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THE COMPLEMENTARY ROLES OF TRADITIONAL AND SOCIAL MEDIA IN DRIVING MARKETING PERFORMANCE

ABSTRACT

The media landscape has dramatically changed over the past decade, with traditional media (e.g., newspapers, television) now supplemented by social media (e.g., blogs, discussion forums). This new media landscape is not well understood with respect to (i) the joint impacts of traditional and social media on marketing performance (e.g., sales), (ii) how these media types influence each other, and (iii) the mechanisms through which they affect marketing outcomes. These issues are examined with 14 months of daily performance data and media activity for a microfinance website. The authors find that both traditional and social media have strong effects on marketing performance, though a single unit of social media has a much smaller effect than a single unit of traditional media. However, because social media is created in larger volumes than traditional media, it has a sizeable effect on performance (i.e., social media is high-volume, low-margin, whereas traditional media is low-volume, high-margin). Further, social media acts as a broker of information flow in an informal network comprising traditional and social media outlets.

Keywords: traditional media, social media, performance, publicity, vector autoregression, network analysis.

Over the past decade, the media landscape has dramatically changed with social media outlets (SMOs; e.g., blogs, online discussion forums, and online communities) now supplementing traditional media outlets (TMOs; e.g., newspapers, magazines, and television programs). To the extent that these media outlets each have an effect on marketing performance (e.g. sales), it is critical to understand their relative importance and their interrelatedness. Furthermore, while social media was once the domain of younger, tech-savvy consumers who were faster to adopt new technologies, it is now generally considered to have entered the mainstream and covers a broad demographic spectrum with 75% of Internet-using adults in the United States using such social media (Bernoff, Pflaum, and Bowen 2008; Miller 2009a; Owyang, Bernoff, Van Boskirk, Pflaum, and Polanco 2009). This large number of users makes it critical to understand not only how such social media influences consumers, but also how it operates alongside traditional media. This is the primary focus of this paper. Specifically, we examine how media publicity generated by both traditional and social media outlets affects marketing performance.

Despite the importance of this issue, the generation of such publicity and how it impacts firms' marketing performance is not yet well understood. Past research, for example, has demonstrated that traditional media publicity can affect marketing outcomes (e.g., the literature on celebrity endorsement and star power; Agarwal and Kamakura 1995; Elberse 2007), that online user-generated content such as online book reviews and movie reviews can affect book sales and box office revenues (e.g., Chevalier and Mayzlin 2006; Liu 2006), and that sometimes even negative publicity can have a positive marketing effect (e.g., Ahluwalia, Burnkrant and Unnava 2000; Berger, Sorensen and Rasmussen 2009). However, this same literature has tended to examine the impact of traditional or social media on marketing performance in isolation, ignoring the likely joint effects that TMOs and SMOs have on one another and how this interplay might impact marketing performance. In order to properly understand the total impact of these media sources, an *integrated* perspective is needed that jointly considers traditional and social media effects on key marketing outcomes.

By applying such an integrative approach, we address the following novel questions: (i) what are the relative impacts of TMOs and SMOs on marketing performance? (ii) In what ways do these media types influence each other? And (iii) what are the mechanisms through which these different types of media influence each other and marketing performance? As we later demonstrate, this approach leads to interesting and unexpected insights on how both traditional and social media operate, and how different types of media outlets fulfill different (but complementary) roles in the dissemination of information.

We address the above questions with an empirical analysis of 14 months of data covering the daily marketing performance (sales) and media publicity activity in multiple TMOs and SMOs for a microfinance website, *Kiva.org*. *Kiva*'s sales can be described as small, low-risk loans made by its members (individuals) to entrepreneurs in developing countries and are broken down into dollar sales (amounts of money loaned) and number of sales (number of loans made). Further, each of these variables is broken down into whether the transaction came from a new "customer" (i.e., person who lends money through the website) or an existing one. Accordingly, our data allow us to examine a rich, multi-dimensional dependent variable for marketing performance. Moreover, we are able to see in what ways media activity from various sources affects these specific variables. The media activity data covers daily activity from a variety of TMOs and SMOs over the 14 months that we observed the sales data. We describe the dataset in greater detail later in the paper.

We address our first research question by comparing the direct effects of media activity[1] from multiple TMOs and SMOs on sales (i.e., the *performance response* to media publicity activity). Our second and third research questions are addressed by examining the direct and indirect effects of media activity in specific media outlets on all other TMOs and SMOs in the data (i.e., endogenous *media response* to media publicity activity). These media response effects characterize how media outlets influence each other's publicity-generating actions (e.g., how a brand mention on a blog influences a newspaper to also mention that brand in the future). These relationships imply that an informal network between TMOs and SMOs exists whereby information (e.g., buzz) flows between outlets. We analyze the structure of this network to see whether TMOs and SMOs are differently positioned and hence play different roles in generating publicity and impacting firms' marketing outcomes.

The paper is organized as follows. First, we provide an overview of extant literature on publicity, advertising, and media effects on marketing outcomes and outline our conceptual framework. Second, we describe our data. Third, we outline the methods used to analyze these data and present the results of our empirical analyses. Finally, we conclude with a discussion of our findings and a consideration of their implications for theory and practice.

BACKGROUND AND THEORY

Past Research on Media Effects on Marketing Outcomes

As we mentioned above, publicity—so-called "free press" or "free advertising"—has not been studied extensively in marketing. In particular, little research has examined marketing- and financially-relevant consequences of publicity and media attention for brands and companies. Further, with the exception of literature on integrated marketing

[1] By media activity we are referring to a specific feature or mention of a company, brand, product or service by a specific media outlet. For example, media activity for a new model of the Apple iPhone (i.e., a specific product) occurs each time a TMO or SMO mentions or features this product in an article, program, or post.

communications (IMC; we discuss this literature below), the relationships between media types and outlets have also not been extensively studied—particularly from a publicity-generation perspective (much of the IMC literature, for example, focuses on advertising, not publicity). In contrast, advertising effects on marketing outcomes (typically sales) have received a great deal of attention (e.g., Dekimpe and Hanssens 1995; Jedidi, Mela and Gupta 1999).

Word-of-mouth research. Recently, there has been a growing interest in understanding how word-of-mouth (WOM), particularly online WOM (which is a form of social media), impacts sales, diffusion, and other marketing performance measures (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Liu 2006; Trusov, Bucklin and Pauwels 2009; Van den Bulte and Lilien 2001; Villanueva, Yoo and Hanssens 2008). For example, Godes and Mayzlin (2004) examine how online discussion forum activity affects television show ratings; Chevalier and Mayzlin (2006) show that user-generated online book reviews influence book sales; and Trusov et al. (2009) examine how referrals/invitations to join an online social network affect the website's membership growth.

This growing body of literature on the impacts of various forms of WOM suggests that WOM—or, more generally, social media—indeed can affect marketing outcomes. However, often only one type of WOM is examined in this literature, and not contrasted with traditional media. This means that it is difficult to compare the relative sizes of the effects of traditional versus social media on key marketing outcomes. Also, from a methodological perspective, the examination of the effects of one type of media on an outcome but not the others could give rise to omitted variables bias. In line with a recent call for more comprehensive and multi-faceted research on WOM (Libai, Bolton, Stephen, de Ruyter, Goetz, Bugel, and Risselada 2009), this paper jointly examines the effects of traditional and social media.

