JOURNAL OF COMMUNICATION

Journal of Communication ISSN 0021-9916

ORIGINAL ARTICLE

Network Issue Agendas on Twitter During the 2012 U.S. Presidential Election

Chris J. Vargo[1], Lei Guo[2], Maxwell McCombs[2], & Donald L. Shaw[3]

1 Department of Advertising and Public Relations, University of Alabama, Tuscaloosa, AL, 35487 USA
2 School of Journalism, University of Texas at Austin, Austin, TX 78712, USA
3 School of Journalism and Mass Communication, University of North Carolina at Chapel Hill, Chapel Hill, NC, 27517 USA

This study finds support for agenda melding and further validates the Network Agenda Setting (NAS) model through a series of computer science methods with large datasets on Twitter. The results demonstrate that during the 2012 U.S. presidential election, distinctive audiences "melded" agendas of various media differently. "Vertical" media best predicted Obama supporters' agendas on Twitter whereas Romney supporters were best explained by Republican "horizontal" media. Moreover, Obama and Romney supporters relied on their politically affiliated horizontal media more than their opposing party's media. Evidence for findings are provided through the NAS model, which measures the agenda-setting effect not in terms of issue frequency alone, but also in terms of the interconnections and relationships issues inside of an agenda.

doi:10.1111/jcom.12089

Big Data and computer science methods can further the findings of agenda-setting theory. Using Twitter, a popular microblogging service, we show how supporters of Barack Obama and supporters of Mitt Romney reacted to different media agendas during the 2012 U.S. presidential election. We do so using a network analysis perspective, which shows how issues from the election were talked about in relationship to each other. The results give us a clear, large-scale picture of how the media influenced different audiences. We also offer updates to the emerging theory of agenda melding and the Network Agenda Setting (NAS) model. We have arrived at these conclusions by utilizing several computer science methods, including automated data mining and aggregation, sentiment analysis, network analysis, machine learning, and computer-assisted content analysis.

Why Twitter data?

In a world of social media, Twitter differentiates itself in two ways: Its messages are public and short. The majority of this data is open for all to examine (Vieweg, 2010).

Corresponding author: Chris J. Vargo; e-mail: christopherjvargo@gmail.com

This is different from Facebook, for example, on which the majority of the content is perceived to be private (e.g., person-to-person) or semiprivate (e.g., person to a contained network of people; Kwak, Lee, Park, & Moon, 2010). Twitter places an emphasis on being a public medium by calling itself " … a platform for you to influence what's being talked about around the world … " (About us, 2010). With the exception of more users under the age of 30, Pew Research Center (2013) shows that the major demographic groups of Americans are rather evenly represented on Twitter, ranging from 13 to 20% of all Internet users. For example, 18% of all men and 17% of all women who use the Internet are Twitter participants.

Twitter has always been open for news organizations to join. At no point during registration does Twitter delineate whether a new registrant is a person, business, or organization. Media on Twitter are provided with the same service as individuals. Messages from media are poured into the same sea of information. Where most studies of media effects perform a separate content analysis of media, Twitter provides the opportunity to perform one analysis covering both people and media.

Some early work shows that the general body of messages on Twitter follows the agendas of the news media. Vargo's (2010, 2011) first- and second-level agenda-setting analyses on aggregated Twitter data suggest that traditional newscasts and newspaper articles can forecast the total amount of Twitter chatter an issue receives. Parmelee and Bichard (2012) confirm this finding in their exhaustive interviews with Twitter users. Respondents reported being influenced by mainstream media. This research opens the door to a key question. Is it naïve to think that all Twitter users respond uniformly to mainstream media agendas? We know that not all media exert the same power (McCombs, 2004). An investigation of different Twitter participants and different media types can better explain the power of agenda-setting effects. Such an analysis requires a large-scale content analysis. To exhaustively address these questions, we sampled Twitter's public stream for 17 weeks surrounding the 2012 general election and retrieved 38 million messages. What follows is a Big Data agenda-setting analysis.

From agenda setting to agenda melding

Agenda-setting research concentrates on the relationship between media content and audience reception. Many agenda-setting studies have demonstrated that media are effective in transferring issue and attribute saliences to audiences (McCombs, 2004). Time and again, the majority of research confirms that there are agenda-setting effects even in this digital era (Vargo, 2010, 2011). Recently, a few agenda-setting studies have concentrated on the role of the audience (Shaw & Weaver, 2014; Weaver, Wojdynski, McKeever, & Shaw, 2010; Shaw, Hamm, & Terry, 2006). If the audience had no interest in media content, issues and attributes would not transfer to the audience, that is, there would be no agenda-setting effects. Assuming that the role of the audience is an active one (Weaver et al., 2010), agenda melding research can illustrate how audiences pick and choose among different media agendas in an active way (Shaw & Weaver, 2014). The core hypothesis of agenda melding is that distinctly identifiable audiences value issues and attributes differently. Obviously, each of these audiences melds agendas from various media into a comfortable, but different, mix of issues and attributes (Shaw, McCombs, Tran, & McKeever, 2010).

To explain the process of agenda melding, Shaw and Weaver (2014) have identified two types of media: vertical media and horizontal media. These terms can be traced back to two-step flow theory, which uses “horizontal” and “vertical” to describe how news flows through audiences (Weimann, 1991). Specifically, vertical flow describes the transfer of information from some higher source down to more general audiences. Based on this concept, Shaw and Weaver (2014) coined the term “vertical media,” suggesting that these media transmit information vertically and reach out to the largest audiences possible. To attract mass audiences, these types of media tend to cover civic and public life: the mayor’s office, courts, schools, police, fire, health, transportation, and many other activities (Shaw et al., 2010). According to Shaw and Weaver, the use of the term “vertical” emphasizes these media’s attempt to “shout from the top of a pyramid to any and all in the vast desert below” (2014, p.145). This metaphor conveys vertical media as being above the masses; this separation is recognition of vertical flow’s authoritative function as defined by two-step flow.

Two-step flow theorists also noted that as societies became less rigid and less stratified, people began to rely less on authorities and institutions. Instead, more information was transmitted “horizontally.” Horizontal flow is observed when audiences turn to sources closer to their own social status, demographics, interests, and preferences (Weimann, 1991). Noting that some media are aligned to this horizontal flow, Shaw and Weaver (2014) also coined the term “horizontal media.” Instead of perched above professing to all, many different types of niche media reach out to specific communities of people. Horizontal flow, however, is not limited to media organizations. Bloggers, journalists, talk show hosts, and celebrities alike transmit information horizontally. This important distinction broadens horizontal media beyond niche media to include individuals that broadcast news to specific communities of people.

The 2008 agenda melding study

The first major agenda melding study of horizontal and vertical media was centered on the 2008 U.S. presidential election (Shaw & Weaver, 2014). In-depth interviews were conducted with a stratified sample of 70 Democratic, Republican, and Independent voters in the Chapel Hill area of North Carolina, the site of the original agenda-setting study. These interviews determined the key issues among voters.

