Informing Mitigation of Disaster Loss through Social Media

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Abstract

When confronted with natural disasters, individuals around the world increasingly use online resources to become informed of forecasted conditions and advisable actions. This study tests the effectiveness of online information and social media in enabling households to reduce disaster losses. The 2011 Bangkok flood is utilized as a case study since it was one of the first major disasters to affect a substantial population connected to social media. The role of online information is investigated with a mixed methods approach. Both quantitative (propensity score matching) and qualitative (in-depth interviews) techniques are employed. The study relies on two data sources – survey responses from 469 Bangkok households and in-depth interviews with twenty-three internet users who are a subset of the survey participants.

Propensity score matching indicates that social media enabled households to reduce flood losses by an average of 37% (USD 3,708), using a nearest neighbor estimator. This reduction is massive when considering that total flood losses for the full sample averaged USD 4,903. Social media offered information not available from other sources, such as localized and nearly real-time updates of flood location and depth. With this knowledge, households could move belongings to higher ground before floodwaters arrived. These findings suggest that utilizing social media users as sensors could better inform populations during disasters. Overall, the study reveals that online information can enable effective disaster preparedness and reduce losses.

1.0 Introduction

Costs of weather-related disasters have increased dramatically in recent decades [Munich Re Group, 2005; Miller et al., 2008; IPCC, 2012]. A growing policy challenge is identifying interventions that strengthen disaster preparedness and mitigate losses. Social media may offer enormous potential to improve disaster communication, save lives, and reduce disaster losses. Worldwide, social media has an immense presence with over one billion users on Facebook and 500 million users on Twitter. Disaster management agencies are beginning to establish a presence on these networks. Understanding the effect of social media information on flood losses would have broad implications for incorporating online applications into disaster communication efforts. For example, the U.S. Federal Emergency Management Agency is testing the use of social media for distributing emergency updates.

When confronted with natural disasters, individuals around the world increasingly use online resources to inform themselves of forecasted conditions and advisable actions. Key features of online information are its ability to be searched, real-time updates, and self-publishing capabilities. In some cases, social media can distribute news updates faster than traditional media or government sources [Guan and Chen, 2014]. For example, social media users can report earthquakes faster than current U.S. Geological Survey procedures are able to, which was illustrated during the 2008 earthquakes in China [Earle et al., 2010]. Social media can also be useful for disaster recovery. The usefulness of Facebook group pages during disasters and recovery efforts was demonstrated during the 2010 Haiti earthquake and Australian floods [e.g. Muralidharan et al., 2011; Bird et al., 2012].

The case of the 2011 Bangkok flood represents an important research opportunity to identify if and how online activity can inform disaster preparation and recovery. This event ranks as the world's most costly flooding disaster in the past 30 years [A.M. Best, 2012; Orie and Stahel, 2013]. Furthermore, it was one of the first major disasters to affect a substantial population connected to social media. Nearly one-quarter of the Thailand's population had internet access in 2011 and 60% of internet users actively used Facebook [World Bank, 2014]. When Hurricane Katrina struck New Orleans in 2005, Facebook was not available to the general public and Twitter was undergoing beta testing.

This study is the first to investigate the role of online information in mitigation of flood loss. To do so both quantitative (propensity score matching) and qualitative (in-depth interviews) techniques are employed. This is an important improvement over past studies that are limited to descriptions of online activity during disaster. The study relies on two data sources – survey responses from 469 Bangkok households and in-depth interviews with twenty-three internet users who are a subset of the survey participants. Surveys and interviews were conducted in three districts of Bangkok that were most affected by the disastrous 2011 Thailand flood. Results indicate that social media use enabled households to reduce mean total losses by more than a third, using a nearest neighbor estimator. Overall, the study reveals that online information can enable effective disaster preparedness and reduce losses.

2. Methods and Research Design

A mixed methods approach was employed to explore the role of online information in mitigation of flood loss. Quantitative (propensity score matching) and qualitative (in-depth interviews) analyses test the hypothesis that online activity allowed households to reduce flood losses by informing mitigation decisions before the flood.

The study relies on two data sources – survey responses from 469 Bangkok households and in-depth interviews with twenty-three internet users who are a subset of the survey participants.

Survey responses were analyzed using propensity score matching, while in-depth interviews are assessed with a qualitative, explanation building approach. Propensity score matching (PSM) is used to test for evidence of a causal relationship between social media and flood losses. In-depth, qualitative interviews complement the quantitative analysis, and provide explanations for statistical associations.

PSM allows households that followed flood information on social media to be matched with households without flood-related social media use. This matching is done in such in a way that balances observable characteristics between these two groups. Differences in flood losses between households with social media use and the matched comparison group will represent the effect of social media use.