Publicity research. Social media is a relatively new form of publicity, and yet the impact of more traditional forms of publicity on marketing outcomes has received disproportionately less attention than that of WOM and, of course, that of firm-sponsored activities (e.g., advertising, promotions). Much of the extant research on effects of media publicity centers on the how *negative* publicity, *bad* news, or *unfavorable* reviews influence outcomes such as sales and demand (e.g., Ahluwalia, Burnkrant and Unnava 2000; Basuroy, Chatterjee and Ravid 2003; Berger et al. 2009; Eliashberg and Shugan 1997; Goldenberg, Libai, Moldovan, and Muller 2007). Consistent with the findings on how WOM impacts performance, this literature generally finds publicity can affect product success. Like the recent online WOM literature, often one source of publicity or media attention is examined, thus precluding comparisons across media types and outlets.

Celebrity endorsement research. Another body of research that considers publicity, albeit of a different nature, is the work on the value of celebrity endorsements. The "Oprah effect," for example, is a hybrid form of traditional media publicity and celebrity endorsement. Celebrity endorsements have been shown to have positive value in terms of a firm's stock market value (Agrawal and Kamakura 1995), and, outside marketing, to affect voting in presidential elections (Wood and Herbst 2007). Economists and political scientists have also examined the "Oprah effect" with respect to how her endorsement of a book ("Oprah's Book Club") affects sales (Butler, Cown, and Milsson 2005), and how her coverage of the 2000 presidential election affected voting behaviors (Baum and Jamison 2006).

Limitations of past research. A limitation of past work on the effects of WOM, media publicity, and celebrity endorsement is that the impact of only one media type (i.e., source of publicity) is considered. Particularly in the case of the research on WOM, looking across studies we see rather robust effects indicating that both traditional and social media sources of buzz can affect the success (or failure) of a product, brand, or company. However, multiple types of media outlets (i.e., TMOs and SMOs) and multiple outlets within each type need to be examined together in order to draw comparisons between them and, critically, to understand how they influence each other and operate jointly. Thus, the current literature lacks a comprehensive understanding not only of the impacts of publicity on marketing performance, but also of the interplay between media outlets.

This can be a problematic for a number of reasons. First, methodologically, estimating the impact of one type of media on a marketing outcome without controlling for other types of media or influence is a possible omitted variable problem and leads to biased estimates of the impact of the included media variable.[2] Second, comparisons of the nature and size of publicity effects on performance—a central aim of this paper—cannot be made without a relatively comprehensive set of media types represented in the data. Finally, understanding the nature and size of the endogenous effects of different media types/outlets on each other—another central aim of this paper—is obviously impossible unless multiple media types are jointly studied. Thus, while past research has established that various types of traditional and social media are important because they can impact a range of marketing performance metrics, more integrated and multi-faceted study is warranted.

Media as an Integrated System

Integrated media. The question of how traditional and social media compare with respect to the nature and size of their respective impacts on marketing performance cannot be answered without first realizing that media outlets, traditional and social, are unlikely to exert any publicity influence on marketing outcomes in isolation. Rather, all media types are likely related in the sense that they have an influence on *each other*. For example, the technology editor of the *New York Times* reportedly uses the technology blog *TechCrunch.com* as a daily

[2] This bias is illustrated by Van den Bulte and Lilien (2001) in the case of social contagion effects on diffusion.

source of new story ideas (Arrington 2009). Thus, in order to understand how traditional *and* social media affect marketing performance we must also understand how TMOs and SMOs influence each other's content (and publicity) generation and see these various outlets as parts of a system.

The notion that media types and outlets are integrated with respect to publicity-generation and marketing performance outcomes shares conceptual similarities with the idea of integrated marketing communications (IMC) where a firm's advertising and promotions activities are coordinated across media channels (cf. Schultz, Tannenbaum, and Lauterborn 1993). IMC-related research has shown, for example, that multimedia synergies across marketing communications are valuable and sales responses are interdependent across channels (Naik and Raman 2003), that there is a complex interplay among marketing (and communications) efforts (Smith, Gopalakrishna, and Chatterjee 2006), that promotions in one media channel (e.g., advertising) can increase the effectiveness of activities in other channels (e.g., free-standing insert coupons in newspapers; Leclerc and Little 1997), and that for multimedia advertising, long-run effectiveness can differ considerably across media types (Vakratsas and Ma 2005). Whereas IMC is mostly focused on allocating advertising and promotions efforts across media types (i.e., firms' decisions), our focus is on the relationships between media types and outlets themselves with respect to publicity (which is not usually within a firm's direct control).

Network representation of media interdependence. The notion that media types and specific media outlets are interdependent can be taken a step further. If media are interdependent, then they can be thought of as a complex system—or network. We argue that media outlets, traditional and social, are part of an informal interconnected "network" or system of media outlets. In this network, media outlets are "nodes" and directional "ties" between them reflect influence in the sense that media outlet A (e.g., the blog

TechCrunch.com) links to media outlet B (e.g., the *New York Times*) if information about a given topic (e.g., a brand) flows from A to B; i.e., A is said to influence B's publicity-generation on that topic. This conceptualization helps in understanding how information flows across media and, ultimately, affects marketing outcomes. Of course, a network representation of how media outlets are related to each other is not perfect; it does, however, provide a convenient way to think about how the media as a whole collectively operates as an interconnected, endogenous system.

The following example illustrates these concepts. Suppose that a new, unknown independent musician is mentioned in a niche magazine with a small readership. It is unlikely that this traditional media activity would result in much of a sales increase for that artist's debut album. However, people who read the article will become aware of the artist and this might prompt some of them to blog about the artist, which builds further awareness and buzz. This might prompt some more social media activity and perhaps some minor traditional media activity, but have only a minimal impact on sales. However, eventually, a sufficient amount of awareness and buzz might be generated such that a journalist at a major TMO such as the *New York Times* publishes a review about the musician. Since the *Times* has a large readership and a broad audience, this piece of traditional media activity might trigger a noticeable sales increase. Thus, if we just considered the direct performance response we would conclude that the *Times* is responsible. However, if we trace back the influence through various media outlets we find that the impact actually originated with a niche magazine, and various social media outlets were the conduit through which information flowed to eventually reach the *Times*. In this simple example we see that although traditional media may have ultimately been responsible for affecting marketing performance, the network of TMOs and SMOs acted as a critical facilitator in this process.

DATA

Our data come from the website *Kiva.org*, an intermediary for microfinance loans. Microfinancing is the provision of small (i.e., "micro") financial services (e.g., loans) to people in developing countries who do not have access to major financial institutions, have no collateral to post against the loan, and who do not require large sums of money to finance their business activities. Microfinance has engendered widespread support and has become one of the ways that the United States, the United Nations, and other wealthy countries are trying to combat poverty around the world. It was also recently recognized by experts and thought-leaders as one of the 30 best innovations of the last 30 years in a joint PBS-Wharton survey (it was ranked 17th, which was above, for example, automatic teller machines, barcodes and scanners, and computer graphical user interfaces; Wharton 2009).