To empirically identify vertical and horizontal media respectively, a content analysis was conducted to examine the issue agendas of various media including nightly news networks, mainstream newspapers, cable news networks, and talk shows. Shaw and Weaver noted that the relatively “new” media — cable news networks and talk shows — covered more issues than the “old” media — nightly news networks and mainstream newspapers. More importantly, these “new” media appeared to cover issues “selectively,” as if they were skimming a small group of news items from the traditional media and also selecting other items altogether. Overall, the results show that the two groups of media are substantially different. Therefore, nightly news networks and mainstream newspapers were categorized as "vertical media," because of their established authority and mainstream focus. New cable news networks and talks shows were labeled as "horizontal media," because of their niche focus.

Specifically, this 2008 study content analyzed a set of vertical media including nightly news programs on NBC, CBS, ABC, CNN, and FOX, and horizontal media, which included sampled coverage of television or radio talk shows from Rush Limbaugh, Stephanie Miller, Jon Stewart, Stephen Colbert, Ron Savage, and Ed Schultz. The voters' issue agendas were then compared with the issue agendas of these horizontal and vertical media.

Different segments of voters responded to different types of media differently. Looking across all 70 of the voters, a correlation of .87 was found with vertical media. It appeared that vertical media was still very much in control of the issue agenda. Agreement with horizontal media agenda was considerably less at .39. Shaw and Weaver observed that each of the 70 voters used vertical media more than they did the horizontal media. In addition, the agenda-setting effects of vertical media and horizontal media differed by political party. Republicans reflected a higher correlation with vertical media (.92) than did Democrats (.84). Moreover, Republicans also correlated higher with horizontal media (.46) than did Democrats (.39).

These agenda melding findings were exploratory and limited. The respondent size was low (i.e., 70 people in one town), the types of media sampled were limited (i.e., television nightly news programs and talk show hosts), and the analysis was simple correlations.

As a replication and expansion of this 2008 study, the present study hypothesizes that distinctive audiences meld agendas from various media — vertical media and horizontal media — differently. To address the shortcomings of the 2008 study and to broaden the concept of agenda melding, this study focuses on expanding the analysis in two key areas using the 2012 U.S. presidential election. (a) Using a series of Big Data analytics, this study seeks to test more exhaustively the preliminary findings of the 2008 study. Specifically, we broaden our content analysis to a corpus of 38 million messages from Twitter. This corpus is used to compile the issue agendas of different audiences (i.e., Barack Obama supporters and Mitt Romney supporters) and different media (i.e., mainstream newspapers, talk shows, journalists, and news programs). (b) We examine agenda melding from a networked perspective by drawing upon the NAS model.

Network Agenda Setting model

The 2008 agenda melding study, and the bulk of agenda-setting studies use *individual* counts to measure the salience of media messages. These measurements generally answer the following question: How often was issue "X" mentioned during period "Y"? These measurements are calculated for both the media and the audience in question. Although this directly addresses the agenda-setting hypothesis, these *individual counts of salience* are not an exhaustive measure of an agenda. There is more to an

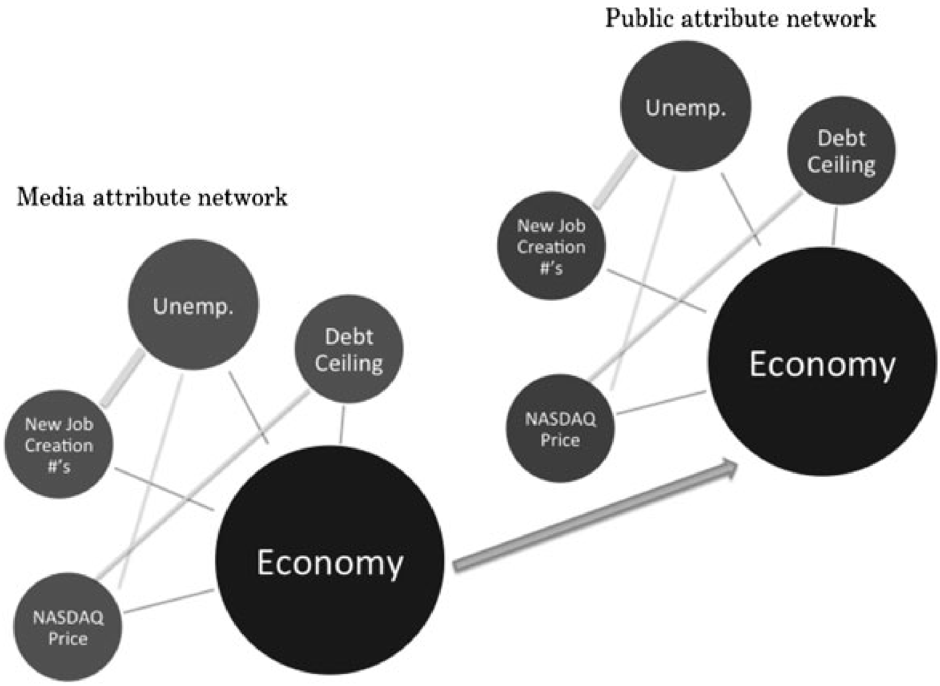

Figure 1 An example of Network Agenda SettingNAS effects.

agenda than simply a frequency count. Going beyond the individual measurements of issue saliences, this study leverages the NAS model. This has been discussed as a "third level" of agenda-setting effects, a perspective that details more inclusive and stronger agenda-setting effects than previous research (Guo, 2013; Guo & McCombs, 2011a, 2011b). Specifically, the NAS model asserts that issues can be either implicitly or explicitly linked in news coverage or the public's mind. Contextual meanings are constructed because of such links. For example, an agenda for a news organization is not just how it covers one issue for a given time period. Rather, how often issues are mentioned *together* during the same news period measures the relationships between different news items. Figure 1 illustrates the relationships that can be captured if the media agenda and the public agenda are conceptualized as networks.

The NAS model further proposes that the salience of these network relationships for issues or attributes can be transferred from the news media to the audience's mind. For example, according to the NAS model, if the U.S. news media recurrently cover the country's foreign policy and its domestic economic problems together, the audience will also consider the two issues interconnected. The NAS model suggests that the news media can construct the public's perceived importance of *interconnections* among issues.

The NAS model is distinct from the first two levels of agenda-setting theory. The first and second levels of agenda setting compare the salience of issues and attributes

(McCombs, 2004; McCombs, Llamas, Lopez-Escobar, & Rey, 1997; McCombs & Shaw, 1972). Focusing on the frequency in media content and public surveys demonstrates a *hierarchical* agenda (Guo, 2013). The NAS model is based on an associative network model of memory (Anderson & Bower, 1973; Collins & Loftus, 1975; Kaplan, 1973; Monroe & Read, 2008), which asserts that individuals tend to make associations among different elements in their minds in order to make sense of social realities. Arguably, the news media play an important role in how we connect different items (Lang, 2000). In this sense, the NAS model looks for links between issues or attributes on the media agenda. Network media agendas are compared with network public agendas.

