This paper employs social network analysis to explain variation in the pricing of 846 banner advertisements appearing in a community formed by eighty-nine “liberal” and eighty-four “conservative” Weblogs. As predicted, Weblogs that bridge “structural holes” between otherwise disconnected segments of the community command significantly higher prices for their advertisements. Also as predicted, the price of banner ads increases with the number of impressions received, with the size of the ad, when the ad is located higher on the page, and when fewer other ads appear.

**Keywords:** online advertising, social network analysis, social capital, social networking, Weblogs, social media
Pricing Banner Advertisements in a Social Network of Political Weblogs

INTRODUCTION

Much of the empirical research on the effectiveness of Web banner advertising may be divided into two broad categories—a concern with communication outcomes and a concern with cost effectiveness. In the former group belong studies of the effects of exposure to Web banners on an audience’s cognitive, affective, and behavioral responses. Dependent variables in these studies include brand recall and recognition (Briggs and Hollis 1997; Li and Bukovac 1999; Dreze and Hushherr 2003), attitude toward the brand (Dahlen, Rasch, and Rosengren 2003), click-through rate (Gatarski 2001; Robinson, Wysocka, and Hand 2007), and purchase intention (Dahlen, Ekborn, and Morner 2000; Gong and Maddox 2003). Independent variables typically include characteristics of the banner ad itself, e.g., the type of appeal (Xie, Nothu, and Lohtia 2004); the information content of the ad copy (Calisir and Karaali 2008), particularly its relevance and degree of personalization (Tam and Ho 2006); the use of animation, sound, or motion (Yoo and Kim 2005; Chen et al. 2009); as well as the banner’s size (Sigel, Braun, and Sena 2008; Burns and Lutz 2008), design (Lohtia, Donthu, and Hershberger 2003), location (Ryu et al. 2007), visual complexity (Huhmann 2003), and color scheme (Moore, Stammerjohan, and Coulter 2005).

Empirical studies on the cost effectiveness of Web banner advertising can be further divided into two groups—algorithmic and strategic. Noting that advertisers compete for the premium space on a publisher’s Web page, researchers in the former group have treated revenue maximization as an online variant of the well-studied bin-packing problem (Dyckhoff 1990). Accordingly, they developed and tested a variety of scheduling algorithms to optimize advertisement inventory (Nakamura 2002), display frequency (Amiri and Menon 2003; Kumar, Jacob, and Sriskandarajah 2006), and budget allocation (Fruchter and Dou 2005).

The “strategic” studies employ a broader frame of reference for the revenue maximization question. Namely, they consider competitive and cooperative relationships that exist among different participants in the online advertising industry (e.g., Sherman and Deighton 2001). And while their designs and results may differ, they do all agree on one point: the motivations and behaviors of several parties can influence the ad pricing decisions. For example, in their examination of the pricing of banner advertisements Li and Jhang-Li (2009) examine the roles of four key players in the online advertising industry—advertisers, visitors, publishers, and channel providers under two market conditions—duopoly, i.e., the presence of two heterogeneous channel providers (e.g., Google for search advertising and Double-Click for display) and monopoly, where the two channels “are merged into a single dominant player with monopolistic power in the market.” Kumar, Dawande, and Mookerjee (2007) include advertisers, publishers, and visitors in their model, while Fruchter and Dou (2005) include the role of advertisers, visitors, and two types of publisher—specialized and generic portals.

CONTRIBUTION

This paper makes three important contributions to IS research. To our knowledge it represents the first application of social network analysis (SNA) to research on Web-based advertising performance. SNA is a very robust method and is routinely used in fields as diverse as sociology, business administration, computer science, and the economics of technological innovation. This is also the first study to develop a pricing model for Web banner ads including variables other than the number of impressions received—a variable which is by far the most important and influential. Finally, this is one of a very small handful of studies anywhere in the IS fields that constructs a social network based on hyperlinks between competing sites (Weblogs) and then explains variation in their performance—i.e., advertising prices and revenues—based on position within that network.

More specifically, the study provides evidence that advertising prices are function not only of (1) the number of impressions a Web site receives, but also on (2) the size of the ad, (3) its location on the page, (4) the number of competing ads, and most importantly the position that the Weblog occupies within a network formed by hyperlinks in a community of similar sites (political Weblogs). That position is known generally in the literature as “network constraint” and is measured here by the degree to which a particular website serves to bridge otherwise disconnected segments of a network. The findings here are somewhat counter-intuitive to the echo-chamber argument that has been advanced against political Weblogs, i.e., that they form insular communities disinterested in dissenting views. This study shows quite clearly that Weblogs that bridge otherwise disconnected segments of the political blogosphere—either within their political orientation or across it—command significantly higher prices for their advertising, all else being equal.

This research is expected to be very interesting to researchers focusing on pricing and performance models of Web-based advertising. It may be moderately interesting to publishers of Weblogs seeking to justify higher prices for their ad space, as well as for their advertisers, especially those looking to optimize their advertising expenditures. Finally, the findings should also be of interest to owners of social networking sites that wish to determine which members have the most social capital—i.e., occupy the most influential positions within one or more social networks—rather than simply who has the most “friends” or “followers.”
Unfortunately, the supply of scholarly research on how to “crack the code of social network advertising” falls far below demand from industry professionals (Williamson 2008). Only within the last two to three years have published empirical studies begun to appear that explicitly examine advertising models for social networking sites (e.g., Enders et al. 2008) or that apply the concepts and methods of social network analysis to the study of interactive marketing and advertising (e.g., Okazaki, 2009). However, none of these studies directly address whether and how position and function in an online social network impacts measures of advertising effectiveness or influences the price of advertising therein.

The absence of any such studies is especially striking given the extensive literature on brand communication and cost effectiveness of Internet advertising. In short, while the interactive aspects have been examined exhaustively, the networked nature of the phenomenon has attracted little or no formal attention from scholars. This paper addresses that gap in the literature. I do so by identifying the extent to which one widely employed measure of social network structure—network constraint (Burt 1995)—explains variation in prices for banner advertisements within an online social network.

The remainder of this paper is organized as follows. Section 2 contains an extensive literature review and the formulation of five hypotheses. In Section 3 I describe the data sample and research methods employed in this study, while in Section 4 I discuss the results of the data analysis. Section 5 contains a discussion of the implications of the results and suggestions for future research.