Kiva.org is a "microlending marketplace" where regular consumers can join (for free) and make small loans (as little as $25) to pre-approved borrowers, all of whom are entrepreneurs in developing countries.[3] The small loans are then bundled into larger loans and wired to the borrowers (the bundled loans are typically still very small; the average bundled loan is approximately $430). Since it's founding in late 2005, 559,000 lenders have loaned $92 million to 226,000 borrowers. These borrowers are spread over 181 countries, and the current loan repayment rate is 98.5%. The average individual lender made only 4.7 separate loans, which is low and suggests that attracting new lenders is important. *Kiva* spends very little on advertising, making media publicity particularly important for raising awareness and attracting new lenders (as well as "reminding" past lenders to lend again).

Variables Used in Analysis

[3] During the time of our dataset, borrowers could only come from developing countries. Recently, however, *Kiva* has extended its platform to allow entrepreneurs in the United States to solicit loans as well.

Kiva provided daily loan data for the period January 1, 2007 to March 2, 2008 (427 days), which we combined with media publicity data from several other sources. We now describe the variables used in our analysis.

Loan activity variables. For each day we know (1) the total amount of money that was loaned ("loan value," in US dollars) (i) by new (first-time) lenders and (ii) by repeat lenders, and (2) the number of loans made ("loan volume") (i) by new lenders and (ii) by repeat lenders. Loan value and loan volume are analogous to sales revenues and sales volumes, respectively. Descriptive statistics are reported in Table 1, and we plot each of these daily time series in Figure 1. We also have data on the number of borrowers who asked for money on *Kiva.org* each day, which we use as a control variable.[4]

[INSERT TABLE 1 & FIGURE 1 ABOUT HERE]

Media activity variables. As mentioned above, *Kiva* relies heavily on media publicity to reach potential lenders. Our media activity variables are listed in Table 2, and cover newspapers and television for traditional media, and blogs and online discussion forums for social media sources. For each type of media, our data tracks the daily number of media "events" that featured or mentioned *Kiva.org*.[5] For example, a television event occurred on September 4, 2007 when Oprah Winfrey devoted part of her show, *Oprah*, to publicizing *Kiva*. For social media, events were much more frequent than for traditional media (i.e., multiple events per day), and a blog event, for example, occurred whenever a blogger mentioned *Kiva*.

[INSERT TABLE 2 ABOUT HERE]

We now describe each of the media types and, where applicable, media outlets.

[4] Loan demand—the number of borrowers/entrepreneurs in developing countries who want to borrow money from *Kiva* lenders—is exogenous to media activity and loan activity since these entrepreneurs generally do not have access to TMOs and SMOs in the United States, and do not deal directly with *Kiva* (they deal with field agents who serve as intermediaries between *Kiva*, other sources of loans, and the borrowers)

[5] Depending on the size of the media outlet, an individual outlet was treated as a separate variable (e.g., the major national newspapers and *Oprah*) or multiple outlets were combined (e.g., regional/local newspapers, national/network television news, blogs, and online discussion forums).

First, for traditional print media we used the Dow Jones Factiva databases to gather daily print media event data. Print media included U.S. mainstream national newspapers,[6] and US local/regional newspapers. There were 12 events in national newspapers, and 40 in regional newspapers during our observation window.

Second, we used *Kiva*-supplied media tracking data to construct the time series for television events. *Kiva* provided dates and detailed descriptions of each event, which we validated through Google searches and checks of media outlets' websites. There were 11 television events, including news and segments on *Oprah*.

Third, we collected measures of the number of social media events each day by counting blog posts and discussion forum posts.[7] For blog posts we used Google blog search (www.google.com/blogsearch) to compile a daily time series of numbers of blog posts mentioning *Kiva.org*. There were 2,483 blog posts about *Kiva* (this excludes posts authored by traditional media outlets, which were excluded from this count to avoid double-counting). For discussion forums we gathered data from two sources: (1) the Omgili forum search engine (www.omgili.com), which indexes millions of discussion threads and over 100,000 separate discussion forums, and (2) daily posting activity logs for the Kivafriends.org online discussion forum and "fan" community for *Kiva*. We found 23,862 *Kiva*-related forum posts.

EMPIRICAL ANALYSIS

Modeling Approach and Objectives

We use vector autoregression (VAR) time series analysis to examine how TMO and SMO activity affected media and loan activity over the 427-day period from January 1, 2007 to March 2, 2008. In this time we recorded 26,408 separate *Kiva*-related media events (63

[6] National newspapers were the *New York Times*, the *Wall Street Journal*, *USA Today*, and the *Washington Post*.
[7] Although not an exhaustive set of social media sources, this set is consistent with the types of SMOs examined in previous literature (e.g., Godes and Mayzlin 2004). Historical data from other sources of social media activity, particularly major social networks (e.g., Facebook) and micro-blogging (e.g., Twitter), were not available for our observation window.

from traditional media, and 26,345 from social media). We have two related modeling objectives: to address our first research question related to the nature and relative sizes of the impacts of publicity from TMOs and SMOs on marketing performance by estimating the effects of media activity by media type/outlet on loan activity and address our second and third research questions related to uncovering and understanding relationships between different media types/outlets.

Vector Autoregressive Modeling Framework

To estimate how media activity affects marketing performance (*performance response*) and their interrelatedness (*media response*) we employ VAR and persistence modeling techniques. The VAR model is a multivariate version of the univariate autoregressive (AR) time series model. A VAR model regresses a vector of time series variables ("endogenous" variables) on *p*-period lags of themselves and of each other (the cross-variable effects allow for endogeneity to be controlled for). Both AR and VAR models have been used extensively in the marketing literature to study market response and market dynamics both in more "traditional" areas such as sales response to advertising and other marketing mix components (e.g., Dekimpe and Hanssens 2004; Pauwels, Hanssens and Siddarth 2002), and in newer areas such as the growth of online social commerce and social networking websites (e.g., Stephen and Toubia 2009; Trusov et al. 2009).

Based on our research questions, we need to regress the loan activity (marketing performance) variables on the media activity variables, and the media activity variables on each other. As is conventional in autoregressive models, we also allow for past values of the loan activity variables and the media activity variables to influence their current values (i.e., autoregressive lag effects). We also allow for current media activity to be affected by past values of loan activity (i.e., feedback effects) since, for example, increased loan activity might have helped *Kiva* grab more media attention. We estimate this system of regression equations, with each equation regressing an endogenous variable on *p* lags of itself and the other variables in the system. Since it is plausible for media activity to have immediate (i.e., same day) effects (e.g., due to digital delivery), we allow for instantaneous media activity effects throughout the model.