In addition to exploring the network structure as a whole, the NAS model also examines the specific role of each element in the media or public networks. Although traditional agenda setting examines the prominence of issues, for example, by using simple frequency counts, the NAS model turns to the *centrality* of issues — the location of individual issue nodes in terms of how close they are to the center of a network. Rather than measuring how many times a single issue is reported in the news media or mentioned by survey respondents, the measurement of centrality investigates the degree to which an issue is involved in relationships with other issues (Wasserman & Faust, 1994), thus providing more contextual information about the entire picture of an issue agenda.

Overall, based on the concepts of network and centrality, the NAS model suggests that the media network agendas are aligned with the public network agendas and further that the media network agendas can predict public network agendas. Preliminary tests have provided empirical support for the NAS model. Using data from a second-level, attribute agenda-setting study regarding the 2002 Texas elections (Kim & McCombs, 2007), Guo and McCombs' (2011a) reanalysis found a significant correlation between how the media associated attributes in their portrayal of the political candidates and the public's networked images of these candidates. A network analysis on data collected during the 2010 Texas gubernatorial election also showed strong correlations between the media and public network attribute agendas of the political candidates (Guo & McCombs, 2011b).

From the networked perspective suggested by the NAS model, we first examine agenda melding by investigating the correlations between candidate supporters and vertical media during the 2012 election. We hypothesize that the network issue agenda of (a) Obama supporters and (b) Romney supporters is positively correlated with the vertical media's network issue agenda (H1a&b).

As agenda melding theory states, we also expect candidate supporters to correlate with horizontal media. Specifically, we assume that the network issue agenda of (a) Obama supporters and (b) Romney supporters is positively correlated with the network issue agenda of horizontal media (H2a&b).

Extrapolating from the 2008 agenda melding study, we expect the network issue agendas of vertical and horizontal media to offer significant explanatory power on the network issue agendas of both Obama and Romney supporters (Shaw & Weaver, 2014). According to the findings in the 2008 study, we hypothesize that vertical media will offer more explanatory power for the network issue agendas of (a) Obama supporters and (b) Romney supporters than horizontal media (H3&b).

Expanding on the initial agenda melding model, the horizontal media in this study are also classified by the political party they primarily represent. As such, we expect to see that Republican horizontal media will offer more explanatory power for the network issue agendas of Romney supporters (H4a). Likewise, we expect the network issue agendas of Obama supporters to be better explained by Democratic horizontal media than by Republican horizontal media (H4b).

Methods

Our two dependent variables, Romney supporters and Obama supporters, were identified through the use of sentiment analysis. These groups' tweets about the issues were compared with tweets about the issues posted by different types of media. In line with the distinctions made by the concept of agenda melding, the media were categorized into three types: vertical, horizontal Republican, and horizontal Democratic. In turn, each of these supporter and media groups was stratified according to which candidate was being discussed. All in all, eight groups' discussions on Twitter about links between a candidate and the key election issues were analyzed:

Four sets of tweets about Obama: (a) Obama supporters' tweets about Obama and the issues, (b) vertical media tweets about Obama and the issues, (c) Democratic horizontal media tweets about Obama and the issues, and (d) Republican horizontal media tweets about Obama and the issues.

Four sets of tweets about Romney: (a) Romney supporters' tweets about Romney and the issues, (b) vertical media tweets about Romney and the issues, (c) Democratic horizontal media tweets about Romney and the issues, and (d) Republican horizontal media tweets about Romney and the issues.

Each of these groups' public Twitter messages underwent a computer-assisted content analysis, which detected the presence of eight key election issues. A daily count was produced for each of the issues for each of the eight groups across 4 months. Network analysis, correlation measures, and other network statistics were calculated to compare the issue networks of these groups. Finally, regression analyses were conducted to examine the predictive power of different types of media.

Data capture: The Twitter application programming interface

Thirty-eight million public tweets were retrieved from August 1, 2012, to November 28, 2012 — 3 weeks after the Election Day, November 6. These microblog posts were retrieved from public Twitter accounts via the Twitter streaming application programming interface (API), which allows for keyword search queries (Twitter, 2013). Specifically, tweets that included a candidate's name were retrieved. During periods of high traffic, such as debates and on Election Day, the API automatically limited the rate of tweets sent via the API.

Supporter selection: Sentiment analysis, machine learning, and *t*-test analysis

Users of Twitter rarely identify themselves as Republican or Democrat. This limitation of Twitter user profiles requires identification of users not by self-proclaimed political alignment, but by the contents of the messages that users broadcasted publicly. We identified two groups of users: Obama supporters and Romney supporters. These are the positively vocal people for that given candidate on Twitter. As such, we refrain from calling them Democrats and Republicans, although their affiliations may coincide.

To identify Romney and Obama supporters in the dataset of tweets, we first divided the dataset into tweets that mentioned Obama and not Romney or other Republican primary candidates and conversely, Romney and not Obama or other Republican primary candidates.

We then employed sentiment analysis for the detection of sentiment toward a candidate in the tweets. Our goal was to collect all of a given user's tweets about a candidate, measure each tweet's sentiment toward the candidate, and determine an average sentiment score for that user regarding that candidate. Given that the dataset was over 20 gigabytes of plain text, this task greatly exceeded the scope of manual content analysis. Therefore, our analysis relied on a lexicon-based sentiment analysis tool.

A variety of lexicon-based (or dictionary-based) sentiment analysis tools exist. A lexicon-based approach starts with lists of words that are coded for polarity (Thelwall, Buckley, & Paltoglou, 2012). These words come from sources outside of the text under analysis ("out of the box") and some tools may also include degree measurements of strength for each word. Such established wordlists have been annotated and validated by a series of human coders over a long period of time. As such, many scholars have used these "out-of-the-box" solutions with Twitter, and applied these tools "as is" to analyzing Twitter sentiment (O'Connor, Balasubramanyan, Routledge, & Smith, 2010; Hannak et al., 2012).

In this article, we chose to use the lexicon-based sentiment analysis tool, SentiStrength, which was particularly developed for short texts (Thelwall, 2010; Thelwall et al., 2012). The tool has "human-level accuracy for short social web texts in English," and has been widely used in a wide range of research projects (Thelwall, 2010). Specifically, SentiStrength's sentiment approach relies on wordlists that drive scores for words associated with positive affect, negative affect, negation, and affective boosting. Instead of using SentiStrength "as is" as other studies do, we improved its results with a machine learning and *t*-test approach.