In-depth, qualitative interviews complement the quantitative analysis and provide explanations for statistical relationships. Responses from internet users provide further understanding of how households used online information before, during, and after the flood.

2.1 Description of study participants

Households are categorized by the information source they relied on before floodwaters entered the Bangkok Metropolitan Area. Categories are defined based the information source a household relied on before flooding occurred. This alleviates concerns that online activity was influenced by the severity of flooding, since internet use declines considerably during the flood. Households that followed flood information on social media (i.e. Facebook) prior to flooding are referred to as *social media* households (n=55, 12% of the sample), as presented in Table 1.

2.2 Household survey implementation

Two rounds of surveys were conducted in-person with 469 Bangkok households in January-February 2012 and again in January 2013. The surveys inquired about economic costs incurred due to the 2011 flood, socioeconomic status, and flood-related online activity. In addition to the surveys, in-depth qualitative interviews were conducted in December 2012 with *social media* households (12 respondents) and *conventional internet* households (11 respondents). Survey responses were analyzed using propensity score matching, while in-depth interviews are assessed with a qualitative, explanation building approach.

All interviews were conducted at respondents' homes. The survey inquired about economic costs incurred during the 2011 flood, socioeconomic status, and flood-related online activity. During the second round, respondents were asked about their general internet use and flood-related online activity in 2011. Questions were related to specific information that respondents found online before, during, and after the flood. Internet-related questions were selected and designed based on in-depth interviews with internet users and pilot interviews. One member from each household provided survey responses regarding the behavior of all internet users in the household. Respondents were not asked about information they shared with others. If *social media* households shared information with *conventional internet* or *offline* households, this would reduce the treatment effect of social media on flood losses. A full description of fieldwork procedures for the two survey rounds can be found in [Nabangchang et al., 2015]. Informed consent was obtained from all respondents and survey protocols were approved by the institutional review board of the University of North Carolina at Chapel Hill.

2.3 In-depth Interviews

In-depth interviews complement the quantitative analysis and provide insight into the underlying processes through which internet use and flood losses are related. Qualitative, in-depth qualitative interviews were conducted with 23 households who were *social media* households (12 respondents) or *conventional internet* households (11 respondents). The 23 households are a subset of the full survey sample of 469 households. In-depth interview respondents were selected to represent a broad range of wealth and age groups. In-depth interviews were conducted in person during December 2012, just before the second round household survey. The purpose of the in-depth interviews was to explore alternative explanations for how internet use may have influenced household decisions and actions during various stages of flooding.

Interviews were semi-structured, with several open-ended questions designed to guide discussion. Respondents described what types of information they sought online before, during, and after the flooding event. They also discussed whether the information was useful for taking preventative measures, coping with the flood, or post-flood recovery and repairs.

2.4 Modeling Strategy: Propensity Score Matching

Propensity score matching is used to determine if a causal relationship exists between social media and flood loss reduction. PSM provides a useful alternative to an experimental research design, particularly for settings such as a post-disaster situation where experiments would not be feasible and/or ethical to implement. In the absence of non-random assignment, this technique selects a suitable control group to be compared to those who received treatment. In this study, a comparison group is selected among the 414 households that did not use social media to follow flood-related information. A suitable comparison group is selected based on their observed characteristics having a similar distribution as the treated group.

Estimation of the average treatment effect on the treated (ATT) is done in three steps. First, the probability of using social media prior to the flood is estimated, which produces balancing scores for each household. Second, these balancing scores are used to identify a suitable comparison group from the 414 households that did not use social media to follow flood-related information prior to flooding. The mean differences in flood losses are compared between *social media* households and the comparison group. Third, regression of flood losses on key covariates is done to estimate treatment effects, using the matched sample.

Balancing scores are estimated using a logit regression model of the probability of a household using social media before the flood, *P(T)*, as a function of control variables (X_i) that include characteristics of the household (annual spending, number of cars owned, number of household members), dwelling (size, indicator for one-story building), and survey respondent (age, education level, marriage status).

$$Prob(T = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_i x_i)}} \qquad (1)$$

Matching methods then use balancing scores to identify suitable comparison households. In this study, several matching methods are used – nearest neighbor and kernel matching. While the nearest neighbor estimator matches one comparison household to one treatment household, the kernel method matches treated households to a weighted average of those in the comparison group.