Formally, the VAR model is as follows:

$$\mathbf{y}_t = \boldsymbol{\alpha}_\mathbf{0} + \boldsymbol{\alpha}_\mathbf{1} t + \boldsymbol{\alpha}_2 t^2 + \boldsymbol{\alpha}_3 S + \boldsymbol{\Gamma}_0 \mathbf{y}_t + \sum_{l=1}^{p} \boldsymbol{\Phi}_l \mathbf{y}_{t-l} + \boldsymbol{\varepsilon}_t \quad (1)$$

Where $\mathbf{y}_t$ is a vector of $k = 13$ endogenous loan and media activity variables (see Tables 1 and 2 for details), $\boldsymbol{\alpha}_\mathbf{0}$ is a $k \times 1$ intercept vector (constant trend), $\boldsymbol{\alpha}_\mathbf{1}$ is a $k \times 1$ vector of linear time trends, $\boldsymbol{\alpha}_\mathbf{2}$ is a $k \times 1$ vector of quadratic time trends, $\boldsymbol{\alpha}_\mathbf{3}$ is a $k \times 1$ vector of "Christmas" effects ($S = 1$ if day t is in the last two weeks of December or the first two weeks of January, and $S = 0$ otherwise) because *Kiva* gift certificates were promoted by some media outlets as Christmas presents, $\boldsymbol{\Gamma}_0$ is a $k \times k$ matrix of instantaneous (same day) cross-variable effects (with the diagonal values set to 0, and instantaneous feedback effects of loan activity on media activity set to 0; only instantaneous media effects are allowed), $\boldsymbol{\Phi}_l$ is a $k \times k$ matrix of lag l autoregressive effects and endogenous cross-variable lagged effects, p is the best-fitting autoregressive lag, and $\boldsymbol{\varepsilon}_t$ are white-noise disturbances distributed $N(0, \Sigma)$.

Specification Tests

Stationarity. All loan and media activity variables are modeled in their levels (i.e., daily values of each variable, not cumulative "stock" values). VAR models in levels are appropriate when the time series are stationary (i.e., the "stationarity" condition; cf. Dekimpe and Hanssens 2004), which means that they do not have a unit root. Augmented Dickey-Fuller (ADF) unit root tests confirmed that all 13 time series in our analysis were stationary (i.e., the ADF test's null hypothesis of an evolving series was rejected in all cases; *p*s < .01).[8]

[8] As further evidence of stationarity, the moduli of all roots of the autoregressive characteristic polynomial were less than one (i.e., the variables do not have unit roots). The highest was .73 for the model that we report below.

Endogeneity. Our conceptualization of the TMOs and SMOs being implicitly "networked" implies that all media activity variables should be endogenous variables in the VAR model in Equation 1. Another possibility is that some of these variables are exogenous, meaning that they can influence other variables but those other variables cannot influence them. Conceptually, the appropriate model specification is to treat all variables as endogenous. This specification was confirmed with a series of Granger causality tests (Granger 1969), one variable at a time.[9] Consistent with our conceptualization, all loan and media activity variables were found to be endogenous based on these tests (i.e., the null hypothesis that a variable is exogenous and caused by itself and not by any of the other variables was rejected in all cases; *p*s < .01).

Other specification tests. The best-fitting autoregressive lag was $p = 1$.[10] The model fit the loan activity data well (see Table 3 for fit statistics). Media activity plays an important role in driving loan activity (marketing performance), and the full model fits significantly better than a null model where loan activity variables were regressed only on lags of themselves (see Table 3).[11] The inclusion of linear and quadratic time trends, and the Christmas effect was confirmed with a set of Wald tests: (1) joint hypothesis that all linear time trends were zero was rejected ($\chi^2[13] = 35.70$, $p < .001$), (2) joint hypothesis that all quadratic time trends were zero was rejected ($\chi^2[13] = 30.72$, $p < .001$), and (3) joint hypothesis that all Christmas effects were zero was rejected ($\chi^2[13] = 35.70$, $p < .001$).

[INSERT TABLE 3 ABOUT HERE]

Performance Response to Media Activity: Effects of Media Activity on Loan Activity

[9] As Trusov et al. (2009) point out, incorrect specification of the lag *p* can lead to erroneous conclusions of the presence or absence of Granger causality. Following Hanssens (1980), we estimated the VAR model repeatedly with an increasing number of AR lags (up to lag $p = 15$) for the series of Granger causality tests.

[10] Additional lags were tried but those models had inferior fit based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). We also tried versions without instantaneous (same day) media effects, but these models had inferior fit and media effects on performance that were highly significant in the instantaneous version were not detected.

[11] This was confirmed by a Wald test of the joint null hypothesis that all media activity effects on all loan activity variables were zero, which was easily rejected ($\chi^2[234] = 1{,}107.76$, $p < .001$).

For both loan value and loan volume, and for new and repeat lenders (as *Kiva*'s "customers"), media activity in traditional media had the largest impact on performance. Parameter estimates are reported in Table 4. Media activity in the *New York Times*, the *Washington Post*, and on the *Oprah* television show had large positive affects on all loan activity variables. The other TMOs and the SMOs each had less of a direct impact (if any).

[INSERT TABLE 4 ABOUT HERE]

To more completely understand the relative sizes the performance responses to the various TMOs and SMOs, we used the estimated VAR parameters to compute impulse response functions (IRFs; this is sometimes called persistence modeling, see Dekimpe and Hanssens [2004] for details). IRFs simulate the over-time impact of a "shock" (i.e., increase) in a variable on the full dynamic system (Bronnenberg et al. 2000; Dekimpe and Hanssens 2004; Pauwels 2004). We looked at the cumulative IRFs for the four loan activity variables in response to each of the media activity variables measures of the cumulative, over-time impacts of media activity. These cumulative returns to media activity are reported in Table 4.[12] The cumulative IRF for a given media activity and loan activity outcome tells us the total contribution that a single media event of a given type makes to *Kiva* in terms of additional loan activity. For example, the cumulative IRF for the effect of an article about *Kiva* in the *New York Times* on loan activity allows us to approximate the total over-time contribution of a single additional article to loan activity.

The IRFs indicate that traditional media events in the popular, mainstream press or on television (i.e., in national newspapers or on television shows like *Oprah*) tend to have very large *per-event* returns (e.g., on average, one *Oprah* event returns an extra $164,003 in loans from 4,679 new lenders, and $89,105 from 2,965 repeat lenders). On a per-event basis, all TMOs generated substantially larger returns than the SMOs did. For example, on average, a

[12] In all cases 95% of the cumulative impact was reached within four days of the media event, and 99% of the total impact was realized within seven days.

unit increase in forum posts generates only $197 in additional loans from 5 new lenders, and a mere extra $72 in loans in only 3 repeat lenders (and blogs appear to have small, negative returns).

Clearly, on a per-event basis, traditional media has a larger impact on marketing performance than social media. However, whereas traditional media publicity events for a particular product, brand or company occur relatively infrequently, the buzz in online social media tends to be an almost-continuous stream of new posts and comments. Thus, media activity from SMOs occurs at a much faster rate than from TMOs, which results in a much larger stock of social media activity than traditional media activity within a finite time frame. The SMOs in our data over the 427 days we observed produced an average of 61.7 events per day. The TMOs, on the other hand, produced .15 events per day. When the greater frequency and larger stock of social media is taken into consideration, we see that social media has some value.

The performance response effects imply that TMOs and SMOs play different roles in influencing marketing performance. One way to think of these roles is that traditional media is analogous to a low-volume but high-margin product, whereas social media is more like a high-volume but low-margin product. For example, during our observation window *Kiva* was featured 11 times on television (news and *Oprah*). Based on the IRFs, these 11 television publicity events increased loan value by $911,576 (new and repeat) and brought in 29,616 additional loans (new and repeat). In the same time, the 26,345 blog and forum posts raised an additional $6,533,096 in from an extra 166,066 loans. While we make no claims of this result generalizing beyond the current dataset, it does highlight that both traditional and social media can clearly contribute value. In the case of *Kiva* at least, both positively impacted marketing performance although they did this in different ways. Hence, to address our first research question, it appears that both traditional and social media can affect marketing performance, and that on a per-event basis traditional media has a substantially larger effect, but on an aggregated basis social media's collective effect is not small (provided that the frequency of social media events is high).