LITERATURE REVIEW AND HYPOTHESES

Simply stated, social network analysis involves defining the structure of relationships or ties among a set of actors. Those actors may include “individuals within groups, teams, and organizations, organizations and firms themselves, computers and Web sites, members of online communities, etc.” (Krebs 2009). Ties occur between pairs of actors or nodes in the network and the pattern of linkages among all pairs is what defines the social structure of the network. Network relationships are typically displayed in two ways. The first is in an adjacency matrix, as shown in Table 1 below, where a “1” in a cell, e.g., row = “D” and column = “B,” signifies the existence of a link between the corresponding nodes, i.e., nodes “D” and “B.” The second method is as a sociograph constructed from the data in the corresponding adjacency matrix, as shown in Figure 1.

| Table 1: Generic Adjacency Matrix for Six Nodes, A Through F |
|---|---|---|---|---|---|---|
| A | B | C | D | E | F |
| A | -- | | | | | |
| B | 1 | -- | | | | |
| C | 1 | 0 | -- | | | |
| D | 1 | 1 | 1 | -- | | |
| E | 0 | 0 | 1 | 0 | -- | |
| F | 1 | 0 | 0 | 0 | 0 | -- |

Figure 1: Sociograph constructed from network data in Table 1.

Social network analysis has been applied to a wide variety of academic fields and settings. Chief among them are the social sciences where it is frequently used in studies of individual, group/team and organizational performance (Burt 2005); the information sciences, most notably in studies of the interdisciplinarity of academic journals (Leydesdorff 2007); criminology, particularly the analysis of terrorist, gang, and extremist activity (Xu and Chen 2005); and artificial intelligence, including the study of distributed expertise (Campbell et al. 2003) and computer-supported learning (Palonen and Hakkarainen 2000).
In each of these fields ties among actors and nodes have been defined differently. For example, in the first they are defined by both formal (reporting) and/or informal (social) relationships (Burt 2001). In the second case, it is citations to academic papers, while in the last, e-mail exchanges are used. Variation in definitions aside, what really distinguishes SNA from other approaches to the above questions is the emphasis it places on relationships rather than attributes of the actors (Wasserman and Faust 1994), and consequently on their interdependence rather than independence. As Borgatti and Li (2009) state, “[a] fundamental axiom in network analysis is the notion that actors are not independent but rather influence each other” and have important consequences for any number of key performance indicators.

This does not mean that the social network approach dismisses attribute-related explanations—far from it. In truth, the arguments are analogous and in many ways complementary. For example, while human capital theories might resort to individual characteristics to explain differences in the performance of a group of managers or scientists—some individuals are, after all, “more able ... more intelligent, more attractive, more articulate, more skilled” (Burt 2001, p. 32)—the social network argument treats social structure as “a kind of capital that can create for certain individuals and groups a competitive advantage in pursuing their ends. Better connected people enjoy higher returns” (ibid., p. 32).

Not surprisingly, debate has arisen concerning the definition of “better connected” and the mechanisms by which social structure confers advantage. Burt (2001) defines two distinct but related ways in which actors may be better connected. He terms them brokerage and closure. The “closure argument is that social capital is created by a network of strongly interconnected elements,” while the “structural hole argument is that social capital is created by a network in which people broker connections between otherwise disconnected segments” (ibid., p. 31).

In both cases the management of information flows in the network is mechanism by which advantage is achieved. Brokers, i.e., those who bridge structural holes, are advantaged by their “position in the social structure” in three distinct ways. First, because they are in contact with numerous distinct and disconnected groups, brokers have access to a wider variety of, and thus less redundant, information. Second, brokers have earlier access to this less redundant, more diverse information. Being stationed at the intersection of the information flow between groups permits brokers to be among the first to learn about the activities and interests of the different groups. Finally, brokers have some influence on information diffusion between the groups that they bridge. They are “more likely to know when it would be rewarding to bring together separate groups” and thus have “disproportionate say in whose interests are served when the contacts come together” (Burt 2001, pp. 16–17).

The closure argument also relies on information flows, but the mechanism is different. Just like peer groups and gossip networks, a dense pattern of connections means that the behavior of each node is observed by most members and reported on to all other members. Such a structure increases the odds of an actor “being caught and punished for displaying belief or behavior inconsistent with preferences” of other members. As such, social capital in closed networks accrues from its ability to decrease variation in a group behavior and to reinforce the status quo. But this should not be understood in a negative light. The cohesion, trust, and collaboration characteristics of closed networks are a precondition to realizing the value of brokerage: effective brokerage must occur between two or more groups whose members are well integrated and closely linked. Closure is, then, “a complement to brokerage such that the two together define social capital in a general way in terms of closure within a group and brokerage beyond the group” (Burt 2005, p. 7).

Despite the complementary nature of brokerage and closure, their consequences for performance are not equivalent. Burt’s (2000) review of research on social networks and social capital in organizations concluded that “closed networks—more specifically, networks of densely interconnected contacts—are systematically associated with substandard performance. For individuals and groups, networks that span structural holes are associated with creativity and innovation, positive evaluations, early promotion, high compensation, and profits” (Burt 2001, p. 45).

Several studies in the recent decade report a positive relationship between the spanning of structural holes and performance of individual managers (Rodan and Galunic 2004), groups and teams (Balkundi et al. 2007), firms (Moran 2005) and industries (Soda, Usai, and Zaheer 2004; Iyer, Lee, and Venkatraman 2006). The benefits of brokerage have also been found in nonmanagerial settings and with noneconomic measures of performance. Four recent studies in particular—two of citation patterns and two of online social networks—are especially relevant to this study.

Oh, Choi, and Kim’s (2006) study of citation patterns in the management Information Systems field reports that “knowledge capital derived from a network rich in structural holes has a positive influence on an individual researcher’s academic performance” (ibid., p. 265). In their study of highly creative scientists in the field of nanotechnology, Heinze and Bauer (2007) find that “scientists who effectively broker otherwise disconnected colleagues...
receive higher citation scores” (ibid., p. 827). Ganley and Lampe (2009) analyzed Slashdot, a technology-related news Web site which permits users to “declare relationships with other users” and which contains “Karma,” a peer reputation and ranking system. They found “the bridging of structural holes [to be] strongly related to the status of participants in the beginning and middle part of their Karma-building experience....” Finally, Okoli and Oh (2007) find brokerage among participants in an open-source community—Wikipedia’s open content encyclopedia community—to be positively associated with “recognition-based performance,” i.e. “the formal status they are accorded in the community” (ibid., p. 240).

While there is considerable evidence that brokerage is also associated with superior performance in information-intensive and online settings, there has yet to be an examination of role of social structure in relation to any aspect of online advertising. Still, it is justified to hypothesize that

\[ H1: \text{All else equal, Web sites that broker gaps in their social network will command significantly higher prices for the advertisements appearing on their pages.} \]

Four other variables have been shown by prior research to have an effect on the advertising prices, and/or on related measures of advertising performance such as click-through-rates and communication effectiveness—the number of impressions received by an advertisement, the size of the ad, its location, and the relative space dedicated to ads.