To test the validity of SentiStrength on our corpus, we initially tested a randomly selected set of 380 all English, nonspam, nonmedia tweets containing complete sentences. This sample size is in line with other validity checks performed in single machine learning tasks (Witten & Frank, 2005). According to standard machine-learning approach (Witten & Frank, 2005), a human coder manually coded each tweet as positive, negative, or neutral. The judgments were then used to train a machine-learning model to classify features that associate with positive and negative categories. The features used are typically sets of words, word pairs, and word triples found in the initial texts. The trained model then looks for the same features in new texts to predict their polarity (Pak & Paroubek, 2010; Pang, Lee, & Vaithyanathan, 2002). In this article, the model was built using the naïve Bayes classifier in the program LightSIDE (Mayfield & Rose, 2013).

The model revealed 133 and 189 additional terms for positive and negative affective dimensions, respectively, that were not in the original sentiment lexicons. Once these terms were added to the SentiStrength lexicon, another set of 380 random tweets were chosen and coded by a human coder. The SentiStrength score agreed with the human coder 82.8% of the time. Here, we note that the sentiment tool, although working quite well for informational tweets, still has difficulty with ambiguous context. Given this problem, we only selected people on Twitter for whom we had at least one tweet per week during the 4 months analyzed. By selecting users with more judgments, we insured our predictions would be more accurate.

Next, pivot tables were created for each remaining user in the two datasets. Each user had a sentiment score, ranging from −4 to +4 for each of his or her tweets about that dataset's candidate. An average score was calculated across all of that user's tweets. This averaged sentiment count for a candidate was then subjected to a one-way directional *t* test, with the degrees of freedom being one minus the number of tweets that user had about that given candidate. A probability of .10 was used as the cut-off. This value identified a substantial number of significant results for each candidate. In all, 2,875 and 2,457 candidates were chosen as supporters for Obama and Romney, respectively.

Media selection: Horizontal and vertical media

The specific horizontal and vertical media chosen for this study duplicate those in the 2008 agenda melding study (Shaw & Weaver, 2014). As noted earlier, Shaw and Weaver labeled traditional newspapers and television networks as "vertical media" and talk shows and cable news networks as "horizontal media." Their content analysis demonstrates that these two groups of media are empirically different in their news coverage. Here, we replicate their selections by picking 54 newspapers and broadcast news networks to represent the vertical media issue agenda.[1] Tweets were sorted by the candidate they mentioned and put into the appropriate grouping.

The Democratic horizontal media data was constructed from MSNBC, its television shows, and the reporters it listed on its official Twitter page, and the official Twitter accounts from the leading seven Democratic talk shows were added. A total of 65 different sources were chosen to represent Democratic horizontal media.[2] For the Republican horizontal media, FoxNews, its shows, and all the reporters listed on its Twitter page were chosen, and the leading seven Republican talk shows and their Twitter accounts were added. In all, 49 different sources were chosen to represent Republican horizontal media.[3]

Issue selection

To have the well-populated time series data for analysis, we chose to select the most salient issues of the election. To begin this stage of the study and get a sense of what the most common words were, the entire corpus of Tweets was stemmed, and stop words were removed. Then, a frequency list was generated. The first two authors then examined all words that occurred more than 1,000 times. Those words that corresponded directly to issues were then placed into issue construct lists. The most popular constructs were: economy, foreign policy, individual liberties, federal programs, immigration, education, environment, and big government. These issues appeared to be the only issues with salience sufficient enough to be continually measured throughout the 17-week analysis.

Computer-assisted content analysis

A computer-assisted content analysis was conducted in the form of expanded search queries. Each message from candidate supporters, horizontal media, and vertical media was searched for the presence of the keywords discovered from the issue-discovery step. This option was chosen because of the extremely large amount of data in each of the datasets. For each issue, lists of keywords were identified through a qualitative assessment of a random sample of media and public tweets. The first two authors then examined all words that occurred more than 1,000 times. One hundred and forty-four unique words specific to the issues arose. The authors placed those words into issue constructs. The coders agreed with word construct assignments 91.6% of the time. The queries were then performed using Excel's large-data plug-in PowerPivot. The plug-in allowed thousands of search formulas to run in different workbooks. When a tweet matched one or more keywords for an issue, it was flagged by the Excel equation. The queries for each issue were then tested for validity by selecting 200 random tweets from across the eight different groupings, or at least 20 per category as suggested by information retrieval scholars. The computer-assisted content analysis was then compared with the results of a manual content analysis. The results were found to be valid. Search query results agreed with human assessors at an average of .91 across all issues, no query scored below .82.

Network analysis

The last step in preparing the data involved arranging the data for network analysis (Guo, 2012). As outlined earlier in this section, each candidate had four sets of tweets that mentioned him: his supporters, vertical media, Democratic horizontal media, and Republican horizontal media. These eight datasets were then pivoted by day. For each day, the data showed whether a particular individual or a particular media organization mentioned any of the eight issues.

To operationalize the links among the issues, issues that were mentioned on the same day are considered as implicitly linked. The decision was made because it is rare for a single tweet to mention two issues because of its 140-character limit. Therefore, the number of times any two issues were mentioned by a given media organization or

Table 1 The Network Issue Agenda of Obama Supporters on Twitter (August 1–7, 2013)

	A	*B*	*C*	*D*	*E*	*F*	*G*	H
A	0	38	34	16	9	14	20	1
B	38	0	20	15	4	8	12	1
C	34	20	0	11	5	11	10	0
D	16	15	11	0	2	3	5	0
E	9	4	5	2	0	3	3	0
F	14	8	11	3	3	0	2	0
G	20	12	10	5	3	2	0	0
H	1	1	0	0	0	0	0	0

Notes: A = economy; B = foreign policy; C = individual liberties; D = federal programs; E = immigration; F = education; G = environment; H = big government.

an individual on the same day were calculated to measure the pair of issues' strength of association.

For network analysis, the data was then converted to network matrices that tallied the ties among the issues to build the matrices for each grouping. In order to reflect the changes in the network issue agendas during the election, and at the same time provide rich information for each network issue agenda, the matrices for each group were constructed by week. A total of 17 weeks were identified during the 4-month period: Aug 1–7, Aug 8–14, Aug 15–21, Aug 22–28, Aug 29–Sep 4, Sept 5–11, Sept 12–18, Sept 19–25, Sept 26–Oct 2, Oct 3–9, Oct 10–16, Oct 17–23, Oct 24–30, Oct 31-Nov 6, Nov 7–13, Nov 14–20, and Nov 21–28.

Table 1 provides an example matrix, which illustrates the network issue agenda of Obama supporters during the first week, August 1–7. Each letter represents an issue, and the number in each cell represents the connection value between the two corresponding issues. For example, the cell associated with A and B is 38, which means that A-economy and B-foreign policy were mentioned 38 times by the same Obama supporters on the same days during the first week of the analysis. Likewise, the cell that corresponds to C and H is 0, meaning that no Obama supporters mentioned C-individual liberties and H-big government on the same days. These two issues had no connection on Obama supporters' network issue agenda during the week. Notably, the matrix is symmetrical because this study does not consider the directions between issues.

