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Mass Media Use, Neighborliness, and Social Support

Assessing Causal Links With Panel Data

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This study assesses pathways of causal influence between two mass media use measures (campaign exposure and news attention) and two indicators of social capital (neighborliness and social support). This assessment encompasses the evaluation of a health media campaign that targeted African Americans in New Orleans following Hurricane Katrina. Analysis of panel survey data indicated a significant over-time increase in neighborliness but not social support. Among the three cross-lagged effect models of influence, the best fit was of the mass media use causes social capital model. Similarly, among the three synchronous effect models of influence, the best fit was of the mass media use causes social capital model. This analysis provides support for the media campaign's effectiveness and, more broadly, allows for the extension of recent research that has used panel data to strengthen inferences of causation in different mass communication scenarios.

Keywords: *social capital; media effects; health media campaign; campaign effects; neighborliness; social support*

Civic cohesion and participation have been at the head of a long stream of research in the areas of mass communication, sociology, and political science. In reflecting on this research, it can be noted that conceptual definitions have varied, including community integration (Friedland & McLeod, 1999; Tonnies, 1887/1988). social isolation (de Tocqueville, 1663/1984), anomie (Durkheim, 1933/1997), civic participation (Shah, McLeod, & Yoon, 2001), and community involvement (Stamrn, Emig, & Hesse, 1997). The operational definitions of these conceptual partners have much in common. Operational measurement includes perceptions of community, community orientation, association membership, civic participation, public attendance, neighborliness, and trust. Recent research in this area has employed another term, *social capital,* which can be defined as intangible resources of social connections and social networks that can be accessed and mobilized in purposive action (Lin, 2001). The vital importance of social capital rests in its positive associations with important outcomes, such as the health, safety, and education of individuals and communities alike (Beaudoin, 2007, in press; Kawachi & Berkman, 2000; Putnam, 2000; Verba, Schlozman, & Brady, 1995).

These associations suggest the promise that social capital can have. If social capital is predictive of sought outcomes related to health, safety, and education, then how can we build social capital? How can we encourage individuals and communities to interact more closely and trust one another more? The benefits of uncovering and, subsequently, exploiting such social mechanisms present a substantial and significant stimulus for sustained and enhanced research in this area. To this end, this study assesses the influence that the mass media can have on the social capital process, with a specific focus on a radio campaign with socially tailored messaging.

Various determinants of social capital have been demonstrated by previous research. These determinants include residential stability, time pressures, and ethnicity (Musick, Wilson, & Bynum, 2000; Putnam, 2000). Important to the study presented here is another determinant: mass media use. A J.arge body of work has well addressed the association between news media use and various indicators of social capital, such as civic participation, interpersonal trust, neighborliness, and association membership (Beaudoin & Thorson, 2006; McLeod et al., 1996; McLeod, Scheufele, & Moy, 1999; McLeod, Scheufele, Moy, Horowitz, et al., 1999; Norris, 1996; Shah, Kwak, & Holbert, 2001; Shah, McLeod, & Yoon, 2001; Stamni et al., 1997; Stamm & Fortini-Campbell, 1983). For example, Shah, McLeod, and Yoon (2001) demonstrated that newspaper hard and soft news use predicted interpersonal trust and civic participation, when controlling for demographics, social situation, and social orientation. In addition, with a model of urban respondents, Beaudoin and Thorson (2004) found that local TV news use and newspaper use predicted social networks.

Other research has pointed out that TV news viewing and entertainment TV viewing have differential effects on indicators of social capital (Norris, 1996, 2000). While the relationship between general entertainment TV viewing and social capital indicators has been shown to be negative (Beaudoin & Thorson, 2004, 2006), Shah (1998) took a closer look at the relationship specific to different genres of TV programming. He found that civic engagement was negatively associated with science fiction TV viewing but positively associated with social drama TV viewing. Yet another body of research has begun to explore the manner in which health media messages may be able to fuel the development of social capital indicators, including civic perceptions, civic participation, interpersonal networks, and interpersonal trust (Beaudoin & Thorson, 2007; Beaudoin, Thorson, & Hong, 2006; Thorson & Beaudoin, 2004).

These associations constitute critical nexuses between news and social capital, entertainment programming and social capital, health media campaigns and social capital, and, more broadly, information use and social empowerment. This previous empirical work has been used as a basis in theorizing upon the causal qualities of the association between mass media use and social capital (Shah, McLeod, & Yoon, 2001), but the empirical assessment of the causal relationship has lagged behind. To flesh out the primary direction of effect, other work has used cross-sectional data to

test recursive models (Shah, Schmierbach, Hawkins, Espino, & Donavan, 2002) and trends and associations at the individual level (Beaudoin et al., 2006; Beaudoin & Thorson, 2007; Thorson & Beaudoin, 2004) and at the community level (Beaudoin, in press).

These efforts have found primary support for the mass media's influence on social capital but, unfortunately, can only lead to assumptions about the direction of causality between media use and social capital. In their use of cross-sectional data, these studies are limited in their ability to demonstrate the three primary elements of causation—that X and Y covary, that X precedes Y, and that the relationship between X and Y is not spurious (Menard, 1991). This limits our ability to understand the causal mechanisms involving the mass media and social capital, which, by extension, limits our capacity to implement media initiatives that aim to spur social capital as a means to improving health, safety, and education.

Panel data pose a potential advancement. Panel data, which consist of the over-time measurement of variables for a single unit, provide for the more eloquent testing of causation and, specific to this study, the more eloquent testing of the causal relationship between mass media use and social capital. A systematic approach to assessing causation with panel data, including cross-lagged and synchronous effect models, has been articulated by previous research (Finkel, 1995). With general bases in this approach, two important recent studies have used panel data in modeling causal relationships involving the mass media. In one study, Eveland, Hayes, Shah, and Kwak (2005) used panel data to explore the causal relationship between political knowledge and two-communication related variables: news use and interpersonal discussion. The authors tested six structural equation models, three cross-lagged and three synchronous, demonstrating support for the influence of the two communication measures on political knowledge. In the other study, Shah, Cho, Eveland, and Kwak (2005) used panel survey data to test a complex model involving media use, information-seeking, messaging, interpersonal discussion, and civic participation. The authors tested muitiple models, finding support for the influence of media information use on citizen communication, which, in turn, influenced civic participation. These two recent studies have taken important steps in regards to the testing of communication effects, pointing out the benefits of panel data for modeling and refining our understanding of important mass media processes.

The study presented here aims to advance the examination of the causal relationship between mass media use and social capital, employing the work of Finkel (1995) as a basis and building on the recent work of Eveland and colleagues (2005) and Shah and colleagues (2005). To this end, the current study uses panel data to assess causal relationships between two mass media use measures (news attention and campaign exposure) and two indicators of social capital (neighborliness and social support). This study implements combined structurai and measurement models as a means to comparing different models that are theorized upon in the literature review. To address the causal ambiguity that underlies most assessments of the

relationship between mass media use and social capital, cross-lagged and synchronous effect models are tested.

The analysis is conducted on a sample of African Americans *(N* = 500) in New Orleans following Hurricane Katrina. This sample allows for assessing social capital processes among a poor and underserved minority population most in need of social empowerment in the context of a media campaign that aimed to provide such benefit. This ethnic focus helps address another gap in previous research, one involving the development of social capital among African Americans. Social capital is critically important to African Americans who, with limited access to traditional resources such as income and education, need to rely heavily on social networks and social resources (Musick et al, 2000; Saegert, 1989). In fact, for Blacks, "neighboring becomes more a matter of necessity than choice" (Lee, Campbell, & Miller, 1991, pp. 527-528). As a result, social capital has emerged as a potential solution to African Americans' disproportionate share of health, safety, and education problems in the United States (Smedley, Stith, & Nelson, 2003). Although recent research has assessed the association between news use and social capital indicators among this ethnic group (Mastin, 2000), as well as the manner in which the association varies between African Americans and others (Beaudoin & Thorson, 2006), further research is required to elucidate the mass media's potential role in the development of social capital among this minority group.