**Impressions**

Cost-per-impression (CPM) has long been the dominant method of pricing display advertising—both online and off (Hoffman and Novak 2000; Evans, 2008). A survey of fifty-one interactive agencies’ pricing, measurement, and pre-testing practices reported that cost-per-thousand impressions (CPM) to be the most popular method of pricing banner ads (Shen 2002). Just over 90 percent of respondents stated that they “always or frequently” used CPM in pricing banner ads, significantly greater than the percentage stating that they always or frequently used click-through (33.4 percent), flat-fee (19.6 percent), unique visitor (13.8 percent), or cost per action/outcome (5.9 percent).

\[ H2: \text{All else being equal, the price commanded will increase with the number of impressions the advertisement receives.} \]

**Size**

In print media it is common practice to price banner or display advertisement according to size. Prior research has shown that advertisement prices increase nonlinearly with size (Busse and Rysman 2005). Larger print advertisements have also been shown to act as a positive indicator of advertising costs and effort, an indicator which they use to draw inferences about product quality (Homer 1995). In online advertising, advertising size has been shown to positively impact brand recall (Li and Bukovac 1999; Chatterjee 2008) and the intention to click on banner ads (Cho 1999), though not always on actual click-through rates (Robinson, Wysocka, and Hand 2007; Sigel, Braun, and Sena 2008). Thus, despite prior research specifically linking advertising size to price, it is reasonable, based on print and new media industry practice, to hypothesize that

\[ H3: \text{All else being equal, the price commanded for banner ads will increase with the size of the advertisement.} \]

**Location**

A banner advertisement’s location has been shown to influence brand recognition (Calisir and Karaali 2008) and recall (Razzouk and Seitz 2003), pre-attentive processing (Ryu et al. 2007), and the level of attention given to content and advertisement areas of a Web page (Wang and Day 2007; Dewan, Freimer, and Zhang 2002). The study of Dewan et al. (2002) recommended specifically that “Web advertising located in the earlier and later stages of a (browsing) path should be priced higher than advertising in the middle phases because during these two phases the audience is more sensitive to peripheral advertising” (p. 1404).

\[ H4: \text{All else being equal, banner advertisements appearing in the upper regions of the Web page will command higher prices.} \]

**Number of Ads**

The large majority of Web site provide content or information for free and, as in the radio and TV industries, they earn revenue by allowing advertising targeted at the site’s visitors. As noted by Hofacker and Murphy (2000), free-content sites like Weblogs or news or information providers typically earn their ad revenue in one of two ways—(1) the advertiser pays per impression or (2) pays each time a visitor clicks on an ad and is taken to another Web site. In one of the first studies of clickable banner ads on content Web sites, these authors found that while click-through rates did not decrease when the number of banner ads on Web page increased from one to two, the ratio of advertising-to-content does result in customer disutility, lower advertisement revenues, and lower advertisement prices. Thus, the last hypothesis is that
H5: All else being equal, the price commanded for banner ads will decrease with the number of ads appearing on the page.

DATA AND METHODS

I tested the hypotheses presented in Section 2 with a data set collected from North Carolina-based Blogads.com™, a channel provider that serves banner advertisements to over 1500 popular Web sites and Weblogs. Founded in 2002, Blogads.com describes itself as “a network of influential bloggers who collaborate to promote and sell blog advertising.” As the channel operator, Blogads.com takes only 30 percent of the advertising fee charged by the publishers after deducting credit card and other transaction costs. Banners come in three sizes of banner advertisements—“Hi-Rise,” “Standard,” and “Mini.” Their dimensions in pixels, file types and sizes, and character limits are provided in Table 2 below.

<table>
<thead>
<tr>
<th>Type</th>
<th>Max Image Size (pixels)</th>
<th>Max File Size, jpeg/gif (kB)</th>
<th>Max File Size, flash/swf (kB)</th>
<th>Max Characters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hi-Rise</td>
<td>150 x 600</td>
<td>35</td>
<td>70</td>
<td>300</td>
</tr>
<tr>
<td>Standard</td>
<td>150 x 200</td>
<td>16</td>
<td>32</td>
<td>300</td>
</tr>
<tr>
<td>Mini</td>
<td>150 x 100</td>
<td>5</td>
<td>10</td>
<td>100</td>
</tr>
</tbody>
</table>

Prospective advertisers identify and select Weblogs from a directory sorted in two ways: (1) by the number of impressions or (2) by “hives,” i.e., groupings based on common interests, demographics, geography, etc. Importantly, it is the publishers of Weblogs, not the company, that create the “hives” and set the conditions for membership. Dozens of hives have been created along several demographic variables and interest groupings. Examples include gender and sexual orientation, race and ethnicity, politics, environment and sustainability, travel, guns, and economics. While Blogads believes that the hives have network effects—“allying with other quality bloggers increases your revenues”—only anecdotal evidence is offered to support this claim (Blogads 2011a). The first is a testimonial by a Los Angeles based blogger, Matt Welch:

Network effects will work very well here. The more participating blogs from Los Angeles, the easier it is for advertisers to make a useful, targeted group buy (and therefore pay me more money!). This also works for subjects—media, baseball analysis, DIY music, whatever.

The second piece of evidence is Blogads claim that “multi-blog orders drive 75% of revenues” (ibid.). This means that 75 percent of advertising revenues come from advertisements placed on several blogs at a time, presumably when they choose by hive and thus advertise on all blogs within the hive at once.

In addition to prices, both directories contain several other pieces of information about each Weblog, information that can inform the advertiser’s decision making. Prices across and within hives can be compared according to an ad’s duration (one or two weeks, one month or three months), its location on the page (top, left, right, or premium), its size (see Table 3), its file type (static or animated), and the total number of Blogads.com banner ads appearing on the page.

All data used in this study was collected between mid-November and early December of 2006 on Blogads’ two largest hives—the then eighty-nine-member “Liberal” hive and the then eighty-four-member “Conservative” hive. But political blogs were not chosen as the focus of this study just because they constituted the largest grouping within Blogads. Rather, they were chosen because their relative size reflected the rankings and notoriety that they had already gained within the broader blogosphere (Sifry 2005). In its first “State of the Blogosphere,” Technorati—the first Web site devoted to ranking Weblogs and maintaining a directory of them—made special note of the disproportionately positive contribution of political blogs to blogosphere’s overall “posting volume” (Sifry 2004). Specifically, the report noted that

Many of the volume increases were due to political events. Large spikes occurred around the Iowa Caucuses (the Howard Dean scream), the time of the Nick Berg beheading, when both conservative and liberal bloggers posted prolifically on the new form of terrorist threat... (ibid.).