As the last step in network analysis, the networks of the different groups were then compared by utilizing the quadratic assignment procedure (QAP), which addresses the strength and specification of ties from one network to another and calculates a correlation coefficient (Simpson, 2001).

To answer H1, which hypothesizes that the network issue agenda of candidate supporters is positively correlated with the vertical media's network issue agenda, QAP correlation tests were performed to compare the network matrix of Obama supporters and that of the vertical media and to compare the network matrix of Romney supporters and that of the vertical media in each of the 17 weeks.

To answer H2, which hypothesizes that the network issue agenda of candidate supporters is positively correlated with the network issue agenda of horizontal media, QAP tests were conducted to explore the correlations between the network matrix of Obama supporters and that of the Democratic and Republican horizontal media, and between the network matrix of Romney supporters and that of the Democratic and Republican horizontal media in each of the 17 weeks.

To answer H3 and H4, which investigate the extent to which the three types of media could explain the candidate supporters' behaviors on Twitter, we needed a statistic that would move from correlation to the estimation of parameters.

A centrality measure of each issue was used as a parameter. In this study, we used the measurement of "degree centrality," the most straightforward centrality measurement in network analysis, which refers to the number of connections between a node (an issue in the analysis here) and all the other nodes in the network (Wasserman & Faust, 1994). The more ties an issue has with other issues in describing a given candidate, the higher degree centrality value the issue has, and the more centrally it is located in the resulting networks.[4]

Given the weekly scope of network issue agendas, we chose an analysis that allowed for simple trends over time.[5] After reviewing the degree centrality measures of each issue for Obama supporters and Romney supporters, good fits were found for linear trends based on the standard errors in the regressions (see Appendix 1 and 2).

Therefore, we found it appropriate to create models with linear regressions. An Ordinary Least Significance (OLS) regression was performed with a Durbin–Watson statistic. The Durbin–Watson statistic inside of the OLS regression determines the relationship between dependent and independent variables separated from each other by a given time lag. Provided that the Durbin–Watson assessment could address the autocorrelation of the dependent and independent variables, then the autocorrelation was a violation of typical OLS assumptions.

A total of 48 regression models are examined, 24 for each candidate supporter. OLS regression requires one dependent variable. Therefore, Obama and Romney supporter agendas were tested at the individual issue level with one model for each of the eight issues. Issues in all three media types were used as independent variables, totaling in 24 models for each candidate supporter.

For any given model, eight independent variables existed, one for each of the eight issues analyzed. All eight independent variables were entered into each regression, in part to offer the entire network issue agenda as explanatory power. For example, one model examined the extent to which the degree centrality of the eight issues in the vertical media agenda could predict the degree centrality of the issue of economy on the Obama supporters' agenda. We argue that the use of eight variables in each model is necessary because of the interconnectedness of the degree centrality measure. Only offering one independent variable would ignore the networked agenda, and with it the network characteristics that offer explanatory power. Adjusted R^2

values were computed because of the seasonality that the 17-week cycle inevitably possesses.

Results

Testing H1a regarding tweets about Obama, the network issue agenda of Obama supporters was positively correlated with the vertical media's network issue agenda in 15 of the 17 weeks analyzed. The QAP correlation coefficients during those 15 positive weeks range from .54 to .91, with a median of .72. Testing H1b regarding tweets about Romney, the network issue agenda of Romney supporters is significantly correlated with the vertical media's network issue agenda in 13 of the 17 weeks analyzed. During those 13 weeks, the QAP correlation coefficients range from .44 to .88, and the median value is .77. These findings provide considerable support for H1a and H1b that candidate supporters' network issue agendas were strongly aligned with the vertical media's network issue agenda during the election period.

Regarding H2a&b, results show that the network issue agendas of candidate supporters were positively correlated with the network agendas of the horizontal media most of the time. For tweets about Obama, the network issue agenda of Obama supporters and that of the Democratic horizontal media were significantly correlated in 14 of 17 weeks. During those 14 weeks, the QAP correlation coefficients range from .56 to .86, with a median of .72. The network issue agenda of Obama supporters was positively correlated with the network issue agenda of the Republican horizontal media in 15 of 17 weeks, with the QAP coefficients ranging from .51 to .86 and a median of .69. For tweets about Romney, the network issue agenda of Romney supporters was positively correlated with the network issue agenda of the Republican horizontal media in 13 of 17 weeks, with QAP correlation coefficients during that period ranging from .50 to .85. The median is .74. The network issue agenda of Romney supporters and that of the Democratic horizontal media were significantly correlated in 14 of 17 weeks. The QAP correlation coefficients range from .56 to .92 and the median is .73. Both H2a and H2b were supported, meaning that candidate supporters' network issue agendas corresponded well with the horizontal media's network issue agendas.

H3a hypothesizes that the vertical media will better predict the network issue agendas of Obama supporters than horizontal media network issue agendas. Table 2 shows that the vertical media offered the highest explanatory power, that is, the highest r^2 value, for seven of the eight issues analyzed. For immigration and environment issues, the compatible Democratic horizontal media was more explanatory. In general, the averaged R^2 value across all eight issues suggests that the vertical media were the most explanatory, offering an increase of .20 R^2 over the Democratic horizontal media. H3a was supported.

For H3b regarding the prediction of Romney supporters network issue agenda on Twitter, Table 3 shows that the vertical media offered the highest explanatory power, the highest R^2 value, for only one of the eight issues, foreign policy. For the other

Table 2 Obama Supporter R^2 Value Comparison Across All Three Media Types

	Vertical Media Adjusted R^2	Horizontal Republican Adjusted R^2	Horizontal Democrat Adjusted R^2	Strongest Adjusted R^2
Economy	.698	.212	.405	Vertical
Foreign policy	.593	.332	.442	Vertical
Individual liberties	.824	.295	.407	Vertical
Fed. programs	.793	.000	.296	Vertical
Immigration	.194	.392	.631	Horizontal
Education	.854	.000	.325	Vertical
Environment	.633	.317	.599	Vertical
Big government	.972	.838	.920	Vertical
Average	.695	.298	.503	Vertical

Table 3 Romney Supporter R^2 Value Comparison Across All Three Media Types

	Vertical Media Adjusted R^2	Horizontal Republican Adjusted R^2	Horizontal Democrat Adjusted R^2	Strongest Adjusted R^2
Economy	.273	.712	.563	Horizontal
Foreign policy	.731	.727	.714	Vertical
Individual liberties	.744	.782	.510	Horizontal
Federal programs	.412	.474	.373	Horizontal
Immigration	.393	.689	.487	Horizontal
Education	.000	.225	.283	Horizontal
Environment	.242	.714	.513	Horizontal
Big government	.305	.379	.259	Horizontal
Average	.388	.588	.463	Horizontal

seven issues, the compatible (Republican) horizontal media were more explanatory. As Table 3 demonstrates, the averaged R^2 value across all eight issues also suggests the Republican horizontal media was the most explanatory, offering an increase of .20 R^2 over the vertical media. H3b, which hypothesizes that the vertical media could best explain the network issue agendas of Romney supporters, was not supported. Instead, the Republican horizontal media better explained the network issue agendas of Romney supporters on Twitter during the 2012 election.