In addition, the context of this study, post-Hurricane Katrina New Orleans, allows for the assessment of mass media and social capital processes following a natural disaster. While news is vital in such disaster settings (Bucy, 2003; Carey, 2002), graphic television depictions can lead to the development of psychological illness (Ahern et al., 2002; Pfefferbaum et al., 2001). In fact, one recent study found that news reliance was related with higher levels of depression among hurricane shelter residents following Hurricane Katrina (Beaudoin, 2007). In such disaster settings, social capital is also critical, predicting positive health outcomes and positive advances in reconstruction and recovery (Allen, 2006; Beaudoin, 2007; Campbell, Williams,^ Gilgen, 2002; Moore et al., 2004; Nakagawa & Shaw, 2004; Rocha & Christoplos, 2001).

Social **Capital**

Social capital has been conceptually defined in different ways. This study relies on the conceptual definition of Lin (2001) as a basis. Lin indicated that "social capital consists of resources embedded in social relations and social structure, which can be mobilized when an actor wishes to increase the likelihood of success in a purposive action" (p. 24). This definition emphasizes three important characteristics of social capital. First, it indicates that social capital consists of social resources. This characteristic of social capital is consistent with Bourdieu's (1986) definition of

social capital as "the aggregate of the actual or potential resources which are linked to the possession of a durable network of more or less institutionali/ed relationships of mutual acquaintance and recognition" (p. 248).

Second, Lin's (2001) definition indicates that these social resources exist in—and result from—social relations and social structures. This characteristic, again, is consistent with Bourdicu, who suggested that social resources result from social networks and social relationships. Positioning social networks as a productive mechanism of social capital also relates to Putnam's (2000) definition of social capital as the "connections among individuals—social networks and the norms of reciprocity and trustworthiness that arise from them" (p. 19).

Third, Lin's (2001) definition holds that social capital can lead to "success in purposive action." The suggestion that social capital can lead to productive outcomes is consistent with Coleman's (1988) contention that "social capital is productive, making possible the achievement of certain ends that in its absence would not be possible" (p. S98).

Social capital has been operationally defined in different ways as well. Some operational measures, such as interpersonal trust, are cognitive in nature, while other operational measures, including association membership, are structural in nature (Beaudoin & Thorson, 2004, 2006; Putnam, 2000; Shah, Kwak, & Holbert, 2001; Shah, McLeod, & Yoon, 2001). Yet other operational measures—including volunteering, social support, voting, neighborliness, and behaviors toward youth—appear best fit for classification as "outcomes of social capital." Such outcomes have been used in two ways: as elements of social capital and civic engagement indices (Moy, Scheufele, & Holbert, 1999; Putnam, 2000; Shah, Kwak, & Holbert, 2001) and as individual social capital indictors (Beaudoin et al., 2006; Beaudoin & Tao, in press-a, in press-b; Beaudoin & Thorson, 2007; Norris, 1996; Putnam, 1993, 1995a, 1995b, 2000; Thorson & Beaudoin, 2004).

This study implements two social capital indicators: neighborliness and social support. Neighborliness involves various forms of informal contact with neighbors, including visiting, borrowing and sharing, and helping with tasks around the house (Beaudoin & Thorson, 2004; Putnam, 1995a). The concept of social support has been frequently implemented in public health research (Aneshensel & Frerichs, 1982; Cohen & Wills, 1985) but less often in tandem with the concept of social capital (Almedon, 2005; Beaudoin & Tao, in press-a, in press-b; Cooper, Arber, Fee, & Ginn, 1999). In the social capital framework, social support can be viewed as a positive outcome that results from social relations and social structures—and can stimulate the further development of social relations and social structures.

Mass Media Use and Social Capital

As previously noted, there is abundant support for the positive association between news use and various indicators of social capital (Beaudoin & Thorson,

2004; McLeod, Scheufele, & Moy, 1999; McLeod, Scheufele, Moy, Horowitz, et al., 1999; Norris, 1996; Shah, 1998; Shah, Kwak, & Holbert, 2001; Shah, McLeod, & Yoon, 2001). This relationship has also been supported by studies that have focused on the current study's subpopulation: African Americans (Beaudoin & Thorson, 2006; Mastin, 2000). While these studies demonstrate the strong relationship between news use and social capital indicators, they are limited in their ability to comment on causation. Amid such causal ambiguity, there are three potential forms for the relationship between mass media use and social capital: (a) mass media use causes social capital: (b) social capital causes mass media use; and (c) a model of reciprocal influence in which mass media use causes social capita! *and* social capital causes mass media use. Each of these three possibilities is discussed in greater depth next.

Mass media use causes social capital. The idea that the mass media can influence social capital has a genera] basis in Bandura's (2002) contention that media influence on behavior change is mediated by connections to the social system. Other recent theorizing has articulated a dichotomy by which the news media influence social capital (Shah. McLeod, & Yoon, 2001). Symbolically, the news media can foster a sense of community identity, bringing people closer together, while spurring the development of self-efficacy among individuals and the development of collective agency among groups. In addition, the news media provide people with ideas and information that can facilitate deliberation and discussion. As Newton (1999) explained, the mass media disseminate information that can mobilize people. Similarly, previous research has commented on the relationship between socially oriented media campaigns and social capital, theorizing that such media messages can draw people closer together and encourage the development of norms of reciprocity and trust (Thorson & Beaudoin, 2004; Wallack, 2000).

Several studies, as previously noted, have found empirical support for this causal direction, from mass media use to social capital. Testing recursive models with cross-sectional data, Shah and colleagues (2002) found that time spent online influenced public attendance and civic volunteerism. Using longitudinal cross-sectional data, a line of studies (Beaudoin et al., 2006; Beaudoin & Thorson, 2007; Thorson & Beaudoin, 2004) has offered support for the influence of a socially oriented media campaign on various social capital indicators, including interpersonal trust, civic perceptions, civic participation, and community attachment. Also using longitudinal cross-sectional data, but with a community-level approach, Beaudoin (in press) demonstrated the influence of news use on perceptions of place. Only the recent study of Shah and colleagues (2005) has used panel data in its attempt to assess related causal relationships, finding that media information use influenced citizen communication, which, in turn, influenced civic participation.

Social capital causes mass media use. Despite commonly pointing out the limitation of assessing causality with cross-sectional data, the bulk of previous studies in this area has somewhat tacitly upheld the idea that the mass media influence social capital. There is, of course, the possibility that causal influence could move in the opposite direction, from social capital to mass media use. It could be that people who have higher levels of social capital (e.g., higher levels of civic participation, interpersonal trust, neighborliness, and association membership) are most likely to use and pay attention to news coverage—especially that about local, social, and governmental affairs—and most likely to recall and attend to local media campaign messages about health and social causes.

This relationship, indicative of the influence that social capital could have on mass media use, has intuitive appeal. If people are active in their communities, they are more likely to expose themselves to and pay attention to related information. As well as having intuitive appeal, this direction of causation has a basis in the theory of selective attention. This theory explains how humans attend to some stimuli while ignoring others (Zillmann & Bryant, 1985) and, subsequently, how they retain some pieces of stimulus information but not others (Cowan, 1988). In this way, people can focus on information of interest while focusing out information of less interest.