Media Response to Media Activity: Endogenous Cross-Media Effects

These performance response results cannot be fully understood without consideration of how the various media types and outlets influence activity in each other (i.e., the endogenous cross-media effects). Note that the IRFs above do take such effects into account since they trace the impact of a shock in a variable on the *full* dynamic system. Nevertheless, it is worth understanding in greater detail the interplay between the TMOs and SMOs in our data. As discussed earlier, in our VAR model we allowed for current values of the media activity variables to be influenced by their own one-day lagged value, same-day and lagged values of all other media variables (the cross-media effects), and one-day lagged values of the loan activity variables (performance feedback effects). We took a significant parameter estimate for a cross-media effect of one media variable (A) on another (B) as meaning that the activity of media type/outlet A influences the activity of media type/outlet B. (Given the number of these parameters, we do not report them here but they are available from the authors, and significant relationships are summarized in Figure 2.)

Among the nine TMOs and SMOs in our data, we find a high degree of interrelatedness. This supports our conceptualization of these various types of media outlets as being part of a connected system or network, at least in the sense that these results provide evidence to suggest that these media outlets act interdependently. Moreover, we find that traditional media and social media influence each other. Mainstream traditional media activity can not only increase the amount of online social media buzz (e.g., more forum and blog posts), which is not surprising, but can also *be influenced* by social media. This further supports the notion of media outlets of both types being part of a single media network.

Illustration of Cross-Media Effects as an Informal Network of Media Outlets

Objective. In this section we use descriptive network analysis techniques commonly used in fields such as sociology and economics to gain further insight into the endogenous cross-media effects found in the VAR modeling reported above. An advantage of VAR models is that they estimate interdependencies for the full endogenous system of variables. However, this can result in many parameters that are difficult to *collectively* interpret in a meaningful way. With both this disadvantage and the abovementioned notion of an informal network of media outlets in mind, we use a graphical approach to represent the VAR model-estimated effects of the media outlets on each other. Note that we use this approach only to aid in a more intuitive interpretation of the interdependencies between media outlets implied by VAR model estimates. The estimates of cross-media effects at a basic level tell us that activity from outlet A and activity from outlet B are in some way related.

Interdependence structure implied by VAR model. Although the familiar interpretation of VAR models is that they show how endogenous time series variables affect each other (in the short- and the long-run), a more general interpretation of a VAR model is that it characterizes the interdependence structure among the variables in the dynamic system. In other words, if the time series variables in the system can be thought of as nodes in a network, then a significant effect of one node on another can be represented by a directed influence tie connecting these nodes. We represent the interdependencies between the nine TMOs and SMOs in our data by constructing a directed graph based on the significant cross-media influence relationships. This graph, or network, is shown in Figure 2. Below we analyze the structure of this network[13] to understand in greater depth how the various media types/outlets are related, and, in response to our third research question, to see whether different types of media play different roles in disseminating information (over influence ties)

[13] We treat this network, based on analysis of 427 days of data, as a static, non-evolving network. It is plausible to instead consider an evolving network. However, since the parameters of the VAR model upon which the structure of this network is based are time-invariant, this is not possible here.

throughout the media network. A network representation of these interdependencies is a convenient way to analyze information flows in this context.

[INSERT FIGURE 2 ABOUT HERE]

Influence ties. The notion of an influence tie in this network requires clarification. As described above, we took significant media response effects from the estimated VAR model as proxies for latent (and implicit) influence relationships between media outlets. Specifically, a directed tie from media type/outlet (node) A to node B exists if node A was in the VAR results to have a significant effect on node B. We define this type of influence in general, broad terms and caution that we do not see these influence ties as necessarily meaning that people at media outlet A explicitly influenced people at media outlet B, resulting in media outlet B publishing, say, a news article. Rather, as we noted above in the case of the *New York Times* technology editor reading the *TechCrunch.com* blog every morning for story ideas, these empirical relationships capture interdependence between media outlets/types. We assume that if there is an influence tie between two media nodes in this network then information (e.g., buzz for *Kiva*) flows along that tie in the direction of the tie.

Network analysis. We apply sociometric techniques typically used to analyze the structures of social networks. We compute several centrality and brokerage metrics to understand the positions and roles the various TMOs and SMOs have in this network. Our aim is to compare the media outlets across these metrics to see if any outlets are systematically more likely to be in an information brokerage role. This means that they are centrally positioned and lie between other outlets so that influence between outlets frequently has to flow through them, thus making them a broker or connector in this influence network. This helps in understanding the mechanisms through which TMOs and SMOs affect marketing performance.

In Table 5, for each media outlet (node) we report five centrality metrics and two information flow brokerage metrics. Each metric is defined in Table 5. The centrality metrics are standard sociometric indices. The brokerage metrics are based on Burt's (1995) theory of structural holes. A "hole" in a network is a non-existent tie between two nodes, and a node that spans or "bridges" a hole has an advantage because it regulates information flow between the two joined nodes (e.g., if X and Y are not directly connected then there is a structural hole between them. If A connects X and Y, such that X → A → Y or Y → A → X or both, then A bridges/spans the hole between X and Y).

[INSERT TABLE 5 ABOUT HERE]

In Table 5 we report the raw scores on each centrality and brokerage metric for each outlet, as well as standardized versions (Z-scores) to facilitate comparisons across media outlets. Social media, in particular discussion forums, has the highest score on all seven metrics, with scores for forums ranging between 1.07 to 2.33 standard deviations above the mean on each metric. The TMOs generally do not score as highly. This suggests that social media, particularly forums (which are synonymous with online communities), acts as an information flow broker in this influence network. Although, as we found above, on a per-event basis, SMOs have a much smaller impact on marketing outcomes than TMOs, the SMOs appear to be important for propagating information (e.g., buzz) throughout the media network.

Examining particular metrics helps to further understand this. First, to be an information broker, a node in a network needs to have access to information from "upstream" source (i.e., be accessible to those who influence it), as well as access to "downstream" sources that it can influence. Four of the centrality measures are related to this type of accessibility (in- and out-degree, in- and out-closeness). A good broker should not only have high in- and out-degrees (direct accessibility from and to others), but also have high in- and out-closeness (accounting for direct and indirect accessibility, and reachability or distance from others). Social media discussion forums scored highly on these four centrality metrics, and blogs, although not as high-scoring, were always at least at the mean or slightly above. In fact, the average Z-score for SMOs over these four centrality measures was .77, versus -.22 on average for all the TMOs.

Second, information brokers should also have high betweenness centrality. As described above, a node's betweenness is increasing with the proportion of shortest paths in the network between other nodes that it lies on. Social media discussion forums were extremely high on betweenness (Z = 2.16) compared to all other media types. The mean Z-score for all SMOs on betweenness was .92, versus -.26 for the TMOs.