H4a&b hypothesize that candidate supporters' network issue agendas will be better explained by the candidates affiliated party's horizontal media than the opposing party's horizontal media. For Obama supporters, Table 2 shows that the Democratic horizontal media offered higher explanatory power, that is, higher R^2 value, for all the eight issues than the Republican horizontal media. The averaged R^2 value across all eight issues suggests that the Democratic horizontal media offered an increase of .20 R^2 over the Republican horizontal media. H4a was strongly supported.

Table 3 shows that for Romney supporters the Republican horizontal media offered higher explanatory power, that is, higher R^2 value, for all but one of the eight issues than the Democratic horizontal media. The averaged R^2 values across all eight issues indicate that the Republican horizontal media offered an increase of .13 R^2 over the Democratic horizontal media. H4b was well-supported. More detailed results for all 48 models are presented in Appendix 1 for Obama and Appendix 2 for Romney.

Conclusions and discussions

Through a series of computer science methods, this study provides an empirical test of two emerging agenda-setting theories — agenda melding and NAS model — with large datasets on Twitter. In general, we found that the network issue agendas of candidate supporters were positively correlated with the network issue agendas of various media types during most of the 2012 U.S. election period. The ways in which the news media associated different election issues to discuss Obama and Romney corresponded well with how the candidate supporters talked about the two political candidates. The basic NAS hypothesis was confirmed. More importantly, our results demonstrate that distinctive audiences "melded" agendas of various media differently. Although vertical media could best predict Obama supporters' behaviors on Twitter, the Republican horizontal media offered the greatest predictor power in explaining Romney supporters' network agenda. Obama supporters were more attentive to Democratic horizontal media than Republican horizontal media. Likewise, Romney supporters tended to Republican horizontal media more. Taken as a whole, the availability of Big Data analytics offered by this digital mediascape has enriched our understanding of, and provided large-scale empirical evidence for, these emerging media effects theories.

Specifically, this study makes significant theoretical and methodological contributions to the literature in the following aspects:

Agenda melding

This is one of the very first studies that empirically examine the concept of agenda melding. By expanding the 2008 agenda melding study (Shaw & Weaver, 2014), this study confirms the basic agenda melding thesis: Different segments of voters meld agendas differently using different mixes of media sources. In particular, regarding Obama supporters, the study found that vertical media could best explain the issue agendas (.70), a result in line with the 2008 study. However, although vertical media seek to reach the largest audiences possible by definition, such media did not play a significant role in predicting the network issue agenda of Romney supporters during the 2012 election. In fact, the vertical media exerted the least influence among Romney supporters (.39), an R^2 value lower than the Republican horizontal media (.59) and the Democratic horizontal media (.46). These findings suggest that Romney supporters, a distinct community of people, relied on niche media and talk shows—especially those compatible with their political values—rather than mainstream media organizations for information during the 2012 election. This empirical exploration of agenda melding provides more details in explaining the media effects among different types of media and different groups of audiences, an important advancement of the traditional agenda-setting research.

Network Agenda Setting model

As a second theoretical contribution, this study provides rich evidence for the NAS model, the third level of agenda-setting theory. Rather than focusing on individual counts of issues, we investigated the media and public agendas from a networked perspective, that is, how the media and individuals associated different election issues to discuss the two political candidates. These results suggest that vertical or horizontal media did not simply transfer the salience of discrete election messages to the candidate supporters, they instead transferred the salience of the *interconnections* among such issues, or an issue network. By drawing insight from the NAS model, this study is able to explain the media effects during the 2012 election on Twitter in a more nuanced fashion. Conversely, by testing the NAS model through a huge dataset on Twitter, this study confirms the predictor power of the model, suggesting that it is a promising area to explore for future projects.

Limitations

In order to test the concept of agenda melding, this study examined media effects on two different segments of audiences: Obama supporters and Romney supporters. Essentially, these two groups were operationalized as the most positively vocal people for a given candidate on Twitter. We did this largely out of necessity because, as mentioned earlier, Twitter users rarely divulge their political affiliation explicitly on Twitter. We draw the conclusion that these supporters are not representative of a typical voter, an "average" Republican or Democrat. Future research should combine Big Data analytics and traditional survey method to identify average Republican or Democratic voters.

Notes

1 Vertical media Twitter usernames: CBS, USATODAY, Denverpos, Newsday, Sfchronicle, CCTimes, WSJ, Detnews, Njdotcom, SFGate, HoustonChron, Ajc, DispatchAlerts, nydailynews, starledger, Oregonian, Azcentral, Freep, Nytimes, startelegram, PBS, baltimoresun, GlobeMetro, Ocregister, Stltoday, PhillyDailyNews, chicagotribune, Guardiannews, orlandosentinel, TelegraphNews, PhillyInquirer, Cincienquirer, Insidebayarea, PilotNews, TheBuffaloNews, PlainDealer, clevelanddotcom, Latimes, PioneerPress, theobserver, StarTribune, CNN, Mercnews, PittsburghPG, Usweekly, Suntimes, courierjournal, MiamiHerald, sacbee_news, Washingtonpost, TB_Times, dallasnews, Nbc, Seattletimes.

2 Democratic media Twitter usernames: maracamp, AlexWitt, CackalackyJD, mitchellreports, CaseySez, craigmelvin, MHarrisPerry, TheLastWord, mikescotto,

nick_ramsey, morningmika, VeronicaDLCruz, stevebenen, JoshuaChaffee, Melissa_Ryerson, maddow, TheRevAl, MaddowGuestList, cesinnyc, joytamika, WillieGeist, Toure, MaddowAux, giff18, edshow, Lawrence, secupp, MaddowApp, NowWithAlex, msnbc, hardball_chris, PoliticsNation, MaddowBlog, RichardLui, TheDailyShow, chrislhayes, leanforward, Hardballvideo, JansingCo, andersoncooper, JoeNBC, msnbcvideo, Hardball, dailyrundown, AC360, chucktodd, MHPshow, SteveKornacki MorningMusiQ, piersmorgan, ThomasARoberts, upwithchris, thecyclemsnbc, BillKarins, KeithOlbermann, tamronhall, digimuller, BashirLive, Morning_Joe, WeGotEd, alexwagner, negannyc, newsnation, cgodburn, ProducerGuy1.