A model of reciprocal influence. Yet another possibility remains. It may be the most plausible alternative but is certainly not as simple or parsimonious as either of the aforementioned unidirectional models. In this model, one of reciprocal influence, mass media use causes social capital *and* social capital causes mass media use.

This perspective holds that the mass media can influence the manner in which people interact civically, participate in organizations, and trust one another while acknowledging that people who are civically active, participatory, and trusting of others are more likely to access related media information. In such a reciprocal or circular model, media use would spur social capital, which, in turn, would spur media use. This process, via subsequent iterations, would compose a virtuous circle of influence, but one different than that posited for the relationship between social trust and social connections (Brehm & Rahn, 1997; Putnam, 3993).

Method

Intervention

The focal media campaign ran on four New Orleans radio stations from June 12 to August 25, 2006. The reach of the campaign was broad among the campaign's target audience of African Americans. The weekly gross rating points of 142.5 signify that, on average, a member of the target audience heard the radio spots about 1.5 times per week and 16 times during the campaign. The radio spots had topical foci

related lo health and safety issues following Hurricane Katrina, including home cleanup and stress and depression. Each spot had a strong social aspect. For example, one radio spot stressed the importance of working together, while two others emphasized the importance of talking with friends and family or a pastor or other professional about stress and depression. The recommendations of social togetherness would be expected to serve as cues to action and a stimulus to the development of self-efficacy (Janz & Becker, 1994).

The spots were honed for the target audience of African Americans. The wording was simple, spoken by voices known by the listening audience. The scripts were read by two African American radio personalities, one female and one male, in their mid- to late 30s. Background music was new age jazz- and hip-hop-influenced rhythm and blues instrumental. This approach supports research that has demonstrated the effectiveness of specially tailored messages on the current study's audience of African Americans (Beaudoin, Fernandez, Wall, & Farley, 2007).

Sampling Design

Data resulted primarily from panel telephone survey interviews of African American adults (age 18 and older) in the New Orleans area. Survey interviews were conducted from 2 months before the campaign until 2 weeks after the campaign as a means to assessing trends in social capital and its relationships with media use. In the panel sample, 500 respondents were interviewed twice. The first interviews were conducted either before or during the media campaign, which ran from June 12 to August 25, 2006. The second interviews were conducted immediately after the campaign, from August 28 to September 15. In addition, responses from a generally concurrent cross-sectional sample were used to assess testing bias. This analysis tested for significant differences in the social capital indicators between a subset of the second set of panel responses (n - 91) and a set of concurrent cross-sectional sample responses (N - 94).

The survey interviews were conducted by a professional survey center at a large U.S. university. Random digit dialing and the random selection of household members were used. American Association for Public Opinion Research (2004) response and cooperation rates were calculated for three survey components: before the campaign, during the campaign, and after the campaign. The most stringent response rate (RR1) was 11.6% for before the campaign, 10.4% for during the campaign, and 69.3% for after the campaign. The last figure is considerably higher because it included the second set of panel interviews. The low levels of the first two response rates may be misleading because, following Hurricane Katrina, prevalence was much higher than usual for nonfunctioning telephone numbers and telephone numbers called without an answer. Because of this environment, another response rate (RR3) and one cooperation rate (COOP1) were also calculated. The RR3 approximates the actual eligibility of cases of unknown eligibility. Using a

proportional allocation method (Smith, 2003), the RR3 was 43.9% for before the campaign, 44.6% for during the campaign, and 72.2% for after the campaign. The COOP1 was 48.8% for before the campaign, 51.4% for during the campaign, and 86.4% for after the campaign.

Measurement*

Demographics and disaster exposure were inserted in the models as exogenous variables. Education was from no formal education (0 years) to doctoral degree (20 years). Household income was from *less than $25,000* (1) to *$150,000 or more* (7). Age and gender were also measured. Disaster exposure was assessed with five dichotomous items (Ahern et al., 2002). One item assessed* whether respondents were in New Orleans when the hurricane hit. The other items assessed whether, in relation to the hurricane, respondents had lost a job, had a home or apartment severely damaged, had a friend or relative die, and had a friend or relative experience other physical injury. An additive index was created for disaster exposure *(M* - 1.81, SD = 1.24).

The models had a latent variable for campaign exposure and another for news attention, as well as two additional latent variables for the indicators of social capital: social support and neighborliness. These variables were positioned as endogenous in the models. There were four news attention items—for radio, television, newspaper, and Internet (Chaffee & Schleuder, 1986). For example, the TV news question was as follows: "About how much attention do you pay to TV news stories about health and safety issues related to New Orleans following Hurricane Katrina?" Responses were on a 7-point scale from 1 *(no attention at all)* to 7 *(very close attention).* Factor analysis (principal components) indicated the same one dimension for the four news attention items at Time 1 (Tl; eigenvalue - 1.94, variance explained - 48.46%, a - .64) and at Time 2 (T2; eigenvalue = 2.01, variance explained = 50.29%, a = .67). The four items for Tl news attention were thus positioned as predictors of latent variable Tl news attention, and the four items for T2 news attention were positioned as predictors of latent variable T2 news attention.[2] Inserting news attention into the tested models provides two benefits. It allows for considering the potential role of the news media and, when considering the role of campaign exposure, serves as a control for respondents' reception of related information from other sources.

The measurement of campaign exposure takes form in four steps. First, there was an explanation of the radio campaign, including the topics of the radio spots and the slogan "Stay healthy and strong New Orleans!" Second, respondents who did not recall the campaign were given scores of 1 for each of the four station-specific campaign exposure variables. Third, respondents who did not use a specific radio station were given scores of 1 for the campaign exposure variable for that station. Fourth, those who recalled the campaign and used a specific station were scored according

to their attention level on a scale from 1 *(no attention)* to 7 *(very close attention).* For example, the attention question for the radio station Q93 was as follows: "About how much attention do you pay to the health and safety messages on Q93 that have the slogan 'Stay healthy and strong New Orleans'?" This process resulted in the construction of four 7-point variables, each constituting campaign exposure for one of the four radio stations. Factor analysis (principal components) identified the same one dimension for the four campaign exposure items at Tl (eigenvalue = 3.05, variance explained - 76.31 %, a - .90) and at T2 (eigenvalue - 2.04, variance explained = 50.93%, a = .68).[3]

There were six items to measure the two indicators of social capital. Three of the items were related to social support (Cohen & Hoberman, 1983), which can be viewed as an outcome of social capital that involves emotional support, comfort and understanding, and help and advice. The items were as follows: (a) "After Hurricane Katrina, about how often have you given advice to people in New Orleans who are not members of your immediate family?"; (b) "After Hurricane Katrina, about how often have you offered emotional support to people in New Orleans who are not members of your immediate family?"; and (c) "After Hurricane Katrina, about how often have you tried to comfort people in New Orleans who are not members of your immediate family?" Responses to these questions, as well as those for neighborliness, were from 1 *(never)* to 5 *(very often).* The other three items were related to neighborliness (Beaudoin & Thorson, 2004; Shah et al., 2002). The items were as follows: (a) "After Hurricane Katrina, about how often have you borrowed from or lent things to your neighbors in New Orleans?"; (b) "After Hurricane Katrina. about how often have you and your neighbors in New Orleans helped one another with tasks, such as house repairs and house cleanup?"; and (c) "After Hurricane Katrina, about how often have you worked on a communiu project in New Orleans?" At Tl, factor analysis (principal components with orthogonal rotation) identified two dimensions: social support (eigenvalue - 1.81, variance explained - 30.10%, a - .72) and neighborliness (eigenvalue - 2.32, variance explained - 38.59%, a = .85). At T2, factor analysis (principal components with orthogonal rotation) identified the same two dimensions: social support (eigenvalue = 1.24, variance explained = 49.74%, a = .71) and neighborliness (eigenvalue - 1.26, variance explained - 21.00%, a-.88).