The ATT is estimated using the matched sample to run post-PSM regression of the outcome on covariates. This approach controls for covariates that are associated with flood losses, but not necessarily the likelihood of using social media, such as depth of flood water (*D*). Flood losses are estimated as a linear function of social media use (*T*), household and personal characteristics (X_k), and neighborhood controls (V_m):

$$Total\ flood\ loss = \beta_0 + \beta_1 T + \beta_2 D + \gamma_k X_k + \omega_m V_m + \varepsilon \qquad (2)$$

In this study, the term ‘flood losses’ includes economic costs incurred during the flooding event and after floodwaters recede. These costs consist of expenditures on emergency supplies, evacuation, travel, and health. They also include foregone income and costs associated with cleaning, repairing, and replacing property. Notably, these losses exclude costs of preventative actions. Excluding preventative costs allows the analysis to establish that online information was sought before the household incurred flood-related costs. Another feature of the study design that allows temporal precedence to be established is the focus on information sought before flooding occurred.

3.0 Results

3.1 Balancing Score

Balancing scores for each household were estimated using a logit regression model of the probability of a household using social media before the flood. These scores are then used in matching methods to identify suitable comparison households. Covariates that are significant at the 5% confidence level are household expenditure, number of cars owned, number of household members, respondent age, and marriage status. Each coefficient has the anticipated sign. Household expenditure and number of cars owned are positively associated with using social media, while age and number of household members have a negative association.

The balancing score (the log odds ratio) is estimated from the predicted values of the logit model. The area of common support is defined as below the maximum of minimum values (-4.99) and above the minimum of the maximum values (0.65) of the balancing score. Households with balancing scores outside the region of common support are not included in the matching analysis. Seven *social media* households are outside the region of common support, while 69 potential comparison households are outside. Therefore, 87% of the treatment group and 83% of the comparison group satisfy the comment support criteria.

5.3 Evidence of Causal Relationship

Significant ATT values are estimated in the PSM analysis. This suggests a causal relationship exists between social media use and reduced flood losses. Flood-related social media use enabled households to reduce flood loss by an average of USD 3,708 (as indicated by the nearest neighbor estimator) or USD 4,886 (kernel estimator). It should be noted that these reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and have multi-story houses), rather than the general population.

In addition, a significantly greater proportion of social media households (87%) considered online information to be useful, compared to conventional internet households (66%). This suggests that social media sites may have offered actionable information not available on conventional internet sites.

A possible alternative explanation for social media being associated with reduced flood losses is that *social media* household may have been younger and thus had fewer assets at risk. Several pieces of evidence suggest that this alternative explanation does not hold. First, the matched sample in the PSM analysis was balanced both on respondent age and household wealth. *Social media* households own assets of similar value as comparison households, as indicated by home value and number of cars owned. Second, the age distribution of household members does not differ between those who did and did not rely on social media.

Nearest Neighbor Matching

The two matching methods – nearest neighbor and kernel matching – allow suitable comparison households to be identified, based on the balancing scores. Each method selects different comparison groups and result in different ATT estimates. Nearest-neighbor matching selects 48 *social media* and 48 comparison households. Compared to the full sample of 469 households, this matched sample has significantly higher flood losses, household expenditure, car ownership, and education (Table 2). In addition, the mean age of the survey respondent in the matched sample is significantly lower than in the full sample. Mean total losses for *social media* households (USD 6,594) are much lower than for comparison households (USD 9,961) (Figure 1). The mean difference in total flood losses between *social media* households and comparison households (USD 3,367) is significant at the 5% level, as indicated by a bootstrapped standard error (Table 3).

This mean difference is large, considering that total losses for the overall matched sample (n=96) have a mean of USD 8,278. The ATT estimated using post-PSM regression analysis is more than the difference in means between social media and comparison groups. This difference is attributable to the regression controlling for additional covariates, such as flood depth and neighborhood controls, which influence flood losses but not the probability of using social media. The ATT of social media use is estimated to be USD 3,708 in the matched sample identified with the nearest-neighbor estimator (Table 3).

{Figure 1. Difference in Flood Loss between Social Media and Comparison Households}

Kernel Matching

Kernel matching produces a larger matched sample (48 *social media*, 345 comparison) than the nearest neighbor estimator. This is to be expected since the kernel matching estimator makes use of all comparison households with balancing scores inside the common support region. Treated households are matched to a weighted average of comparison households. The weighted average mean difference in total flood losses between *social media* and comparison households is USD 4,501. This is comparable to the mean difference found with the nearest-neighbor estimator and is significant at the 5% level. Post-PSM regression analysis indicates that the ATT of social media is USD 4,886 in the matched sample identified with the kernel estimator.

This estimate of ATT is higher than the estimate obtained using the nearest-neighbor matched sample. The kernel matched sample is much larger since it includes all households that meet the common support criteria. This means that a greater variety of comparison households are included in the sample that might have lower education and wealth. Although such comparison households would receive lower weights, they are present in the matched sample.