Finally, based on Burt's (1995) theory of structural holes, information brokers should be those nodes that control information flow between other nodes by bridging holes. The broker metrics in Table 5 again show that discussion forums are by far the highest on the two broker measures. First, ignoring media types, forums are over two standard deviations above the mean (Z = 2.09), suggesting that this particular SMO is much more likely than any other outlet in this network to join two other outlets. Second, considering media types sheds further light on the role of social media and forums in particular. We find that forums bridge structural holes between the various TMOs (Z = 2.33). The mean Z-score for the SMOs on these broker metrics was 1.20, versus -.34 for the TMOs.

Based on this network analysis, SMOs more than TMOs played a critical information brokerage function for media activity related to *Kiva* during our observation window. In this sense, social media helped to propagate information. Moreover, it also seems to link or bridge TMOs. Hence, whereas we found that publicity activity from traditional media tends to have a stronger impact on marketing performance, this does not imply that social media is necessarily less important. Rather, the mechanisms through which traditional and social media affect marketing outcomes, and thus generate value, appear to be different.

DISCUSSION AND CONCLUSION

Summary and Main Contributions

Given the fast-changing media landscape, the ubiquity of online social media and user-generated content, and the increasingly dire predictions about the future of traditional media (in particular the newspaper business), our overall objective was to study the interrelatedness between traditional and social media from a marketing perspective.

We first find that traditional media still has a strong effect on marketing performance (after controlling for the effects of social media activity). On a per-event basis, this effect is much larger than the comparable effect of social media. However, because the volume of social media is substantial, its impact is by no means negligible. Hence, in contrasting traditional and social media, a good characterization is to think of traditional media as low-volume, high-margin, and social media as high-volume, low-margin. Thus, although the loan activity "spikes" in Figure 1 all coincided with traditional media publicity activity (e.g., *Kiva* being talked about by Oprah Winfrey on her television show), social media contributes to the over-time stability (and possibly slight growth) in loan activity. Although our data cannot fully or directly shed light on underlying reasons for this, recent work by Stephen and Berger (2009) suggests that for cultural items (e.g., products, websites, social causes) to stay "alive," peoples' internal enthusiasm toward them needs to be repeatedly reinforced. It seems that social media's real-time, high volume presence is well suited for this purpose. This fits with the information brokerage role of social media identified through the network analysis, and is consistent with the idea of social media's value partly lying in its ability to help propagate information more continuously than traditional media can. We leave more comprehensive investigation of the different ways that traditional and social media affect consumer's behaviors for future research.

Second, we find a high degree of interdependence between traditional and social media outlets. This interdependence, or influence of one media outlet's activity on another outlet's activity, occurred within and between traditional and social media types. This result supports our claim that media outlets that generate publicity for products, brands and companies should be seen as part of a single system.

More interestingly, using sociometric techniques usually employed to identify important and influential people in social networks, we found that social media (more than traditional media) plays a critical role in this particular system. Although we make no claims of generalizability, here SMOs broker the flows of information, buzz, and influence between other media outlets (including bridging between different TMOs). A sociological interpretation of this finding (i.e., if the media outlets were people in a social network) is that these brokers (SMOs here) are advantaged and have high "social capital" (which gives them above-average power and influence in the network; cf. Burt 1995). Translated to a network of media outlets, this means that the SMOs—bloggers and regular people who contribute user-generated content by posting on discussion forums and in online communities—can be quite powerful and help to break news, pique the mainstream media's interest in stories, and keep information propagating. Along these lines, social media may in fact serve a critical "transfer" function, similar to that described earlier in our music example, where it takes information from lesser-known, lower-audience outlets, builds awareness, and eventually draws the attention of mainstream traditional media. To the extent that social media (particularly user-generated content) taps the public consciousness or "collective brain" (Miller 2009b), this finding implies that the individuals who participate in and contribute to social media collectively play a very important information dissemination role in the broader media landscape. Importantly, however, this role of social media is not incompatible with traditional media, which is effective in giving broad, mainstream attention to topics (in this case, *Kiva.org*). Rather, traditional and social media complement each other.

To summarize, our findings contribute to the existing literatures on media and publicity effects on marketing outcomes, and the mostly WOM- and online review-focused social media literature by deepening our understanding of how traditional and social media work together to impact financially relevant marketing outcomes and, critically, how they affect each other and what roles different types of media outlets play. Our findings not only provide some welcome defense of traditional media's relevance in the face of declining traditional media businesses and, in fact, show that traditional media still has a sizable role to play in the overall media landscape, but also show where social media fits into this relatively complex system.

From a practical standpoint, our results emphasize the importance of both types of media. Further, by seeing how information flows through the media network and the importance of social media, marketing practitioners hoping to generate publicity would be well served by focusing on having their stories (or products, brands, etc) picked up by social media so that the process of transferring this information toward the highly impactful mainstream traditional media can begin. Pitching stories directly to traditional media decision-makers (e.g., news editors, television producers, etc) may be less effective than a more grass-roots approach where buzz is generated in social media and eventually becomes "loud" enough for traditional media to take notice. Also, given that social media appears to eventually impact traditional media activity, which in turn has a large performance impact, managers should evaluate investments in social media (e.g., having a Facebook page, being on Twitter, having a discussion forum or brand community) in light of their information brokerage role and their effect on traditional media.

Methodologically, our use of well-known VAR time series modeling methods in conjunction with sociometric network analysis techniques is novel in the marketing literature. Given that VAR models establish sets of relationships between endogenous variables, it makes sense to use them to map the structure of this system graphically—as a directed network—and then use network analysis to gain deeper insights into the endogenous relationships between the components of the system. We encourage others to employ this approach, particularly in even more complex systems where there are many more endogenous variables in the VAR model.

Limitations and Future Research

The current research is not without limitations. First, although we attempted to use data from a variety of reliable sources for multiple media types and outlets, our set of offline and online media variables is not exhaustive. We do, however, cover the major types and, where possible, major outlets within each type. In particular, given that since the time of our data (2007 and early 2008) more social media platforms have emerged (e.g., Facebook and Twitter are now major sources of social media, and are now searchable data sources), future research should consider incorporating additional SMOs. Second, we only examined how media publicity affects marketing performance for a single organization, *Kiva.org*. We, of course, make no claims of generalizability of our findings, and we strongly encourage future research to examine the same set (or an expanded set) of TMOs and SMOs for other products, brands, and companies. It is entirely possible that the roles and mechanisms for TMOs and SMOs that we identified in this dataset are different for other datasets, and understanding this more broadly is an important direction for future research. We hope that researchers consider these and related issues in the future.

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TABLE 1
LENDING ACTIVITY VARIABLES AND DESCRIPTIVE STATISTICS

Variable	**Definition**	**Mean (Standard Deviation)**	**Minimum**	**Maximum**
Loan value (US $), new lenders	The total value of all loans made by new (first-time) lenders on day *t*	14,738 (12,777)	2,950	119,025
Loan value (US $), repeat lenders	The total value of all loans made by repeat (not first-time) lenders on day *t*	36,429 (21,234)	4,750	139,525
Loan volume, new lenders	The total number of loans made by new (first-time) lenders on day *t*	357 (350)	60	2,641
Loan volume, repeat lenders	The total number of loans made by repeat (not first-time) lenders on day *t*	996 (654)	162	3,788
Borrowers	The total number of borrowers asking for loans on *Kiva* on day *t*	66 (39)	0	495

Note: based on *Kiva* lending activity data from January 1, 2007 to March 2, 2008.