Analysis Procedure

There were three steps in statistical analysis. First, repeated measure analysis was implemented to test for differences in social capita! indicators between the first and second times a respondent was interviewed. For this analysis, three-item indexes were created for neighborliness and social support at Tl and T2.

Second, a subset of the second set of panel responses *(n* = 91) was compared to a concurrent cross-sectional sample *(N* - 94) to check for testing bias. For this step,

t tests were used to examine differences in social capital indicators. These two steps of statistical analysis were conducted with Stata 9.

Third, structural equation modeling was implemented using AMOS 7 software. with maximum likelihood method of estimation. Measurement models were first created for each of the latent variables in the posited models.[4] There were measurement models for campaign exposure,[5] news attention,[6] social support,[7] and neighborliness.[8] These measurement models were held constant across the six tested models because of this study's chief aim of comparing the structure of the posited models (Eveland et al., 2005).[9]

Demographics were positioned as exogenous variables in each model. These measures are viewed as being correlated among one another, as well as with the latent variables for campaign exposure, news attention, social support, and neighborliness at T1. At T1, these four latent variables are assumed to be correlated. In addition, in the T2 cross-lagged models, there are assumed correlations among campaign exposure, news attention, social support, and neighborliness. In the T2 synchronous models, campaign exposure and news attention are assumed to be correlated, as are social support and neighborliness. As suggested by Finkel (1995), in each model, there is a causal path from a variable's Tl form to its T2 form, which represents the stability of a measure over time and controls the T2 variable for the Tl level of the variable. The other paths from Tl variables to T2 variables vary according to model type. All such correlations among variables were considered closely and implemented only when consistent with previous theory, empirical research, and modeling.

Model fit was assessed via the change in chi-square and degrees of freedom, as well as four indices. The change in chi-square and degrees of freedom approach is a precise means of comparing nested models. Four other indices were used, primarily for assessing model fit between non-nested models. The root mean squared error of approximation (RMSEA) and comparative fit index (CFI) are measures of relative fit. A model with excellent fit is indicated by an RMSEA of close to .06 or less, as well as a CFI of .95 or better (Hu & Bentler, 3999). The Tucker-Lewis index, an incremental fit index, and the significance of the chi-square are also reported. It should be noted, however, that with increased sample size, even models with a close fit between estimated model and data are often found to have significance levels of .000 (Hu & Bentler, 1995). The other two measures of model fit are population-based, parsimony-adjusted fit indices (Kline, 2004). They are the Akaike information criterion (AIC) and the consistent AIC. Lower values for these two indices represent better fit.

The modeling approach follows that of Finkel (1995), with close reference to Eveland and colleagues (2005) and Shah and colleagues (2005). Six models were honed to test the relationship between mass media (news attention and campaign exposure) and social capital (neighborliness and social support). These models vary in regards to unidirectional and reciprocal path structures and between cross-lagged

(with T1 mass media and social capital variables influencing T2 mass media and social capital variables) and synchronous (with T2 mass media variables influencing T2 social capital variables, and T2 social capital variables influencing T2 mass media variables) structures. Nonsignificant parameters are not pruned from models in this process, although their removal would improve the fit of the models.

Results

Descriptive statistics provide a general picture of the social capital indicators for the first and second interviews of the panel sample. After creating indexes, the mean of neighborliness was 2.19 *(SD* = 1.03) at Tl and 2.32 *(SD* = 1.04) at T2. The mean of social support was 3.65 *(SD* = 1.15) at T1, as compared to 3.58 *(SD* = 1.16) at T2.

Repeated measure analysis with random effects tested for differences in the social capital indicators between the first and second interviews of the panel sample.[10] Social support remained constant between the two interviews (B - -.07, *p* - .204). Neigbborliness increased significantly from the first to second interviews (B = .36, *p* = .002). This analysis indicates that neighborliness increased over time with the advent of the media campaign.

In addition, *t* tests were used to assess whether social capital indicators varied between a subset of the second panel interview responses (*n* - 91) and a concurrent sample of cross-sectional responses (*N* = 94). Neighborliness did not vary, r(185) = .44, *p* - .509. Social support did not vary either, *t*(184) = 1.97, *p* = .163. These findings are at odds with the presence of a testing bias in which respondents' second interviews were influenced by their having been interviewed previously.

Structural Equation Modeling

Variance accounted for is depicted in Table 1. For example, Model 5 accounts for the following variance: 8% of campaign exposure, 25% of news attention, 64% of neighborliness, and 41% of social support.

Next, it is important to refer to the influence that exogenous variables had in the six models. The direct effects of the exogenous variables are depicted in Tables 2 and 3. There are several consistent relationships between the models. Age was negatively associated with campaign exposure and neighborliness. In addition, gender and disaster exposure were positively associated with neighborliness

Next, reference is made to the influence of the endogenous variables in the six models.[11] To begin, it should be noted that, in the six models, each Tl variable predicted its T2 counterpart, indicating over-time consistency. Model 1, which is depicted in Figure 1, has cross-lagged paths from Tl variables to T2 variables. Tl neighborliness significantly predicted T2 news attention, and Tl campaign exposure predicted both T2 neighborliness and T2 social support.

Table 1
Variance Accounted for in Endogenous Variables

Model	T2 Campaign Exposure	T2 News Attention	T2 Neighborliness	T2 Social Support
1. Reciprocal Lagged	.09	.28	.65	.40
2. Mass media use → Social capital lagged	.08	.25	.64	.39
3. Social capital → Mass media use lagged	.09	.27	.62	.38
4. Reciprocal synchronous	.08	.29	.64	.41
5. Mass media use → Social capital synchronous	.08	.25	.64	.41
6. Social capital → Mass media use synchronous	.09	.28	.62	.38

Table 2
Influence of Exogenous Variables on Time 2 Endogenous Variables: Models 1 to 3

Model	T2 Campaign Exposure	T2 News Attention	T2 Neighborliness	T2 Social Support
Model 1: Reciprocal lagged				
Age	–.14*	.05	–.10*	–.05
Education	.01	–.03	.08	–.06
Gender[a]	.07	–.03	.10*	–.04
Income	–.03	–.05	.02	.02
Disaster exposure	–.05	.05	.10*	.06
Model 2: Mass media use → Social capital lagged				
Age	–.14*	–.02	–.10*	–.05
Education	.03	–.02	.08	–.06
Gender[a]	.06	.07	.11*	–.04
Income	–.03	–.04	.02	.02
Disaster exposure	–.04	.10*	.10*	.07
Model 3: Social capital → Mass media use lagged				
Age	–.14*	.02	–.10*	–.06
Education	.01	–.03	.07	–.06
Gender[a]	.07	.04	.10*	–.04
Income	–.03	–.05	.02	.03
Disaster exposure	–.05	.05	.10*	.06

a. Male = 1.
*$p < .05$. Coefficients are standardized.

Model 2, as shown in Figure 2, is a simplified version of Model 1, in that it drops the cross-lagged paths from social capital variables to mass media use variables. Thus, it stresses the causal influence of T1 mass media use variables on T2 social capital variables. Importantly, T1 campaign attention significantly predicted neighborliness and social support at T2.

