidates on Twitter. This study is the first to formally link the content of first and second screens during a political event, examining the immediate, real-time connection between candidate behavior during televised debates and social media expression. In doing so, it is also at the vanguard of linking biobehavioral and computational approaches through the novel method employed to analyze real-time effects of political communication.

Debates are indeed moments of "national conversation," with peaks of social activity that dwarf all other campaign events in the 50 days before the election. But what can we infer about the quality of this conversation? If the expression of the public corresponds to the factors that appear to trigger that expression, then there may be cause for concern. This analysis suggests that the Twitter-using public primarily responds to the visual elements of candidate behavior, including facial displays and expressive gestures, and secondarily to verbal elements, particularly candidate memes or memorable utterances. It remains an open question whether the content of user posts concern these nonverbal features, focus on candidate character, or address more substantive issues. Nevertheless, the patterns observed here provide new insight into the nature of public attention to presidential debates. Future research should look beyond the volume and valence of online expression to examine the actual topics and issues discussed online.

We posit that second screen responses to the candidates' tonal and visual behaviors can be viewed as greater reliance on social rather than factual information or rhetorical efforts. This interpretation is consistent with evolutionary analyses of political behavior, in which nonverbal communication is regarded as a more reliable predictor of leader traits than verbal utterances (see Masters et al. 1986; Bucy and Grabe 2008). If nonverbal cues allow inferences about candidates' competence and integrity (Olivola and Todorov 2010; Rahn et al. 1990), we may need to rethink our assumptions about the information cues that voters actually use, as opposed to the bases of information that normative theorists would prefer the public to rely on.

Our analysis also reveals that while candidate rhetorical strategies and memes do predict differences in the amount of expression and attitudes expressed, they were consistently outperformed by the influence of nonverbal factors, especially candidate facial expressions and gestures. It is notable that the most powerful verbal elements were memes—pithy expressions that are easily repeated or referenced on a short messaging platform such as Twitter. Moreover, it is clear that the sentiment expressed about candidates by Twitter users during the debate is not purely under the candidate's control but often a function of what the opponent is saying and doing. Given the complex interplay of some of these factors, follow-up analyses should consider combined or conditional effects, such as how an angry or threatening tone interacts with corresponding facial expressions, and rhetorical assertions, in statistical modeling.

Future research should also differentiate among social media users to examine how subgroups respond to discrete moments during debates or other televised events. Given the demographic, geographic, and ideological characteristics of Twitter users (Duggan and Smith 2013), some of the observed relationships might reflect the tendencies of younger, more urban, and politically liberal viewers. Consistent with this assessment, the predictive power of specific verbal, tonal, and visual factors was not equivalent across candidates, skewing in a manner that favored Obama—a tendency also revealed by the sentiment scoring. When extending this work, we intend to use profile information, geographic tags, and previous tweets to distinguish among users so that these relationships can be examined within subgroups rather than in the aggregate.

Perhaps most important, this study advances a novel method to examine the power of televised images in a social media age. The effort to connect biobehavioral and computational approaches outlined in this article could readily be applied to other nationally televised political events beyond debates, including convention speeches, election results, inaugural activities, press conferences, or State of the Union addresses. Those interested in frame building could apply these techniques to the study of breaking news events, such as mass shootings, natural disasters, terrorist actions, or health pandemics. This method—tracking real-time expression and matching it to detailed coding of media content around key events or specific programs—has the potential to transform how media effects research is conducted. The 300 to 500 million tweets posted per day allow for considerable overtime variation for such studies. The analysis presented here is just a starting point for what is computationally possible.

Notes

1. Eleven television networks broadcasted the debate live and without advertisements, as did YouTube.

2. We also coded for *agreement* with a position just taken, *pleasantries* exchanged as a matter of routine between the candidates, and *policy statements* about what each candidate would do if elected (beyond responses and contrast statements). These were not as common as the four functions included in our models, however, and appeared too infrequently for analysis.

3. https://dev.twitter.com/docs/api/streaming.

4. For available platform objects, see dev.twitter.com/docs/platform-objects.

5. blog.twitter.com/2012/dispatch-from-the-denver-debate.

References

Abramowitz, Alan I. 1978. The impact of a presidential debate on voter rationality. *American Journal of Political Science* 22 (3): 680–90.

Alexander, Jeffrey C. 2010. *The performance of politics: Obama's victory and the democratic struggle for power*. Reprint ed. New York, NY: Oxford: Oxford University Press.

Alexander, Jeffrey C. 2012. Obama's downcast eyes. Huffington Post. Available from http://www.huffingtonpost.com/jeffrey-c-alexander/obama-debate-performance_b_1938755.html.

Benoit, William L. 2013. *Political election debates: Informing voters about policy and character*. Lanham, MD: Lexington Books.

Benoit, William L., and Allison Harthcock. 1999. Functions of the great debates: Acclaims, attacks, and defenses in the 1960 presidential debates. *Communication Monographs* 66 (4): 341–57.

Bucy, Erik P., and Maria Elizabeth Grabe. 2008. "Happy warriors" revisited: Hedonic and agonic display repertoires of presidential candidates on the evening news. *Politics and the Life Sciences* 27 (1): 78–98.

Burgoon, Judee K., and Jerold L. Hale. 1988. Nonverbal expectancy violations: Model elaboration and application to immediacy behaviors. *Communication Monographs* 55 (1): 58–79.

Carr, David. 15 October 2012. TV debates that sell more than just drama. *New York Times*.