TABLE 2
MEDIA AND PUBLICITY ACTIVITY VARIABLES USED IN THE ANALYSIS

Type	**Media Outlet**[a]	**Number of Events**[b]
Traditional Media Outlets		
National mainstream newspapers	New York Times (NYT)	4
	USA Today (USA)	3
	Wall Street Journal (WSJ)	3
	Washington Post (WPOST)	2
Regional print/local newspapers	(REG)	40
Television	News[c] (TV)	9
	Oprah only (OPRAH)	2
Social Media Outlets		
Blog posts[d]	(BLOGS)	2,483
Discussion forum posts[e]	(FORUMS)	23,862

[a] Where applicable.
[b] Activity, or a media publicity event, occurred when *Kiva* (*Kiva.org*) was featured or mentioned in a given media outlet.
[c] Includes local, network, and cable news; excludes *Oprah*.
[d] Counted using Google blog search engine (www.google.com/blogsearch), searching for *Kiva.org*.
[e] Counted using Omgili forum search engine (www.omgili.com), searching for *Kiva.org*, and including forum posts in the Kivafriends.org online community.

TABLE 3
MODEL FIT STATISTICS

Loan Activity Dependent Variable	R^2	**AIC BIC**
Full model		
Loan value, new lenders	.753	
Loan value, repeat lenders	.760	30.18 34.03
Loan volume, new lenders	.803	
Loan volume, repeat lenders	.810	
No media activity effects (only autoregressive effects)		
Loan value, new lenders	.696	
Loan value, repeat lenders	.755	53.94 54.44
Loan volume, new lenders	.739	
Loan volume, repeat lenders	.805	

TABLE 4
EFFECTS OF MEDIA ACTIVITY ON LOAN ACTIVITY[a]

Variable	Number of Events	Loan Value, New Lenders		Loan Value, Repeat Lenders		Loan Volume, New Lenders		Loan Volume, Repeat Lenders	
		Estimate	Cum. IRF	Estimate	Cum. IRF	Estimate	Cum. IRF	Estimate	Cum. IRF
Intercept		-6162.09***		-4571.31*		-97.54***		-110.73*	
Time, linear		21.98		62.07***		.37		1.50**	
Time, quadratic		-.01	n/a	.04	n/a	.00	n/a	.00	n/a
Christmas		4542.20***		3042.88		116.46***		87.51	
Borrowers$_{t-1}$		117.42***		168.74***		1.91***		3.28***	
Loan value, new$_{t-1}$		.19*	.73	.06	-.27	-.01***	-.04	-.01	-.04
Loan value, repeat$_{t-1}$		-.04	-.07	.20*	1.19	-.00	-.01	-.00	-.01
Loan volume, new$_{t-1}$		14.72***	64.13	4.54	35.61	.91***	3.91	.44**	2.20
Loan volume, repeat$_{t-1}$		-2.70	-9.15	1.92	1.19	-.03	.03	.50***	2.13
New York Times$_{t}$	4	15735.34***	30858.67	17555.23***	37717.57	378.02***	940.44	541.40***	1447.56
New York Times$_{t-1}$		-108.52		6366.54		33.64		199.81	
Wall Street Journal$_{t}$	3	2665.29	10193.22	9039.48	4227.31	92.37	590.87	222.84	1747.42
Wall Street Journal$_{t-1}$		3205.33		15277.30**		106.65		499.05***	
Washington Post$_{t}$	2	24077.54***	64966.87	17675.08**	46516.00	738.11***	2335.89	609.19***	2272.27
Washington Post$_{t-1}$		8839.50*		8135.84		315.35***		330.72	
USA Today$_{t}$	3	-3171.27	2889.97	1715.77	2625.67	-50.89	187.02	192.27	519.04
USA Today$_{t-1}$		-5454.59		-8815.53		-90.60		-217.24	
Regional print$_{t}$	40	-934.83	5087.71	-2759.55*	2050.89	-16.81	277.53	-41.17	278.34
Regional print$_{t-1}$		-555.52		-171.25		10.36		-.83	
Television news$_{t}$	9	6753.35***	30664.85	4448.94	14374.65	200.11***	920.56	168.78*	671.08
Television news$_{t-1}$		-17.78		-3160.42		16.40		-6.64	
Oprah$_{t}$	2	37854.68***	164002.73	17895.47**	89104.94	1267.12***	4679.03	702.05***	2964.60
Oprah$_{t-1}$		27201.29***		15967.72*		502.61***		239.95	
Blogs$_{t}$	2483	277.61**	-25.72	224.90	71.70	4.32	-7.80	5.49	-1.71
Blogs$_{t-1}$		70.76		20.58		.56		1.05	
Forums$_{t}$	23862	22.99*	196.62	40.84*	71.64	.42	4.56	1.10*	2.82
Forums$_{t-1}$		11.21		-32.70		.26		-.78	

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

TABLE 5
MEDIA NETWORK: CENTRALITY AND BROKERAGE MEASURES

Measure:	**In-degree centrality**	**Out-degree centrality**	**In-closeness centrality**	**Out-closeness centrality**	**Betweenness centrality**	**Broker (ignoring media types)**	**Broker (considering media types)**
Definition: for media outlet *i*…	*In*: number of outlets that directly influence *i*. *Out*: number of outlets that *i* directly influences.		*In*: inversely proportional to the average distance between *i* and outlets influencing *i*. *Out*: inversely proportional to the average distance between *i* and outlets *i* influences.		Proportional to the number of shortest directed paths between other outlets that *i* lies on.	Number of incomplete (unclosed) triads (structural holes) where *i* connects the other two outlets (i.e., $a \rightarrow i \rightarrow b$ when ignoring media types, or $a_{type1} \rightarrow i_{type2} \rightarrow b_{type1}$ when considering media types.)	
New York Times	2 (.00)	2 (.00)	.44 (.14)	.42 (.06)	.07 (-.32)	1 (-.45)	1 (.33)
Wall Street Journal	0 (-1.33)	1 (-1.41)	.00 (-1.64)	.39 (-.50)	.00 (-.92)	0 (-.96)	0 (-.67)
Washington Post	1 (-.67)	2 (.00)	.38 (-.10)	.39 (-.50)	.00 (-.92)	0 (-.96)	0 (-.67)
USA Today	4* (1.33)	2 (.00)	.62 (.87)	.42 (.06)	.15 (.36)	3 (.57)	0 (-.67)
Regional print	3 (.67)	3* (1.41)	.57 (.67)	.47 (.99)	.18 (.62)	3 (.57)	1 (.33)
Television news	0 (-1.33)	1 (-1.41)	.00 (-1.64)	.33 (-1.61)	.00 (-.92)	0 (-.96)	0 (-.67)
Oprah	2 (.00)	2 (.00)	.47 (.26)	.39 (-.50)	.14 (.28)	2 (.06)	0 (-.67)
Blogs	2 (.00)	2 (.00)	.50 (.38)	.42 (.06)	.07 (-.32)	2 (.06)	1 (.33)
Forums	4* (1.33)	3* (1.41)	.67* (1.07)	.52* (1.92)	.36* (2.16)	6* (2.09)	3* (2.33)

* Largest media outlet for given measure. Z-scores are in parentheses.