By the summer of 2004, many A-list political bloggers—generally, those with the highest posting frequencies, the largest followings, and the greatest numbers of inbound links—received journalistic credentials from both major political parties to cover their nominating conventions (Adamic and Glance, 2005). Before the year’s end, political blogs rose prominently in rankings of “top blogs” (Technorati.com 2004), a trend which continued unabated (e.g., BlogPulse.com 2005; Technorati.com 2009). Around the same time, social scientists—particularly political scientists—and legal scholars began to undertake systematic and theoretically-grounded studies of Weblogs (e.g.,
Dreznier and Farrell 2004; Coleman 2005; Solum 2006; Volokh 2006). Despite all of the attention that bloggers were receiving from readers, scholars, politicians, pundits, and even each other, attention didn’t translate directly into dollars. However, with hundreds of thousands or even millions of page views per week, it made sound economic sense for bloggers of all stripes to begin accepting advertising. By early 2005, if not sooner, advertising on top political blogs—and on many more nowhere near the top—was widespread if not ubiquitous. Blogads.com succeeded in becoming the channel provider for several top political blogs and in 2003 created “hives” within which bloggers with similar political affiliations were grouped.

Much like the political parties with which they are aligned, the Liberal and Conservative hives are comprised of Weblogs representing any number of demographic groups, interests, and constituencies. This much is evident from the most cursory examination of the names populating each hive. The Liberal Blog Advertising Network (LBAN) is home to several blogs with ideological links to the Democratic Party, e.g., DemBloggers, Democratic Underground, The Democratic Daily, and Democrats.com. Regional Democratic activists in both “blue states” (Young Philly Politics, Blue Oregon, Blue Jersey, and Blue Mass) and “red states” (Blue NC, Left in the West, Burnt Orange Report) are represented, as are members of other traditionally Democratic constituencies, including gays and lesbians (Pam’s House Blend, Republic of T), African-Americans (Oliver Willis, Steve Gilliard), academics (Bitch Ph.D., Juan Cole), the entertainment industry (Hollywood Liberal), Latinos (Latino Pundit), feminists (Feministing), environmentalists (Chris-Floyd). Also represented were leading members of the “netroots” (Daily Kos, My DD), implacable opponents of then-President Bush (Smirking Chimp), his administration’s foreign policy (Agonist), the Republican Party more generally (Crooks and Liars) and its assumed advocate, Fox News (News Hounds, All Spin Zone).

An equally wide and diverse collection of voices were found in the Conservative Advertising Network (CAN). Among them were libertarians (Questions and Observations); economists (Newmark’s Door) and advocates of the Austrian (Chicago Boyz) and Schumpeterian (Tech Central Station) schools of economics; opponents of the ACLU (Stop the ACLU) and abortion (Pro-Life Blogs); religious conservatives (Biblical Womanhood, Hugh Hewitt); unabashed supporters of then-President Bush (Blogs for Bush); conservative law professors (Althouse, Professor Bainbridge) and practicing attorneys (Patterico, Powerline); members of the armed forces (Soldier Life), supporters of the global war on terror (Mil Blogging, Black Five, Sgt. Hook, Blogs of War) and 2nd Amendment rights (The Other Side of Kim); and detractors of film-maker Michael Moore (Moore Watch) and liberal media bias (News Busters) more generally. Also included are consistent advocates of right-wing politics and causes (Hot Air, Right Wing News, Right-Thinking, The Conservative Voice), strident anti-liberals (Barking-Moonbat, Anti-Idiotarian Rottweiler), and supporters of the Republican Party (GOP Bloggers) both in red states (Bama Pachyderm, Florida Cracker, Southern Appeal) and blue states (New England Republican).

The Weblogs within and across these two hives are related in several ways. First of all, they all share the same channel provider for their display advertising—Blogads.com. Second, they produce and provide very similar content, and several are found in the same rankings of top political blogs (Adamic and Glance 2005; Klein 2009). Third, there are many hyperlinks between sites, particularly in the blogroll—the list of blogs that is typically placed in the sidebar and that “serves as a list of recommendations by the blogger of other blogs” (Blogmeister.com 2009). Hyperlinks are the measure of choice in social network analyses of Weblogs in general (Recuero 2008) and political Weblogs in particular (Adamic and Glance 2005), because bloggers regularly read, comment on, and link to one another’s blogs (Furukawa et al. 2007). Finally, because of the above, it is presumed that these blogs share many of the same visitors or readers.

**Independent Variable**

Weekly prices for banner ads appearing on all 173 Weblogs were obtained directly from the Blogads directory of hives. Because advertisements could take one of three sizes (Hi-rise, standard, and mini), could appear in the “top” and “premium” locations or not, could be located on the left or right side of the page, as many as twelve prices were obtained per Weblog. Publishers of Weblogs within the Blogads community make several crucial decisions concerning advertisements that appear on their blog. First, they set their own prices. They are not compelled to keep prices in line with other members of the hive. They are not even given suggested cost-per-impression guidelines. Second, they can accept or reject any advertisement from any advertiser contacting them via Blogads. Third, once they accept an advertisement they can choose the location of the advertisements, the number of ads that will appear in a location, the size of the ads, and the duration of their appearance. And finally, publishers can and do run ads from other channels at the same time, e.g., Google Adsense or Amazon Affiliates.

**Independent Variables**

Network constraint is a measure of social capital that reflects the degree to which a node acts as a bridge or broker between otherwise disconnected segments of a network (Burt 1995). Hyperlinks between Weblogs were used as the
basis for calculating this measure of social structure. Data on each Weblog’s outbound links was obtained using Web Data Extractor™, a software program which crawled each page of a Weblog and extracted the base URL of every Web site to which it created a hyperlink. These links could appear in the body of a post, in the comments fields following a post, or in the blogroll. Table 3 below provides some descriptive statistics on the number and distribution of links within and between the two hives.