Table 3
Influence of Exogenous Variables on Time 2 Endogenous Variables: Models 4 to 6

Model	T2 Campaign Exposure	T2 News Attention	T2 Neighborliness	T2 Social Support
Model 4: Reciprocal synchronous				
Age	–.15*	.03	–.10*	–.07
Education	.03	–.05	.07	–.06
Gender[a]	.10*	.02	.10*	–.05
Income	.02	–.05	.02	.02
Disaster exposure	–.05	.06	.11*	.05
Model 5: Mass media use → Social capital synchronous				
Age	–.14*	–.03	–.10	–.06
Education	.03	–.02	.08	–.06
Gender[a]	.06	.07	.10	–.05
Income	–.03	–.04	.01	.02
Disaster exposure	–.04	.10*	.10*	.05
Model 6: Social capital → Mass media use synchronous				
Age	–.13*	.03	–.10*	–.06
Education	.02	–.05	.08	–.06
Gender[a]	.06	.03	.10*	–.04
Income	–.04	–.05	.02	.03
Disaster exposure	–.05	.02	.11*	.06

a. Male = 1.
*$p < .05$. Coefficients are standardized.

Model 3 (see Figure 3) is also a simplification of Model 1. It posits the causal influence of T1 social capital variables on T2 mass media use variables. There is one such significant path—from T1 neighborliness to T2 news attention.

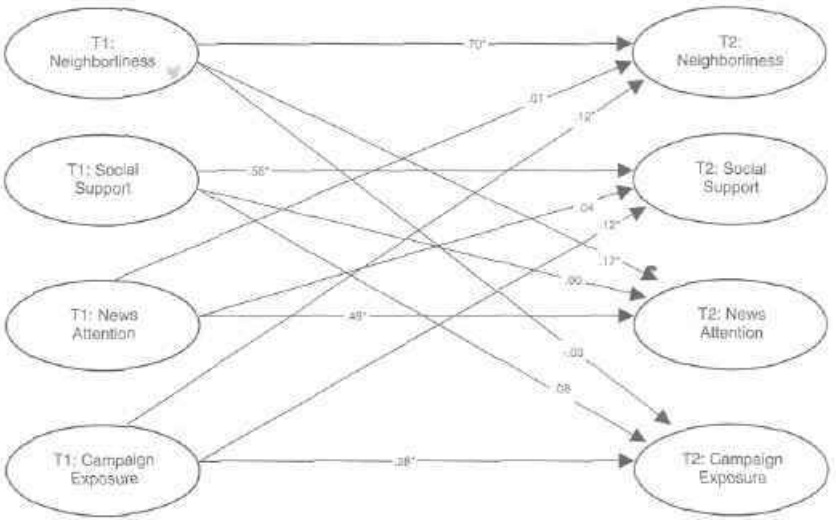
Model 4, as depicted in Figure 4, focuses on reciprocal paths at T2. Reciprocal paths are posited among the T2 variables. T2 neighborliness significantly predicted T2 news attention, and T2 social support significantly predicted T2 campaign exposure. In addition, T2 campaign exposure significantly predicted T2 social support, and T2 news attention significantly predicted T2 social support.

Model 5 (see Figure 5) is a simplified version of Model 4. Influence is again synchronous at T2, but it is unidirectional, from mass media use to social capital. T2 news attention predicted both T2 neighborliness and T2 social support. Similarly, T2 campaign exposure predicted both T2 neighborliness and T2 social support.

Model 6, as shown in Figure 6, is another simplification of Model 4 but with unidirectional influence from social capital to mass media use. T2 news attention was significantly predicted by both T2 neighborliness and T2 social support.

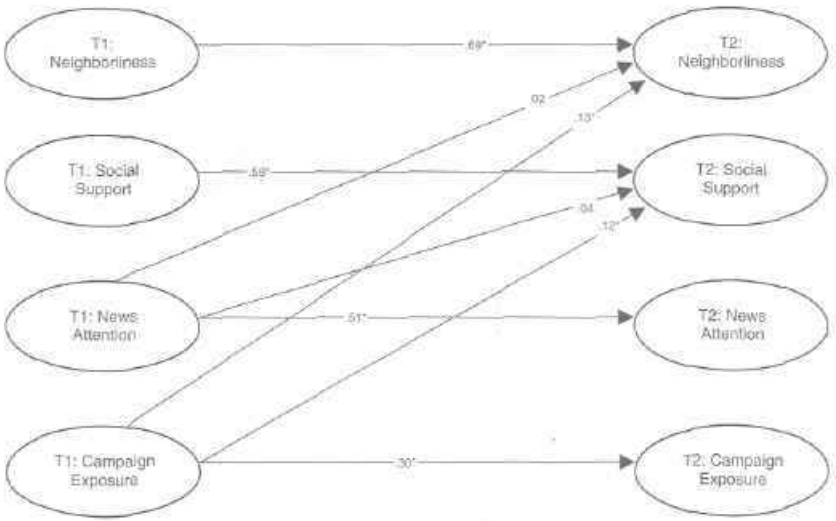
(text continues on p. 654)

Figure 1
Reciprocal Lagged Model (Model 1)



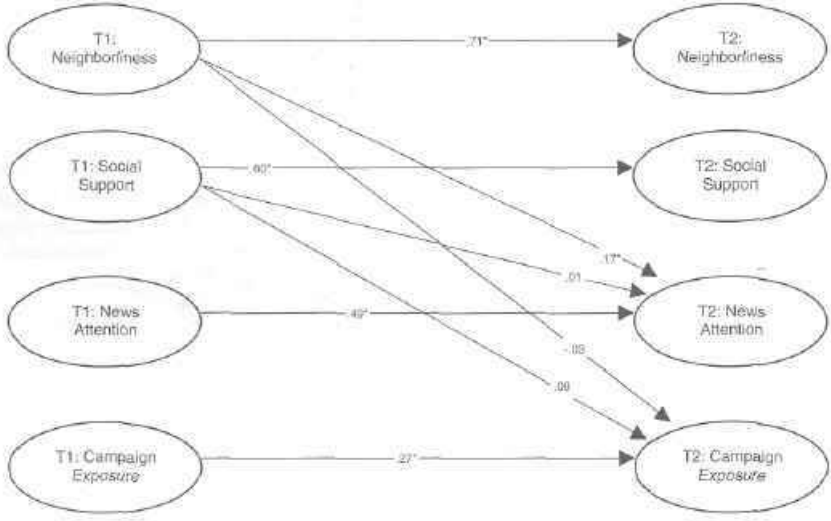
Note: T1 = Time 1; T2 = Time 2.
*$p < .05$.

Figure 2
Mass Media Use Causes Social Capital Lagged Model (Model 2)



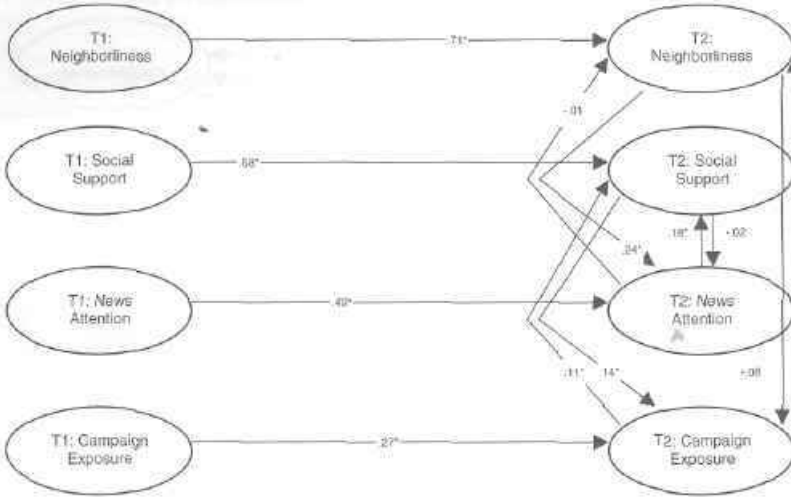
Note: T1 = Time 1; T2 = Time 2.
*$p < .05$.