3 Republican media Twitter usernames: FoxNews, NickKalmanFN, Kilmeade, janicedeanfox, Jennafnc, TeamCavuto, JudgeJeanine, ClaytonMorris, AlanColmes, foxandfriends, SpecialReport, jonathanserrie, RickLeventhal, ShannonBream, foxnewspolitics, kirstenpowers10, edhenryTV, adamhousley, drmannyonFOX, Limbaugh, ShiraBushFNC, kimguilfoyle, HARRISFAULKNER, gretawire, oreillyfactor, OliverNorthFNC, caseystegall, marthamaccallum, megynkelly, IngrahamAngle, HeatherChilders, RickFolbaum, GeraldoRivera, BretBaier, glennbeck, ChrisLaibleFN, lauraingle, Andylevy, seanhannity, DaveRamsey, NicoleBuschFN, MikeEmanuelFox, Greggutfeld, Sdoocy, FaithManganFN, JoyLinFN, MollyLineNews, JonScottFNC, BillHemmer.

4 Centrality and frequency are distinct measurements of issue prominence. Although the two measures are correlated, the most frequently covered issue is not necessarily the most central issue on the media or public agenda. For example, a journalist might write frequently about an issue, but only cover the issue by itself without associating it with other issues. By focusing on the centrality measurements, we not only consider the prominence of individual issues, but also consider how different issues are associated with each other in the network of election issues, thus providing a more holistic view of the issue agendas. To illustrate the similarity/difference between frequency and degree centrality, Pearson's *R* correlation test were calculated for the two measurements for each of the eight groups across the 17 weeks of the election. Of the 136 comparisons (17 weeks $\times$ 8 groups), frequency and degree centrality were significantly correlated in 128 of the cases, with correlation coefficients ranging from .71 to .99. The median is .91. In eight comparisons, frequency and degree centrality were not correlated at all.

5 The authors would like to thank Kai Yang for his help with the computer-assisted network matrix calculations in this study.

References

About US (2010). *Twitter*. Retrieved from http://twitter.com/about

Anderson, J. R., & Bower, G. H. (1973). *Human associative memory*. Washington, DC: Winston.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, **82**, 407–413. doi:1.1037/0033-295X.82.6.407.

Guo, L. (2012). The application of social network analysis in agenda setting research: A methodological exploration. *Journal of Broadcasting & Electronic Media*, **56**, 616–631. doi:1.1080/08838151.2012.732148.

Guo, L. (2013). Toward the third level of agenda setting theory: A network agenda setting model. In T. Johnson (Ed.), *Agenda setting in a 2.0 world: New agendas in communication* (pp. 112–133). New York, NY: Routledge.

Guo, L., & McCombs, M. (2011a). *Network agenda setting*: *A third level of media effects*. Paper presented at the ICA annual conference, Boston, MA.
Guo, L., & McCombs, M. (2011b). *Toward the third level of agenda setting theory*: *A network agenda setting model*. Paper presented at the AEJMC annual conference, St. Louis, MO.
Hannak, A., Anderson, E., Barrett, L. F., Lehmann, S., Mislove, A., & Riedewald, M. (2012). *Tweet'in the rain*: *Exploring societal-scale effects of weather on mood*. In *Proceedings of the Sixth International AAAI Conference on Weblogs and Social Media* (pp. 479–482). Palo Alto, CA: AAAI Press.
Kaplan, S. (1973). Cognitive maps in perception and thought. In R. M. Downs & D. Stea (Eds.), *Image and environment: Cognitive mapping and spacial behavior* (pp. 63–78). Chicago, IL: Aldine.
Kim, K., & McCombs, M. (2007). News story descriptions and the public's opinions of political candidates. *Journalism & Mass Communication Quarterly*, **84**, 299–314. doi:1.1177/107769900708400207.
Kwak, H., Lee, C., Park, H. & Moon, S. (2010). *What is Twitter*, *a social network or a news media*? Proceedings of the WWW 2010 Conference in Raleigh.
Lang, A. (2000). The limited capacity model of mediated message processing. *Journal of Communication*, **50**, 46–71. doi:1.1111/j.1460-2466.2.tb02833.x.
Mayfield, E., & Rose, C. P. (2013). LightSIDE: Open source machine learning for text accessible to non-experts. In M. D. Shermis & J. Burnstein (Eds.), *Handbook of automated essay evaluation: Current applications and new directions* (pp. 124–135). New York, NY: Routledge.
McCombs, M. (2004). *Setting the agenda: The mass media and public opinion*. Cambridge, England: Polity Press.
McCombs, M., Llamas, J. P., Lopez-Escobar, E., & Rey, F. (1997). Candidate images in Spanish elections: Second-level agenda-setting effects. *Journalism & Mass Communication Quarterly*, **74**, 703–717. doi:1.1177/107769909707400404.
McCombs, M., & Shaw, D. L. (1972). Agenda-setting function of mass media. *Public Opinion Quarterly*, **36**, 176–187. doi:1.1086/267990.
Monroe, B. M., & Read, S. J. (2008). A general connectionist model of attitude structure and change: The ACS (attitudes as constraint satisfaction) model. *Psychological Review*, **11**, 733–759. doi:1.1037/0033-295X.115.3.733.
O'Connor, B., Balasubramanyan, R., Routledge, B. R., & Smith, N. A. (2010). *From tweets to polls*: *Linking text sentiment to public opinion time series*. Paper presented at International AAAI Conference on Weblogs and Social Media, Washington, D.C.
Pak, A., & Paroubek, P. (2010). Twitter as a corpus for sentiment analysis and opinion mining. In *Proceedings of LREC 2010* (pp. 1320–1326). Paris, France: European Language Resource Association. Retrieved from http://www.lrec-conf.org/proceedings/lrec2010/pdf/385_Paper.pdf.
Pang, B., Lee, L., & Vaithyanathan, S. (2002). *Thumbs up*? *Sentiment classification using machine learning techniques*. Proceedings of the Conference on Empirical Methods in Natural Language Processing (pp. 79–86) Stroudsburg, PA: ACL.
Parmelee, J. H., & Bichard, S. L. (2012). *Politics and the Twitter revolution: How tweets influence the relationship between political leaders and the public*. Lanham, MD: Lexington Books.

Pew Research Center's Internet & American Life Project 2013. Spring Tracking Survey, April 17 – May 19, 2013. Retrieved from http://pewinternet.org/Reports/2013/social-networking-sites/Findings/Twitter.aspx

Roberts, M., & McCombs, M. (1994). Agenda setting and political advertising: Origins of the news agenda. *Political Communication*, **11**, 249 – 262. doi:1.1080/10584609.1994.9963030.

Shaw, D. L., Hamm, B. J., & Terry, T. C. (2006). Vertical vs. horizontal media: Using agenda-setting and audience agenda-melding to create public information strategies in the emerging papyrus society. *Military Review*, **86**, 13 – 25.

Shaw, D., McCombs, M. Tran, H. & McKeever, R. (2010). *Imagining community*: *Media agenda setting*, *social melding*, *and mediamorphosis*, *a meta analysis*. Proceedings of the 8th International Symposium: Communication in the new Millennium, Anadolu, Turkey. May 23 – 26.

Shaw, D., & Vargo, C. (2012). *The media and social stability: How audiences create personal community*. Beijing, China: International Forum of Higher Education in Media and Communication.