### Table 3: Number and Distribution of Links Between and Within the Liberal and Conservative Hives

<table>
<thead>
<tr>
<th></th>
<th>Conservative-to-Liberal</th>
<th>Liberal-to-Conservative</th>
<th>Conservative-to-Liberal</th>
<th>Liberal-to-Conservative</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sum</strong></td>
<td>1968</td>
<td>3299</td>
<td>782</td>
<td>645</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td>23.4</td>
<td>37.1</td>
<td>9.3</td>
<td>7.2</td>
</tr>
<tr>
<td><strong>Median</strong></td>
<td>21.5</td>
<td>36.0</td>
<td>4.0</td>
<td>4.0</td>
</tr>
<tr>
<td><strong>Standard Dev.</strong></td>
<td>19.9</td>
<td>18.9</td>
<td>11.7</td>
<td>8.5</td>
</tr>
<tr>
<td><strong>N = 0</strong></td>
<td>8</td>
<td>0</td>
<td>22</td>
<td>18</td>
</tr>
<tr>
<td><strong>N = 1–5</strong></td>
<td>11</td>
<td>4</td>
<td>26</td>
<td>30</td>
</tr>
<tr>
<td><strong>N = 6–10</strong></td>
<td>13</td>
<td>4</td>
<td>9</td>
<td>21</td>
</tr>
<tr>
<td><strong>N = 11–20</strong></td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>10</td>
</tr>
<tr>
<td><strong>N = 21–30</strong></td>
<td>11</td>
<td>18</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td><strong>N = 31–40</strong></td>
<td>14</td>
<td>16</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td><strong>N &gt; 40</strong></td>
<td>18</td>
<td>37</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

Several important differences in the number and pattern of links are noteworthy. The eighty-nine Liberal blogs made an average of 37.1 links to other Liberal Weblogs—about 68 percent more than the Conservatives-to-Conservative average of 23.4 (t = 4.63, p < 0.001, equal variance assumed). Liberal Weblogs made an average of 7.2 links to Conservative Weblogs compared to an average of 9.3 from Conservatives to Liberal blogs. That difference itself is significant when controlling for the number of within-hive links (t = –6.87, p < 0.001).

Also notable are differences in the distribution of Weblogs linking within and across hives. About one-fourth of Conservative Weblogs (22 of 84) and one-fifty of Liberal ones (18 of 89) contain no links to blogs in the opposing hive. Another approximately one-fifty of Conservative blogs (26 of 83) and one-third of Liberal blogs (30 of 89) make between one to five links to blogs in the other hive. By contrast, over one-fourth of Conservative Weblogs (18 of 84) and over two-fifth of Liberal ones (37 of 89) have more than forty links to other members of their own hive. Finally, it is notable that not a single Liberal Weblog is without at least one link to another Liberal blog while eight Conservative Weblogs are not linked to other Conservatives. In short, Liberal blogs have more links in total, a higher proportion of links to other Liberal blogs, and greater number of blogs that are highly connected to each other.

Six adjacency matrices were created using hyperlinks among the 173 Conservative and Liberal Weblogs. The first contained links between the eighty-four Conservative Weblogs, while the second contained only links between the eighty-nine Liberal Weblogs. The third matrix was formed from links between all 173 political Weblogs, i.e., hyperlinks from Conservatives to Conservatives, Conservative to Liberals, Liberal to Liberals, and Liberals to Conservatives. Both mutual and unilateral hyperlinks were included. That is to say, a tie exists between Blog A and Blog B if either one hyperlinked to the other or if both hyperlinked to each. A second version of each matrix was produced wherein only mutual links were retained, i.e., only where both Weblogs linked to each other.

While the theoretical distinctions between brokerage and closure are clear, as a practical matter it is not possible to discern from a sociograph or adjacency matrix whether returns to closure or brokerage are superior. This can be determined only by matching measures of social structure with measures of performance and empirically testing the strength of the relationship. One measure of structure that has been developed to test competing social capital arguments is network constraint, “the extent to which a network is directly or indirectly concentrated in a single contact” (Burt 2001, p. 39). Network constraint on a node is high when it has few contacts, those contacts are densely connected, and/or the contacts are indirectly connected to the same central contact. The formula is given by Equation (1) for q not equal to i,j and where p_ijk is the proportion of i’s relations that are invested in contact j.

\[
(1) \quad c_{ij} = (p_{ij} + \sum_{q \neq i, j} p_{iq} \cdot p_{qj})^2
\]

The total appearing in the parentheses is, then, the proportion of i’s relations that are invested in connection with contact j. Network constraint is given by \( \sum c_{ij} \) the sum of squared proportions. The direction of the relationship between performance and network constraint is crucial to determining which type of social capital prevails—brokerage or closure.
More constrained networks span fewer structural holes which means less social capital according to the hole argument. If networks that span structural holes are the source of social capital, then performance should have a negative association with network constraint. More constraint means more network closure and so more social capital according to the closure argument. If network closure is the source of social capital, then performance should have a positive association with constraint (Burt 2001, p. 39).

Version 6.1.5 of the social network analysis software program UCINet (Borgatti, Everett, and Freeman 2002) was used to calculate network constraint from the six adjacency matrices. As shown in Table 4, below, four measures of constraint were then constructed, each of which varied according to the type of link that existed between nodes.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Hyperlinks</th>
<th>Liberal-to-Liberal</th>
<th>Conservative-to-Conservative</th>
<th>Liberal-to-Conservative</th>
<th>Conservative-to-Liberal</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Mutual and Unilateral</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>C2</td>
<td>Mutual Only</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>C3</td>
<td>Mutual and Unilateral</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>C4</td>
<td>Mutual Only</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>

Data for the four other independent variables—impressions, size, location, and number of ads per page were all obtained from the Blogads.com pages for “hive” or “mini-folder” (Blogads.com 2006/2011b). Tables 5a and 5b present descriptive statistics and zero-order correlations for all variables, respectively. Because I hypothesize that returns to brokerage are positive, then I expect that the relationship between constraint and performance—as measured by price—to be negative. Notably, all four measures of constraint are significantly and negatively correlated with advertisement price for the one week.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln (Price)</td>
<td>767</td>
<td>4.49</td>
<td>1.55</td>
<td>2.30</td>
<td>9.55</td>
</tr>
<tr>
<td>Ln (Weekly Page Views)</td>
<td>767</td>
<td>10.69</td>
<td>1.71</td>
<td>6.82</td>
<td>15.7</td>
</tr>
<tr>
<td>Number of Ads</td>
<td>767</td>
<td>3.09</td>
<td>2.35</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>Ad = Hi-Rise#</td>
<td>767</td>
<td>0.33</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Ad = Mini#</td>
<td>767</td>
<td>0.30</td>
<td>0.46</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Location = Premium#</td>
<td>767</td>
<td>0.42</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Hive = Liberal#</td>
<td>767</td>
<td>0.50</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Constraint, C1</td>
<td>764</td>
<td>0.12</td>
<td>0.08</td>
<td>0.05</td>
<td>0.53</td>
</tr>
<tr>
<td>Constraint, C2</td>
<td>752</td>
<td>0.34</td>
<td>0.26</td>
<td>0.07</td>
<td>1.00</td>
</tr>
<tr>
<td>Constraint, C3</td>
<td>767</td>
<td>0.10</td>
<td>0.09</td>
<td>0.03</td>
<td>0.79</td>
</tr>
<tr>
<td>Constraint, C4</td>
<td>705</td>
<td>0.32</td>
<td>0.26</td>
<td>0.06</td>
<td>1.00</td>
</tr>
</tbody>
</table>