Cho, Jaeho, Dhavan V. Shah, Seungahn Nah, and Dominique Brossard. 2009. "Split screens" and "spin rooms": Debate modality, post-debate coverage, and the new videomalaise. *Journal of Broadcasting & Electronic Media* 53 (2): 242–61.

Conover, M., J. Ratkiewicz, M. Francisco, B. Gonçalves, A. Flammini, and F. Menczer. 2011. Political polarization on Twitter. In *Proceedings of the 5th International Conference on Weblogs and Social Media*, 89–96. Menlo Park, CA: AAAI Press.

Davis, Stacy. 1999. Effects of audience reaction shots on attitudes towards controversial issues. *Journal of Broadcasting & Electronic Media* 43:476–91.

Dawkins, Richard. 1976. *The selfish gene*. 1st ed. New York, NY: Oxford University Press.

Druckman, James N. 2003. The power of television images: The first Kennedy-Nixon debate revisited. *Journal of Politics* 65 (2): 559–71.

Duggan, Maeve, and Aaron Smith. 2013. *Social media update 2013*. Pew Research Center's Internet & American Life Project. Washington, DC: Pew Research Center.

Grabe, Maria Elizabeth, and Erik Page Bucy. 2009. *Image bite politics: News and the visual framing of elections*. New York, NY: Oxford University Press.

Green, Melanie C., and Timothy C. Brock. 2000. The role of transportation in the persuasiveness of public narratives. *Journal of Personality and Social Psychology* 79 (5): 701–21.

Hall, Judith A. 1980. Voice tone and persuasion. *Journal of Personality and Social Psychology* 38 (6): 924–34.

Hellweg, Susan A., and Steven L. Phillips. 1981. A verbal and visual analysis of the 1980 Houston Republican presidential primary debate. *Southern Speech Communication Journal* 47 (1): 23–38.

Jamieson, Kathleen Hall, and David S. Birdsell. 1990. *Presidential debates: The challenge of creating an informed electorate*. Reprint ed. New York, NY: Oxford University Press.

Kraus, Sidney. 1996. Winners of the first 1960 televised presidential debate between Kennedy and Nixon. *Journal of Communication* 46 (4): 78–96.

Laplante, Debi, and Nalini Ambady. 2003. On how things are said: Voice tone, voice intensity, verbal content, and perceptions of politeness. *Journal of Language and Social Psychology* 22 (4): 434–41.

Masters, Roger D., Denis G. Sullivan, John T. Lanzetta, Gregory J. McHugo, and Basil G. Englis. 1986. The facial displays of leaders: Toward an ethology of human politics. *Journal of Social and Biological Structures* 9 (4): 319–43.

Mutz, Diana C. 2007. Effects of "in-your-face" television discourse on perceptions of a legitimate opposition. *American Political Science Review* 101 (4): 621–35.

Mutz, Diana C., and Byron Reeves. 2005. The new videomalaise: Effects of televised incivility on political trust. *American Political Science Review* 1:1–15.

Olivola, Christopher, and Alexander Todorov. 2010. Elected in 100 milliseconds: Appearance-based trait inferences and voting. *Journal of Nonverbal Behavior* 34 (2): 83–110.

Peters, Jeremy W. 10 October 2012. Networks like split-screens in debates, even if the candidates don't. *New York Times*.

Rahn, Wendy M., John H. Aldrich, Eugene Borgida, and John L. Sullivan. 1990. A social-cognitive model of candidate appraisal. In *Information and democratic processes*, eds. John A. Ferejohn and James H. Kuklinski, 136–59. Urbana, IL: University of Illinois Press.

Sharp, Adam. 4 October 2012. Dispatch from the Denver debate. Twitter Blogs. Available from https://blog.twitter.com.

Sigelman, Lee, and Carol K. Sigelman. 1984. Judgments of the Carter-Reagan debate: The eyes of the beholders. *Public Opinion Quarterly* 48 (3): 624–28.

Sullivan, Denis G., and Roger D. Masters. 1988. "Happy warriors": Leaders' facial displays, viewers' emotions, and political support. *American Journal of Political Science* 32 (2): 345–68.

Sullivan, Denis G., and Roger D. Masters. 1993. Nonverbal behavior, emotions, and democratic leadership. In *Reconsidering the democratic public*, eds. George E. Marcus and Russell L. Hanson, 307–32. University Park, PA: Pennsylvania State University Press.

Tiemens, Robert K., Susan A. Hellweg, Philip Kipper, and Steven L. Phillips. 1985. An integrative verbal and visual analysis of the Carter-Reagan debate. *Communication Quarterly* 33 (1): 34–42.

Tsekleves, Emmanuel, Leon Cruickshank, Annette Hill, Koko Kondo, and Roger Whitham. 2007. Interacting with digital media at home via a second screen. In *Proceedings of the Ninth IEEE International Symposium on Multimedia Workshops*, 201–6. Washington, DC: IEEE Computer Society.

Wald, Kenneth D., and Michael B. Lupfer. 1978. The presidential debate as a civics lesson. *Public Opinion Quarterly* 42 (3): 342–53.

Way, Baldwin M., and Roger D. Masters. 1996. Political attitudes: Interactions of cognition and affect. *Motivation and Emotion* 20 (3): 205–36.

Yang, Yiming, and Xin Liu. 1999. A re-examination of text categorization methods. In *Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 42–49. New York, NY: ACM.

Zettl, Herbert. 1990. *Sight, sound, motion: Applied media aesthetics*. Boston, MA: Wadsworth.

Zhu, Jian-Hua, J. Ronald Milavsky, and Rahul Biswas. 1994. Do televised debates affect image perception more than issue knowledge? A study of the first 1992 presidential debate. *Human Communication Research* 20 (3): 302–33.