Shaw, D., & Weaver, D. (2014). Media agenda-setting and audience agenda-melding. In M. E. McCombs (Ed.), *Setting the agenda: The mass media and public opinion* (pp. 145 – 150). Cambridge, England: Polity Press.

Simpson, W. (2001, March). *The quadratic assignment procedure* (*QAP*). Paper presented at the Stata Users Group Meeting, Boston, MA.

Thelwall, M. B. (2010). Sentiment detection in short informal text. *Journal of the American Society for Information Science and Technology*, **61**, 2544 – 2558. doi:1.1002/asi.21416.

Thelwall, M. B., Buckley, K., & Paltoglou, G. (2012). Sentiment strength detection for the social web. *Journal of the American Society for Information Science and Technology*, **63**, 163 – 173. doi:1.1002/asi.21662.

Twitter. (2013, March 14). *Twitter.com*. Retrieved from Twitter API Documentation: http://dev.twitter.com/docs/streaming-apis/streams/public

Vargo, C. (2010). *National television news and newspapers as media salience*, *Twitter as public salience*: *An agenda-setting effects analysis*. Unpublished master thesis. University of Alabama, Tuscaloosa, AL.

Vargo, C. (2011, August). *Twitter as public salience*: *An agenda-setting analysis*. Paper presented at the AEJMC annual conference, St. Louis, MO.

Vieweg, S. (2010). The ethics of Twitter research. *Proceedings of the Computer Supported Cooperative Work*, **27**, 1 – 3.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications*. Cambridge, England: Cambridge University Press.

Weaver, D., Wojdynski, B., McKeever, R. & Shaw, D. (2010, May). *Vertical and or versus*? *Horizontal communities*: *Need for orientation*, *media use and agenda melding*. Proceedings of the Annual Convention of the World Association for Public Opinion Research, Chicago, IL.

Weimann, G. (1991). The influentials: Back to the concept of opinion leaders? *Public Opinion Quarterly*, **55**, 267 – 279.

Witten, I. H., & Frank, E. (2005). *Data mining: Practical machine learning tools and techniques*. San Francisco, CA: Morgan Kaufmann.

Appendix A

Obama Supporter OLS Regression Model and Analysis of Variance (ANOVA) Summaries

	Model Summary					ANOVA		
Vertical Media	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.755	.698	53.585	1.906	3	13	13.53	.000
Foreign policy	.644	.593	84.623	2.105	2	14	12.669	.001
Individual liberties	.868	.824	47.021	1.089	4	12	19.667	.000
Federal programs	.832	.793	43.612	2.018	3	13	21.483	.000
Immigration	.244	.194	28.587	1.053	1	15	4.846	.044
Education	.890	.854	44.237	2.447	4	12	24.338	.000
Environment	.679	.633	36.234	1.853	2	14	14.821	.000
Big government	.976	.972	4.546	1.515	2	14	283.628	.000
Average	.736	.695	42.806	1.748	2.625	13.375	49.373	.005

	Model Summary					ANOVA		
Horizontal Democratic	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.480	.405	75.245	2.580	2	14	6.454	.010
Foreign policy	.477	.442	99.096	1.780	2	14	7.226	.007
Individual liberties	.481	.407	86.231	2.472	2	14	6.480	.010
Federal programs	.384	.296	8.514	1.966	2	14	4.362	.034
Immigration	.724	.631	19.329	2.541	4	12	7.853	.002
Education	.409	.325	95.040	2.069	2	14	4.845	.025
Environment	.699	.599	37.908	2.241	4	12	6.968	.004
Big government	.945	.920	7.732	1.162	5	11	37.976	.000
Average	.575	.503	53.637	2.101	2.875	13.125	1.271	.012

	Model Summary					ANOVA		
Horizontal Republican	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.261	.212	86.632	1.103	1	15	5.300	.036
Foreign policy	.457	.332	108.445	1.142	3	13	3.651	.042
Individual liberties	.339	.295	93.977	1.529	1	15	7.699	.014
Federal programs	.000	.000	*	*	0	*	*	*
Immigration	.468	.392	24.822	1.636	2	14	6.162	.012
Education	.000	.000	*	*	0	*	*	*
Environment	.360	.317	49.463	1.105	1	15	8.419	.011
Big government	.889	.838	11.030	1.780	5	11	17.543	.000
Average	.347	.298	62.395	1.383	1.625	13.833	8.129	.019

Note: Asterisks indicated that no model could be fit for Federal programs and Education.

Appendix B

Romney Supporter OLS Regression Model and Analysis of Variance (ANOVA) Summaries

	Model Summary					ANOVA		
Vertical Media	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.273	.224	94.861	1.622	2	14	4.037	.041
Foreign policy	.731	.609	49.218	2.281	5	11	5.987	.006
Individual liberties	.744	.685	47.315	1.622	3	13	12.611	.000
Federal programs	.412	.328	33.411	2.232	2	14	4.899	.024
Immigration	.393	.353	23.523	1.832	2	14	5.649	.016
Education	.000	.000	*	*	0	*	*	*
Environment	.242	.192	43.986	1.786	2	14	3.285	.068
Big government	.305	.206	4.957	1.435	2	14	3.076	.078
Average	.388	.325	42.467	1.830	2.250	13.429	5.649	.033

	Model Summary					ANOVA		
Horizontal Republican	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.712	.616	66.691	2.340	4	12	7.430	.003
Foreign policy	.727	.636	47.525	2.255	4	12	7.976	.002
Individual liberties	.782	.751	42.099	1.878	2	14	25.105	.000
Federal programs	.474	.439	3.508	2.072	2	14	7.157	.007
Immigration	.689	.645	17.436	2.174	2	14	15.505	.000
Education	.225	.174	61.121	2.111	1	15	4.367	.054
Environment	.714	.584	31.572	2.564	5	11	5.485	.009
Big government	.379	.290	4.686	1.790	2	14	4.274	.036
Average	.588	.517	37.705	2.148	2.750	13.250	9.662	.014

	Model Summary					ANOVA		
Horizontal Democrat	R^2	Adjusted R^2	Standard Error	Durbin–Watson	Sig. Coeff.	*df*	*F*	Sig.
Economy	.563	.462	78.992	2.113	3	13	5.579	.011
Foreign policy	.714	.618	48.653	2.361	4	12	7.473	.003
Individual liberties	.510	.397	65.49	1.374	3	13	4.511	.022
Federal programs	.373	.331	33.326	2.135	2	14	5.427	.018
Immigration	.487	.413	22.403	1.539	2	14	6.632	.009
Education	.283	.235	58.8	1.872	1	15	5.926	.028
Environment	.513	.444	36.496	2.158	2	14	7.379	.006
Big government	.259	.153	5.118	1.692	2	14	2.448	.123
Average	.463	.382	43.660	1.906	2.375	13.625	5.672	.028

Note: Asterisks indicated that no model could be fit for Education.