# = categorical (dummy) variable

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln (Price)</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln (Weekly Page Views)</td>
<td>0.77</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Ads</td>
<td>0.00</td>
<td>0.13</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ad = Hi-Rise#</td>
<td>0.40</td>
<td>0.01</td>
<td>-0.01</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ad = Mini#</td>
<td>-0.36</td>
<td>-0.04</td>
<td>0.05</td>
<td>-0.46</td>
<td>--</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location = Premium#</td>
<td>0.01</td>
<td>-0.09</td>
<td>-0.12</td>
<td>0.02</td>
<td>-0.03</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hive = Liberal#</td>
<td>0.28</td>
<td>0.25</td>
<td>0.26</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.20</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constraint, C1</td>
<td>-0.42</td>
<td>-0.44</td>
<td>-0.10</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.20</td>
<td>-0.37</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constraint, C2</td>
<td>-0.32</td>
<td>-0.35</td>
<td>-0.10</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.15</td>
<td>0.16</td>
<td>-0.25</td>
<td>0.72</td>
<td>--</td>
</tr>
<tr>
<td>Constraint, C3</td>
<td>-0.36</td>
<td>-0.38</td>
<td>-0.09</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.15</td>
<td>-0.28</td>
<td>0.77</td>
<td>0.56</td>
<td>--</td>
</tr>
<tr>
<td>Constraint, C4</td>
<td>-0.42</td>
<td>-0.42</td>
<td>-0.07</td>
<td>-0.01</td>
<td>0.03</td>
<td>0.12</td>
<td>-0.22</td>
<td>0.76</td>
<td>0.95</td>
<td>0.77</td>
</tr>
</tbody>
</table>

* = p < 0.001, ** = p < 0.01, *** = p < 0.05
RESULTS

Table 6, shown below, displays the results of the regression of the natural log of advertising price on five groups of independent variables—one for each hypothesis. Notably, in each of the four regression models, the relationship between each independent variable and advertising price is highly significant in the predicted direction (p < 0.001). Hypothesis 1 held that the less constraint there is on a given Weblog, the higher the price it commands for advertisements placed on its pages. The results displayed in Tables 6 indicate that this relationship holds when constraint is measured only from mutual links (Models 2 and 4) and when measured from both mutual and unilateral links (Models 1 and 3). Similarly, it holds for links between blogs with shared political orientations (Models 1 and 2) and with links that cross the partisan divide (Models 3 and 4). Interestingly, the relationship between constraint and prices is strongest in Model 4 where only mutual links between blogs of differing orientations are used—in other words, in the network formed by all 173 “Conservative” and “Liberal” Weblogs. This suggests that all else being equal, Weblogs that bridge holes across the partisan divide command the highest prices of all.

Every one of the variables associated with Hypotheses 2–5 are also significant at the p < 0.001 level or better and in the expected direction. Specifically, price increases as the number of weekly page views goes up (H2), as the ad size expands (H3), and when its location is exclusive and/or highest on the right or left column (H4). Conversely, price decreases for smaller ads (H3) and as the number of ads increases (H5). A noteworthy and unexpected finding is that Weblogs belonging to the Liberal hive command significantly higher prices than their Conservative counterparts (p < 0.001, t = 8.01). Finally, adjusted-$R^2$ is over 80 percent for all four models and thus indicates that these six variables explain more variation than they leave unexplained.

| Table 6: OLS Regression of the Natural Log of Advertisement Price on Political Orientation, Four Measures of Network Constraint, the Natural Log of Weekly Page Views, Banner Size, Banner Location, and Number of Banners |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Variable                        | Hypothesis      | Model 0         | Model 1         | Model 2         | Model 3         |
| Orientation = Liberal           |                 | 0.425***        | 0.363***        | 0.376***        | 0.384***        |
|                                 |                 | (8.01)          | (6.64)          | (6.99)          | (7.19)          |
| Network Constraint: C1          | H1              | -1.346***       | -0.353***       | -1.172***       | -0.624***       |
|                                 |                 | (-3.53)         | (-3.47)         | (-4.05)         | (-5.81)         |
| Network Constraint: C2          | H1              |                 |                 |                 |                 |
|                                 |                 |                 | -0.353***       |                 | -1.172***       |
| Network Constraint: C3          | H1              |                 |                 |                 |                 |
|                                 |                 |                 |                 | -1.172***       |                 |
| Network Constraint: C4          | H1              |                 |                 |                 |                 |
|                                 |                 |                 |                 |                 | -0.624***       |
|                                 |                 |                 |                 |                 | (-5.81)         |
| Ln (Weekly Page Views)          | H2              | 0.680***        | 0.659***        | 0.665***        | 0.659***        |
|                                 |                 | (45.74)         | (41.22)         | (42.86)         | (42.20)         |
| Hi-Rise                         | H3              | 1.020***        | 1.018***        | 1.017***        | 1.014***        |
|                                 |                 | (17.36)         | (17.45)         | (17.22)         | (17.42)         |
| Mini                            | H3              | -0.618***       | -0.620***       | -0.617***       | -0.623***       |
|                                 |                 | (-10.22)        | (-10.33)        | (-10.16)        | (-10.40)        |
| Premium-Top                     | H4              | 0.226***        | 0.289***        | -0.292***       | 0.274***        |
|                                 |                 | (5.02)          | (5.06)          | (5.67)          | (5.42)          |
| Number of Banners               | H5              | -0.079***       | -0.075***       | -0.075***       | -0.078***       |
|                                 |                 | (-7.23)         | (-6.86)         | (-6.86)         | (-7.25)         |
| Observations                    |                 | 767             | 764             | 752             | 767             |
| F-statistics                    |                 | 539.9           | 472.3           | 463.6           | 474.5           |
| Model degrees of freedom (df)   |                 | 6               | 7               | 7               | 7               |
| R-squared                       |                 | 81.0%           | 81.4%           | 81.4%           | 81.4%           |
| Adjusted $R^2$                  |                 | 80.9%           | 81.2%           | 81.2%           | 81.2%           |

Sensitivity Analysis

Models 1–4 were also run on eleven sub-samples of the data: price above and below the median (1–2), weekly page views above and below the median (3–4), the number of advertisements greater than zero (5), standard-sized (6), high-rise (7), and mini advertisements (8), premium and top locations (9), only Liberal blogs (10), and only Conservative blogs (11). In the large majority of these conditions, at least one of the four measures of constraint was significant at the 0.001-level or better. Three of the conditions had one of the four measures significant at only the 0.05-level: price above the median, mini ads only, and premium and top locations only. Finally, in no instance was a
measure of constraint found to be positive and significant. Thus, the negative relationship between constraint and advertising prices is very robust.