Figure 3
Social Capital Causes Mass Media Use Lagged Model (Model 3)



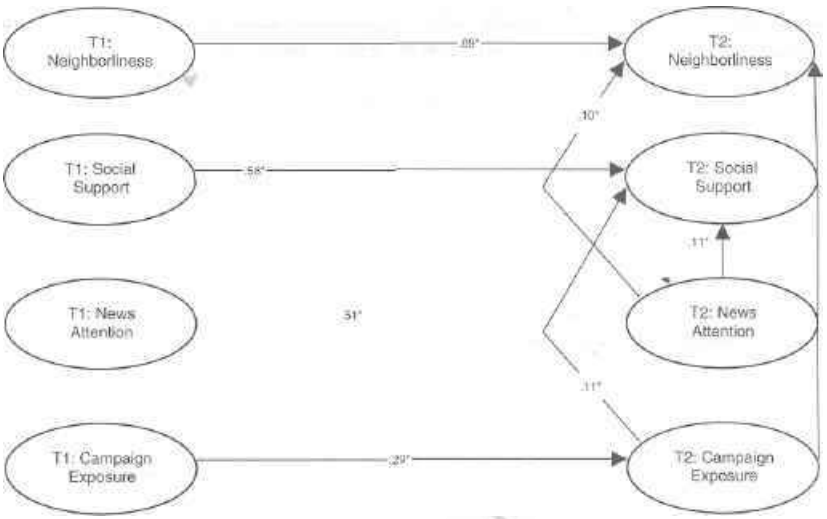
Note: T1 = Time 1; T2 = Time 2.
*$p < .05$.

Figure 4
Reciprocal Synchronous Model (Model 4)



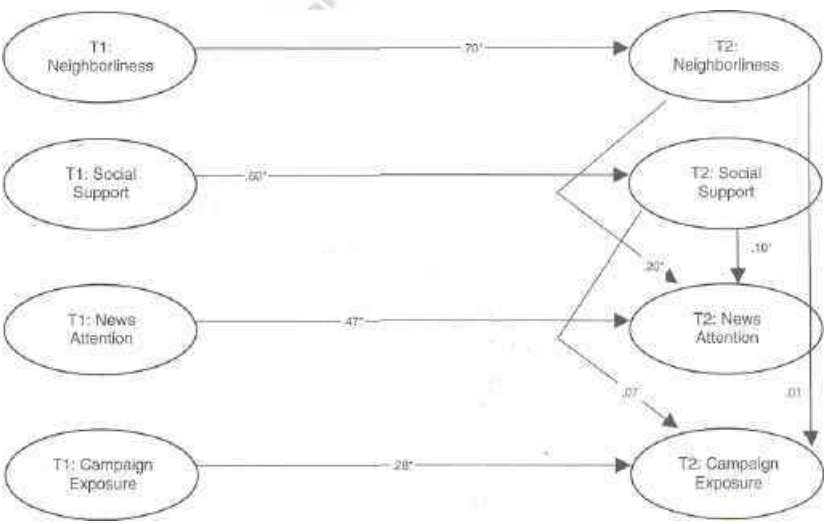
Note: T1 = Time 1; T2 = Time 2.
*$p < .05$.

Figure 5
Mass Media Use Causes Social Capital Synchronous Model (Model 5)



Note: T1 = Time 1; T2 = Time 2.
*p < .05.

Figure 6
Social Capital Causes Mass Media Use Synchronous Model (Model 6)



Note: Tl - Time 1; T2 = Time 2.
*p < .05.

Table 4
Fit Statistics for Models

Model	χ^2	*df*	χ^2/df	CFI	RMSEA	TLI	AIC	CAIC
1. Reciprocal lagged	804.4231*	410	1.9620	.9582	.0439	.9375	1,106.4231	1,893.8289
2. Mass media use → Social capital lagged	807.0644*	414	1.9494	.9584	.0436	.9387	1,101.0644	1,867.6117
3. Social capital → Mass media use lagged	819.2338*	414	1.9788	.9562	.0443	.9359	1,113.2338	1,879.7812
4. Reciprocal synchronous	800.0765*	413	1.9372	.9595	.0433	.9399	1,096.0765	1,867.8385
5. Mass media use → Social capital synchronous	806.5258*	417	1.9341	.9591	.0433	.9402	1,094.5258	1,845.4293
6. Social capital → Mass media use synchronous	814.0526*	417	1.9522	.9577	.0437	.9385	1,102.0526	1,852.9561

Note: CFI = comparative fit index; RMSEA = root mean squared error of approximation; TLI = Tucker-Lewis index; AIC = Akaike information criterion; CAIC = consistent AIC.
*$p < .001$.

It is critical to assess which of the models appears to fit the data best. A useful first step is to compare the nested models in terms of their chi-square values. Of the cross-lagged models, Models 2 and 3 have four more degrees of freedom than Model 1. Thus, the $\Delta\chi^2$ at four degrees of freedom must be greater than the critical value of 9.49 to indicate a significant difference between nested models. The reciprocal lagged model, $\chi^2(429) = 841.7324$, did not fit the data better than the mass media use to social capital lagged model, $\chi^2(433) = 846.9601$. $\Delta\chi^2(4) = 5.2277$. In contrast, the reciprocal lagged model, $\chi^2(429)$ - 841.7324, did fit the data better than the social capital to mass media use lagged model, $\chi^2(423) = 853.6243$, $\Delta\chi^2(4) = 11.8919$. In light of parsimony, this process indicates that the mass media use to social capital lagged model is the best of the three lagged models.[12]

A similar approach can be applied to the three synchronous models. Of the synchronous models, Models 5 and 6 have four more degrees of freedom than Model 4. Thus, the $\Delta\chi^2$ at four degrees of freedom must be greater than the critical value of 9.49 to indicate a significant difference between nested models. The reciprocal synchronous model, $\chi^2(433) = 843.4986$, did not fit the data better than the mass media use to social capital synchronous model, $\chi^2(437) = 849.4669$, $\Delta\chi^2(4)$ - 5.9683. In contrast, the reciprocal lagged model, $\chi^2(433)$ - 843.4986, did fit the data better than the social capital to mass media use synchronous model, $\chi^2(437)$ - 856.3866. $\Delta\chi^2(4) = 12.8880$. In light of parsimony, this process indicates that the mass media use to social capital synchronous model is the best of the three synchronous models.

The relative model fit statistics are depicted in Table 4. This table is especially useful in comparing the two models deemed best fit among the two sets of nested models: the mass media use to social capital lagged model (Model 2) and the mass media use to social capital synchronous model (Model 5). Because these are non-nested

models, the precise $\Delta\chi^2$ test cannot be used. A general comparison, however, indicates rather similar fit between these two models. For example, mass media use to social capital lagged model has a slightly better CFI, while the mass media use to social capital synchronous model has a slightly better RMSEA.

Discussion

The comparison of models indicated that the two models of best fit were the mass media use to social capital lagged model (Model 2) and the mass media use to social capital synchronous model (Model 5). This finding is consistent with the general findings of Eveland and colleagues (2005), although that study focused on the relationship between communication and knowledge. Those authors demonstrated that, among their six models, the best model fit was for the communication causes knowledge synchronous model. Thus, the study presented here and the study of Eveland et al. (2005) have both found primary support for synchronous models in which communication causes outcomes, whether they be related to social capital or knowledge.

Just as important to the current study is the finding that the two models with superior fit shared the direction of causation from mass media use to social capital. This finding is also generally consistent with that of Eveland et al. (2005) in regards to the relationship between communication and knowledge. In terms of the social capital literature, that the best fit is among the two models in which mass media use causes social capital offers general support for previous theorizing (Newton, 1999; Shah et al., 2002), various empirical studies with cross-sectional data (Beaudoin, in press; Beaudoin & Thorson, 2007; Beaudoin, Thorson, & Hong, 2006; Shah et al., 2002; Thorson & Beaudoin, 2004), and the recent panel sample-based empirical research of Shah and colleagues (2005).