FIGURE 1

DAILY LOAN VALUE AND VOLUME

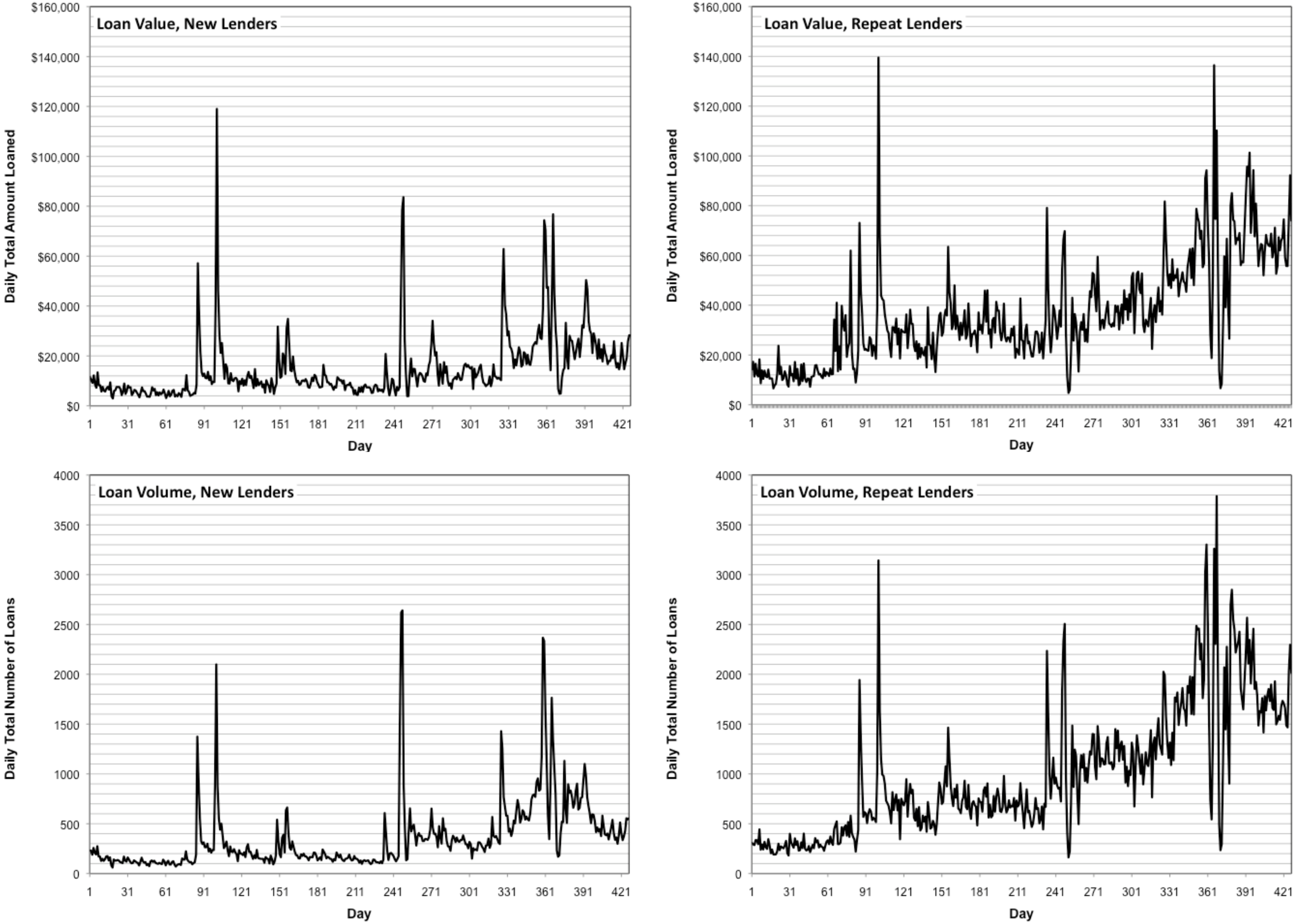
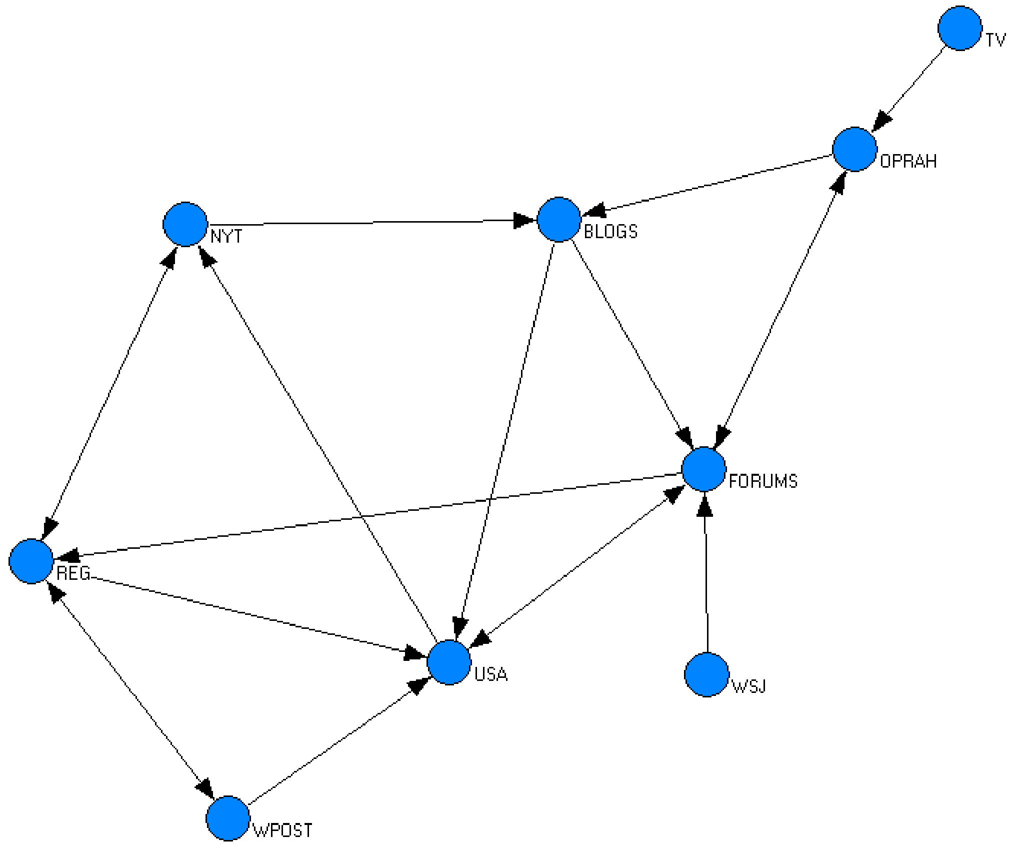


FIGURE 2
MEDIA INFLUENCE NETWORK



Notes:

(1) Node labels: NYT = New York Times, WSJ = Wall Street Journal, WPOST = Washington Post, USA = USA Today, REG = local/regional print/newspapers, TV = television news, OPRAH = Oprah Winfrey's television show, BLOGS = online blogs/weblogs, FORUMS = online discussion forums and communities.

(2) An arrow <u>from</u> one node (A) <u>to</u> another node (B) (i.e., A → B) means that media activity generated by node A has an *influence* on media activity generated by node B.

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