**Multicollinearity Test**

Simply stated, multicollinearity results when two or more variables in a multiple regression are so highly correlated that estimates of their individual regression coefficients are unreliable. Multiple regression analysis attempts to isolate the effects of each of the model’s independent variables. Thus, when a new independent variable is added that is highly correlated to existing variables, several problems can arise. These include “substantially higher standard errors, with correspondingly lower t statistics,” “unexpected changes in coefficient magnitudes or signs,” and “nonsignificant coefficients despite a high $R^2$” (Hamilton 2008, p. 224). Despite the centrality of correlation, the presence of multicollinearity can’t “necessarily be detected, or ruled out, by examining a matrix of correlations among variables” (ibid., p. 225). One of the most common tests of the presence of multicollinearity is the variance inflation factor (VIF), a measure of the variance of the coefficient estimate that is being inflated by multicollinearity. Typically, VIF values of 5–10 or more are taken to indicate the presence of multicollinearity (Chatterjee, Hadi, and Price 2006, p. 238). Table 7, below, shows the VIF scores for the control and independent variables in regression models 1–4. The average VIF scores range from 1.18–1.23, well below the threshold that would indicate the presence of multicollinearity. In every model the VIF values for advertisement location and the number of ads are below average (1.05–1.09), while those for network constraint are above average (1.19–1.38).

**Table 7: Regression Diagnostics: Multicollinearity Tests and Effect Size Estimation**

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multicollinearity: Variance Inflation Factor (VIF)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Political Orientation</td>
<td>1.26</td>
<td>1.19</td>
<td>1.21</td>
<td>1.19</td>
<td>5.5%</td>
<td>6.2%</td>
<td>6.4%</td>
<td>7.1%</td>
</tr>
<tr>
<td>Network Constraint, C1</td>
<td>1.38</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>1.6%</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Network Constraint, C2</td>
<td>X</td>
<td>1.19</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>1.6%</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Network Constraint, C3</td>
<td>X</td>
<td>X</td>
<td>1.24</td>
<td>X</td>
<td>X</td>
<td>2.1%</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Network Constraint, C4</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>1.24</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>4.6%</td>
</tr>
<tr>
<td>Weekly Page Views</td>
<td>1.27</td>
<td>1.18</td>
<td>1.21</td>
<td>1.29</td>
<td>69.2%</td>
<td>71.1%</td>
<td>70.1%</td>
<td>68.4%</td>
</tr>
<tr>
<td>Size = High Rise</td>
<td>1.27</td>
<td>1.27</td>
<td>1.27</td>
<td>1.27</td>
<td>28.8%</td>
<td>28.5%</td>
<td>28.6%</td>
<td>28.9%</td>
</tr>
<tr>
<td>Size = Mini</td>
<td>1.27</td>
<td>1.27</td>
<td>1.27</td>
<td>1.28</td>
<td>12.4%</td>
<td>12.2%</td>
<td>12.5%</td>
<td>13.1%</td>
</tr>
<tr>
<td>Location</td>
<td>1.07</td>
<td>1.06</td>
<td>1.06</td>
<td>1.05</td>
<td>4.1%</td>
<td>4.1%</td>
<td>3.7%</td>
<td>4.4%</td>
</tr>
<tr>
<td>Number of Ads</td>
<td>1.06</td>
<td>1.09</td>
<td>1.09</td>
<td>1.09</td>
<td>5.9%</td>
<td>5.9%</td>
<td>6.5%</td>
<td>2.9%</td>
</tr>
</tbody>
</table>

**Effect Size Estimation**

Effect sizes are measures of the magnitude of the effect of a treatment. They provide information on the substantive effect of variable that is not possible to infer from statistical significance alone. While most commonly used in meta-analyses, the measure is applicable to multivariate regression analysis within a single study as well. The measure most appropriate to this study is partial eta-squared (Bakeman and Robinson 2005) which is “the ratio of the sum of squares for the effect of interest to the sum of squares for that effect plus the sum of squares error” (McCoach and Seigle 2009, p. 209). In simpler terms, it is a measure of the proportion of the total variance that is attributable to a treatment or effect. Cohen (1988, p. 283) provides the following scale for interpreting eta-squared effect sizes: above 0.99 percent is a “small” effect; above 5.88 percent is a “medium” effect; and above 13.79 percent is a “large” effect. Table 7, above, also shows the effect sizes for the control and independent variables of the four models described in Table 6. The effect sizes cover the range from small to large. Notably, the effect size of weekly page views is the largest in every model (68.4–71.1 percent), while that for network constraint is the smallest in three of four models (1.6–4.6 percent). The second largest effect sizes are associated with the advertisements location. Specifically, the effect size for “high-rise” advertisements averages 28.7 percent, while that for “mini” ads averages nearly 12.5 percent. With the effect sizes for location, the number of ads, and political orientation averaging 4–6 percent, network constraint clearly has the weakest of all effect sizes. Only in one of the four models is it not the weakest—the model where only mutual links within and across political orientation were used. Finally, it should be recalled that because “nonerror variation” can be accounted for by other variables in the model, partial eta-squared values are not “measures of unique variation in the dependent variable” (Pierce, Block, and Aquinas 2004, p. 919). And because they are calculated using different values of the total explainable variation, partial eta-squared values can and usually do add up to greater than 100 percent.

**CONCLUSIONS**

The findings of this study have several important implications for research on the effectiveness of online advertising. The key finding is that there was found a statistically significant relationship between social capital—measured as network constraint—and advertisement prices commanded by 173 partisan political Weblogs. Specifically, those
political Weblogs that linked otherwise disconnected segments of the political blogosphere—either within or across political orientations—commanded higher prices for their advertisements, all else being equal. This broadly confirms the “strategic” approach to banner advertising pricing which incorporates into its models the actions and motivations of industry participants, principally advertisers, channel providers, and publishers. What is new in this study is both the relationship among publishers—interconnected and interdependent—and the relationship with their common channel provider—partners rather than price takers. That said, it must be noted that the effect size of this finding is small, though not trivial. For the first study of its kind, this is not a reason for undue concern. Future research should more closely investigate whether significant interactions exist between network and content-related characteristics of political Weblogs, as well as nonpolitical blogs.