It is important to return to the three potential causal forms between mass media use and social capital that were articulated earlier in this article. The findings support the first posited direction of influence—mass media use causes social capital—but not that of the other two potential forms: (a) social capital causes mass media use, and (b) a model of reciprocal influence in which mass media use causes social capital *and* social capital causes mass media use. Thus, support is neither for a selective attention-oriented model, in which people with more social capital are subsequently likely to use the media more, nor for the reciprocal model, in which the influence between mass media use and social capital constitutes a circular system.

The findings related to news attention are different. It is useful to look at the two models of best fit: the mass media use to social capital lagged model (Model 2) and the mass media use to social capital synchronous model (Model 5). In Model 2, the cross-lagged influence of news attention on the two social capital indicators is nonsignificant. In Model 5, the synchronous influence of news attention on the two social capital indicators is significant. The associations in Model 5 support a long

line of cross-sectional research (Beaudoin & Thorson, 2004, 2006; McLeod et al., 1996; McLeod, Scheufele, & Mpy, 1999; McLeod, Scheufele, Moy, Horowitz, et al., 1999; Norris, 1996; Shah, Kwak, & Holbert, 2001; Shah, McLeod, & Yoon, 2001; Stamm et al., 1997; Stamm & Fortini-Campbell, 1983), as well as research that has focused on African American samples (Beaudoin & Thorson, 2006; Mastin, 2000). This finding is also generally consistent with the finding of Eveland and colleagues (2005) that news use did not have significant cross-lagged effects on knowledge but did have significant synchronous effects on knowledge.

The idea of "the interval of effect" casts a useful light on media influence in the cross-lagged and synchronous models. As Finkel (1995) pointed out, the expected time interval of influence of T1 variables on T2 variables is important when considering cross-lagged versus synchronous models. In the current study, significant cross-lagged effects would suggest that the influence of T1 variables on T2 variables takes weeks or months to occur. In contrast, significant synchronous effects would suggest that the influence of Tl variables on T2 variables occurs more quickly. The significant influence of campaign exposure on the social capital indicators in the best cross-lagged model (Model 2) and the best synchronous model (Model 5) offers support for both intervals of influence. In contrast, that the influence of news attention on the social capital indicators is significant in Model 5, but not Model 2, indicates that news effects occurred only over the short term. These findings in regards to the interval of news effects are generally consistent with those of Eveland and colleagues (2005), who demonstrated the influence of news use on knowledge in synchronous models but not cross-lagged models.

The study presented here provides a broad extension upon the findings of Eveland and colleagues (2005) and Shah and colleagues (2005). The current findings are generally similar to those of Eveland and colleagues, despite the current study's use of different outcome variables (neighborliness and social support), different media variables (health-related news attention and campaign exposure), and a different sample (African Americans).

These findings provide general support for the focal media campaign's influence on neighborliness. This social capital indicator increased over the eourse of the campaign, in association with the disseminated campaign messages. The modeling approach offers support for the causal influence of the campaign on neighborliness, whether considering cross-lagged or synchronous models.

It is important to reflect on social support and neighborliness in light of this study's demonstration of an over-campaign increase in only the latter variable. A close look at the measurement items indicates that social support deals with attempts to help others via emotion and information, while neighborliness involves attempts to help others in more tangible ways, including house repairs and sharing items. In theory, the campaign messages seem fit for spurring improvements in both types of behaviors. For example, some messages stressed the importance of talking with others about stress and depression following the hurricane, while others emphasized the need to work together with

neighbors as the public recovered and rebuilt. In terms of this dichotomy, the increase in neighborliness over the campaign suggests one of two things. First, it could be that the media messages were more effective in influencing people to help one another with tangible things than to help one another with emotional and informational things. Second, it could be that it is more difficult to spur emotional and informational forms of help in general or in a posthurricane context. The posthurricane context was certainly unique. Although stress and depression levels were high (Abramson & Garfield, 2006; Beaudoin, 2007; Kessler, Galea, Jones, & Parker, 2006), it may be that people prioritized tangible advancement over emotional advancement and, thus, underwent change in terms of neighborliness but not social support.

It is also important to consider alternative explanations for the significant increase in neighborliness. Between the first and second interviews, what other factors could possibly have contributed to the increase in neighborliness? One potential alternative explanation involves population trends. If the posthurricane resettlement of New Orleans increased during the course of the campaign, it would perhaps make sense that the social capital indicators would increase. There are two problems, however, with this alternative explanation. First, although the resettlement of New Orleans did increase following the hurricane, it primarily took place before the precampaign telephone interviews began, with the population of the city appearing to have remained rather stable throughout the survey window of this study. Second, such a population change would not undermine the fact that the increase in neighborliness was greatest among respondents who were most exposed to the media campaign.

Five main limitations of this study should be noted. The first limitation involves generalization. Because of the population (African Americans in New Orleans) and the context (post-Hurricane Katrina), generalization of these findings to other populations and contexts should be done only with caution. The second limitation involves the telephone survey environment following Hurricane Katrina. This environment was much different than normal. The frequencies of nonfunctioning numbers and noncontacts were higher than usual, which slowed the survey process. Although the RR1 was consequentially low, the RR3 and cooperation rates were customary, which in this environment is a better gauge of survey response. The third limitation involves response bias, which is the tendency of respondents to indicate one type of response more often than another (Macmillan & Creelman, 1990). In terms of the current study, it is possible that respondents may have reported more socially desirable responses, such as higher levels of neighborliness, social support, and news attention. While there is potential for the inflation of these measures in survey research, it would not be expected that such inflation would alter over-time trends in variables or patterns of relationships between variables. The fourth limitation involves the approach to measuring campaign exposure. Although implementing concepts of recall and attention, this approach does not institute a measure of frequency of campaign message exposure (Slater & Kelly, 2002). An improvement in measurement would involve measuring both frequency and attention.

The fifth limitation ties in criticism of using cross-lagged correlations to demonstrate causation with longitudinal panel data. Rogosa (1980, 1987) has argued against the use of such approaches, pointing out the shortcomings of determining spuriousness or causal predominance via the comparison of cross-lagged correlations and verification of related inequality. Conversely, research has pointed out that latent variable modeling, such as that implemented in this study, can mitigate measurement problems (Shadish, Cook, & Campbell, 2002) and that cross-lagged approaches can be effective in testing for spuriousness, as long as the strong assumptions of such modeling are acknowledged (Kenny, 1975). In addition, it should be noted that neither the current study nor that of Eveland and colleagues (2005) base inferences of causation in the comparison of cross-lagged correlations. In contrast, these two studies base their inferences in the comparison of model fit.

More broadly, this study does not contend that it has concretely demonstrated causation as experimental research could do. Simply put, anything short of a laboratory experiment cannot conclusively demonstrate causation. That said, this study's reliance on a panel sample, as well as a cross-sectional sample, is useful in further addressing the causal ambiguity surrounding the relationship between mass media use and social capital. This approach helps attend to various criteria for determining causation, such as temporal relationship, strength of association, plausibility, specificity, and coherence (Hill, 1965). Also, the insertion of demographics and disaster exposure as control variables facilitates the elimination of some alternative explanations, and the regression-based analysis can indicate a dose-response relationship in regards to the campaign and the trend in neighborliness. Furthermore, this research design helps address various threats to internal validity, including history, maturation, selectivity, sensitization, and testing (Valente, 2001). For example, the threats of testing, history, and maturation are mitigated by the comparison of the panel and cross-sectional interviews. The panel design assists in eliminating some alternative explanations for the trend in neighborliness and its association with campaign exposure, and attrition bias was quite small, as noted by the response and cooperation rates for the postcampaign survey interviews.