A second contribution of this study is its confirmation of long-standing findings of the broader literature on cost effectiveness and on communication effectiveness in online advertising. As we recall, several variables in the pricing model were shown to significantly impact the price of online advertising. Regarding the former, the number of impressions an ad receives—a variable which previous studies have shown to have a positive influence on price—was here shown to do likewise. Moreover it was the strongest of all variables in the model, having an adjusted-$R^2$ of almost 60 percent. This strongly confirms research identifying cost-per-impression as the dominant pricing model. Other variables in the model having the predicted effect was the number of ads appearing on the page: prior research has shown it to have a negative impact on advertising prices. Two other variables in this study—advertisement size and location—have shown positive effects on both communication outcomes like brand recall and recognition and on behavioral measures like click-through. Here both were shown to have positive and significant effects on advertisement prices, as well.

Political affiliation of the blogger, as expressed by hive membership, is the final variable in this study that has been shown to affect online advertising prices. Specifically, Liberal bloggers commanded significantly higher advertising prices, all else being equal. I am aware of no studies that assessed the impact of political orientation on any measure of advertising effectiveness. That said, a wide variety of demographic variables and consumer attitudes have also been shown to influence online buying behavior, attitude toward online advertisements, and other measures of advertising effectiveness (Schlosser, Shavitt, Kanfer 1999; Carr and Brackett 2001; Liu and Shrum 2002).

Moreover, several recent studies have identified personality and psychological antecedents that influence how actors in social networks structure their interactions with others. Specifically, brokers tend to be high self-monitors (Oh and Kilduff 2008) and have more “entrepreneurial personalities” insofar as they eschew conformity, security, and stability in favor of advocacy, change, and positions of authority (Burt, Jannotta, and Mahoney 1998, p. 63). Kalish and Robins (2006) report that people who bridge structural holes are relatively more individualistic, are more extraverted, and are more likely to believe they control events in their lives. Finally, Lewis et al. (2008) have made publicly available a new data set which they gathered from Facebook.com. They report that “subgroups defined by gender, race/ethnicity, and socioeconomic status are characterized by distinct network behaviors, and students sharing social relationships as well as demographic traits tend to share a significant number of cultural preferences” (p. 330).

Those findings, along with this study, have important implications for advertising effectiveness in environments characterized by computer-mediated communication and relationship formation, not the least of which are online social networks and social networking sites like Facebook and Twitter. For example, Facebook launched its “Project Beacon” in November 2007 (Facebook.com 2007) as a “core element of the Facebook Ads system for connecting businesses with users and targeting advertising to the audiences they want.” In short, the system allows users to share information about actions taken on participating sites. In practice, this means that

Fandango, the nation’s leading moviegoer destination, is using Beacon so when Facebook users purchase a movie ticket on Fandango.com, they can share their movie plans with their friends on Facebook. Consumers gain a new way to tell their friends about their movie tastes, while Fandango is able to gain greater social distribution on Facebook (ibid.).

Despite pushback from privacy rights advocates, the Facebook’s efforts continue apace, the most recent example being its “instant personalization” feature which allows user profile data to be shared with participating third-party Web sites (Boulton 2010). Specifically, when a Facebook user is logged in and then visits one of the participating Web sites, they will view an “instantly personalized” page, one that takes their “public Facebook information,” e.g. “name, profile picture, gender, and connections” into account (ibid.).

But companies participating in “Project Beacon” and “instant personalization” stand to gain much more than “social distribution” or reap the benefits from viral marketing and e-word-of-mouth. In short, there is the possibility of constructing and analyzing social networks from a variety of behavioral and relationship data, computing several
measures of social structure, matching it with demographic and personality-level data and using it all to explain variation in advertising pricing, click through, cost-per-action, or even communication effectiveness. For example, advertisers could place ads on the pages of those deemed to be brokers and test for differences in any variety of performance and outcome measures.

The same applies to Twitter, the social networking and micro-blog service which recently claimed to be uninterested in “traditional Web banner advertising,” yet not “philosophically opposed to any and all advertising” (Twitter.com 2009). Unlike Facebook, where social structure is among people who have agreed to become online friends, members of Twitter are nominally part of two networks—those who follow their updates and those whose updates they follow. From the perspective of the focal member, were these two groups of members identical, there would be a perfectly-closed and highly-constrained network. However, to the degree that overlap between the followed and the followers is small, then the focal member is a bridge between two otherwise disconnected groups. Anecdotally it has been observed that membership in the two groups is unequal. Interestingly, a Web site has been established that allows people to calculate the ratio of friends and followers (Tffratio.com 2009) and that provides guidance on how to improve the ratio, i.e., get more followers. Twitter’s apparent predisposition toward brokerage may have factored into their deliberations about an advertising model for the service (Twitter 2009):

The idea of taking money to run traditional banner ads on Twitter.com has always been low on our list of interesting ways to generate revenue. However, facilitating connections between businesses and individuals in meaningful and relevant ways is compelling. We’re going to leave the door open for exploration in this area. Do we hate advertising? Of course not. It’s a huge industry filled with creativity and inspiration. There’s also room for new innovation in advertising, marketing, and public relations and Twitter is already part of that.

One notable “new innovation” for facilitating such connections is the development of open-source and site-specific tools for displaying and analyzing personal networks. For example, just recently LinkedIn™, the business-oriented social networking site, has made available an application called InMaps, a color-coded and “interactive visual representation” of the social network formed by a user’s LinkedIn contacts (Imam 2011). According to the company, the application provides LinkedIn users with a better way to “understand the relationships (among their) entire set of LinkedIn connections” and to “better leverage (that) professional network to help pass along job opportunities, seek professional advice, (and) gather insights” (ibid.). Dozens of other software and Web-based applications exist that provide the same functionality as InMaps, all of which are means to the aforementioned ends. The practical implications of these developments for publishers and advertisers are worth stating directly.

Whatever the advertising model that Twitter eventually settles upon or Facebook evolves toward, this much is evident: links between friends, between like-minded and topically-related Weblogs, and between followers and followed—all exhibit quantifiable social structures. But quantifiable is not the same thing as observable. As real-world and online networks grow, tools for displaying, and studying them stands to become increasingly important for all concerned. At present, characteristics of the nodes in these networks are more easily observed than is the structure of the ties that link them. In this study, for example, page views are more easily tracked and taken into account in ad pricing decisions than are network measures such as constraint. By “easy” I mean less computational and human information processing is required to make such decisions. However, as applications become more powerful and as the need for advertisers and publishers to target visitors increases, network-based measures of influence will gain greater importance. At best, examining the characteristics of the nodes of a network allows advertisers and publishers to infer who are the brokers, i.e., who are the least constrained members. In order for this information to be quantified with precision, the use of network analytical tools and methods is an absolute requirement. That said, much more research is required to determine which network measures and which Weblog characteristics taken together best predict advertising prices.

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