This study has implications for future practice and research. The importance of employing mass media stimuli in social capital-oriented initiatives is underscored by the panel data findings of Shah and colleagues (2005) and the current study, as well as the broader findings of social capital's important influence on outcomes such as health, safety, and education (Beaudoin, 2007, in press; Kawachi & Berkman, 2000; Putnam, 2000; Verba et al., 1995). Two lines of future research are also suggested. First, future research should investigate whether the improvement in neighborliness demonstrated in this study brings about subsequent improvements in outcome indicators, including those related to health and safety. Such research could assess whether neighborhoods that had higher aggregate-level indicators of neighborliness subsequently have higher neighborhood-level indicators of health status but lower neighborhood-level indicators of crime. Second, and more broadly, it is important

that mass communication research continue testing causal models with panel data. Specifically, this research should consider other mass communication scenarios—and retest the ones examined in mis study, as well as those examined by Eveland and colleagues (2005) and Shah and colleagues (2005). Such causal models should be examined in different contexts with different populations.

v

Notes

1. Funding for the study was provided through a grant from the Robert Wood Johnson Foundation. I thank the two blind reviewers, Dr. Pamela J. Shoemaker and Soo Yeon Hong at *Communication Research.* and Dr. Titus Levi for his insights related to the focal media campaign. Correspondence should be addressed to Christopher E. Beaudoin. Tulane University School of Public Health and Tropical Medicine. 1440 Canal Street, Suite 2315, TW19, New Orleans, LA 70112; e-mail: beaudoin@tulane.edu.

2. Because previous research has indicated that media effects can vary by medium, six additional models were tested in which news attention was measured not with one index but with four items specific to newspaper, television, radio, and Internet. This additional analysis did not provide support for medium-specific effects in the posited modeling. The fit of the models was not better, and the impact of news was neither different nor greater. Thus, with the goal of parsimony and reference to the approach taken by Eveland and colleagues (2005), the decision was made to rely on one latent variable for news use.

3. Although some previous research has assessed campaign exposure in terms of frequency (Slater & Kelly, 2002), this study assesses campaign recall via two steps—one based in recall, the other based in attention. This approach, though not allowing for weighting, does take into account both concepts of campaign recall and campaign attention.

4. Measurement models were created for the four latent variables: campaign exposure, news attention, social support, and neighborliness. This procedure takes into account the factor loadings and indicator errors at T1 and T2 and temporal stability between these two points in time (Eveland et al., 2005). The measurement errors of items at Tl and T2 were not correlated in these baseline measurement models because of the chance of over-time change in latent variables (Finkel, 1995). In each of these baseline models, there were assumptions of no correlations among measurement errors and no association between latent variables (e.g., Tl news attention and T2 news attention). Any additions suggested by modification indices were subsequently tested by comparing chi-square statistics between the nested models. Each model has partial measurement invariance over time (Byrne, Shavelson, & Muthen. 1989).

5. The fit of the baseline model for campaign exposure was good but not excellent (CFI - .9354). Modification indices signified that the model would be improved by adding eight correlations between error terms and one regression path from Tl campaign exposure to T2 campaign exposure. The resulting model had excellent fit (CFI = .9912), $\Delta\chi^2(9) = 76.8198$, $p < .001$. Modification indices suggested adding one more correlation between error terms, between ad1 T2 and ad2 T2. The resulting model had an even better fit (CFI - .9951), $\Delta\chi^2(1)$ - 5.2013, $p < .025$. Because improvements of several correlations were negligible, correlations between error terms were pruned in three cases. This rendered a final specification model of excellent fit (CFI = .9934), $\Delta\chi^2(7) = 76.9329$, $p < .001$. This final specification model had the following correlations between error terms: stationl Tl and station2 T1; station2 Tl and station3 T1; station2 Tl and station2 T2; station3 Tl and station2 T2; station4 Tl and station4 T2; and stationl T2 and station2 T2.

6. The baseline model for news attention did not fit the data well (CFI - .6152). The modification indices signified that the model would he improved by adding 14 correlations between error terms and one regression path from T1 news attention to T2 news attention. This model had an excellent tit (CFI = .9964). $\Delta\chi^2(15) = 357.7072$, $p < .001$. Because improvements of several correlations were negligible, correlations between error terms were pruned in some cases, rendering a model with excellent fit (CFI = .9918),

$\Delta\chi^2(9) = 345.9926, p < .001$. This final specification model had the following eight correlations between error terms: newspaper T1 and newspaper T2; radio T1 and radio T2; Internet T1 and TV T1; Internet T1 and Internet T2; Internet Tl and TV T2; TV Tl and Internet T2: TV Tl and TV T2; and Internet T2 and TV T2.

7. The baseline model for social support did not have excellent fit (CFI - .8923). Modification indices suggested that the model would be improved by adding two correlations between error terms and one regression path from Tl social support to T2 social support. The correlations were between ss1 Tl and ss2 T2 and between ss3 Tl and ssl T2. This model had excellent fit (CFI = .9998), $\Delta\chi^2(3) = 191.0395$, $p < .001$.

8. The baseline model for neighborliness did not fit the data well (CFI - .5879). With the addition of three correlations between error terms and one regression path from Tl neighborliness to T2 neighborliness, as suggested by modification indices, the model had excellent fit (CFI = .9996), $\Delta\chi^2(4) = 347.7923$. $p < .001$. One of the correlations between error terms was pruned, rendering a final specification model of excellent fit (CFI = .9983), $\Delta\chi^2(4) = 345.67011, p < .001$. The correlations of error terms *in* this model were as follows: n1 Tl and n1 T2; and n3 Tl and n3 T2.

9. Finkel's (1995) other types of models were also considered. Eveland et al. (2005) tested cross-lagged and synchronous models. While also testing those model types, Shah et al. (2005) primarily focused on three other types of models: cross-sectional at one point in time, fixed effects with intra-individual change scores, and auto-regression. For two main reasons, the current study tested cross-lagged and synchronous models. The first reason is that lagging T2 variables by their Tl counterpart is suggested when there is the potential for change in variables between Tl and T2 (Finkel, 1995). The second reason is that the cross-lagged and synchronous models are consistent with this study's goal of assessing three different potential forms of the causal relationship between mass media use and social capital.

10. Hausman tests offered support for using random effects, instead of fixed effects, by having non-significant chi-square statistics for neighborliness ($p = .701$) and social support (p - .612) (Hausman. Hall, & Griliches, 1984).

11. More complex figures—with indicators, their loadings on latent factors, and correlations between error terms—can be provided upon request.

12. In addition, per a reviewer suggestion, another modeling approach, one consistent with hierarchical regression (de Jong, 1999), was implemented to assess the fit of the stability model versus those of the two lagged models. In this approach, the fit of the stability model was first assessed. Then, in a social capital causes media use model, fit was assessed after adding the lagged paths from Tl social capital indicators to T2 media use indicators. The addition of these lagged paths did not result in a significantly improved model, $\Delta\chi^2(4) = 5.7830, p > .200$. Finally, lagged paths from Tl media use indicators to T2 social capital indicators were added to the social capital causes media use model to create a comprehensive model. The addition of these four paths brings about a significant improvement from the social capital causes media use model, $\Delta\chi^2(4)$ - 11.4961, $p < .025$. This indicates that the addition of the lagged paths from the Tl media use indicators brings about a significant improvement in the model, even after controlling for the influence of the lagged paths from the Tl social capital indicators.

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