5.4 In-Depth Interview Results

The vast majority of in-depth interview respondents reported that online information helped them to reduce flood losses. Among *social media* households, 75% reported that the internet helped them to reduce losses, while 64% of *conventional internet* households stated this. The most important types of online information that allowed households to reduce flood losses were information regarding flood progression (65% of respondents stated that this was useful in reducing losses), mitigation actions (39%), and transportation during the flood such as options for boat transport and road closures (22%).

Households that sought flood information online were able to find content that was more relevant to them. During the 2011 Bangkok flood, many of the 469 households in the full survey sample spent considerable time watching television, waiting to catch the information that was relevant to their area. The internet offered the ability to search for any type of information desired by the household. The vast majority of in-depth interview respondents (70%) relied on a mix of television and internet. Some first found information online and then confirmed its credibility via television or direct observation, particularly concerning water level updates. Others first watched television before using the internet to search for further information. These observations are in agreement with a study after a 2011 tropical cyclone in Australia that found households rely on multiple information sources and that social media might serve to filter relevant messages from television and government [Taylor et al., 2012].

Respondents tended to feel that internet use was most useful before the flood. Before flood waters arrived, internet users could follow the flood situation and locate information on mitigation actions. Social media in particular appears to have been a useful source for flood progression information. First-hand reports from a household's extended social network provided updates that were not available from other sources. If a friend's home was flooded, social media users could be updated on the location, timing, and flood depth as floodwaters flowed through the metropolitan area.

Respondents emphasized that information on social media was useful for knowing when and how they should prepare for the flood. Government sources could not predict the path and timing of the flood through the urban environment with much accuracy or lead time. For example, in study areas near Bangkok's domestic airport, respondents mentioned that official predictions indicated that their neighborhoods would not flood, yet they eventually were inundated.

With knowledge of current flood conditions, *social media* households could prepare effectively and successfully move their belongings in time. Furthermore, social media respondents had a better sense of the depth of floodwater to expect. While many other households used the depth of the previous 1995 flood as a reference, social media households tended to know that the 2011 would be more severe. Two social media respondents explicitly stated that knowledge of deeper floodwater led to their decision to move contents to upper floors.

In addition, respondents found advice regarding which flood mitigation actions to take and how to carry out those actions. Some found advice for moving belongings to upper floors, while others learned how to protect large, heavy items that are difficult to move (e.g. refrigerator, other major appliances). Households also found online information regarding how to construct sandbag and concrete block barriers as well as where to buy materials for these barriers. Social media appears to have allowed households to understand the progression of the flood and share ideas for preparation actions.

6.0 Discussion

Low-lying megacities such as Bangkok present new challenges for flood management. Mass evacuations are infeasible and relocation of assets away from these productive centers is undesirable. Given this situation, information can play a vital role in allowing people to take effective actions to reduce flood losses. Social media use allowed households to reduce losses during the 2011 Bangkok flood. Propensity score matching indicates that social media enabled households to reduce flood loss by an average of USD 3,708 (as indicated by the nearest neighbor estimator) or USD 4,886 (kernel estimator). This reduction is massive when considering that total flood losses for the full sample averaged USD 4,903. These reductions are in relation to comparable households (i.e. those who are well-educated, higher-income, and live in multi-story houses), rather than the general population. Social media use appears to be associated with a 37% reduction in mean flood losses, when comparing *social media* households to similar households using nearest neighbor matching.

Social media offered information that was not available from other sources, such as a dynamic view of localized flooding conditions. User updates may have been more useful than government flood predictions in some areas. Government predictions were inaccurate in some neighborhoods and only reported expected volume of water, which did not clearly convey severity of the flooding. Flood depth would have been a more understandable indicator and social media users had access to this information. With knowledge of current flood conditions, *social media* households could prepare effectively for the flood. In particular, in-depth interview responses suggest that social media users focused their *ex ante* mitigation efforts on moving belongings as high as possible.

Social media appears to have offered advantages over conventional internet sites as well as offline sources, particularly in terms of mitigation actions before flooding. However, the benefits of social media during the 2011 Thailand flood largely did not reach lower-income households since these households are less likely to access the internet. Benefits to poor communities could be achieved as disparities in social media use are likely to decrease in the near future due to rapid uptake of smartphones. While few Thais had smartphones in 2011, subscriptions dramatically rose to 35 million in 2013, covering over half the country's population [Webcertain, 2014]. Government interventions could hasten expansion of internet access and ensure that low-income populations are served.

These findings have two major implications for future policies designed to reduce household flood losses. One is that there is an enormous opportunity for government disaster communication to move online. Social media could be a highly effective means of disseminating crucial information related to flood conditions, evacuation warnings, and mitigation actions. In the U.S., the Federal Emergency Management Agency is testing the use of distributing disaster information on social media. In developing countries, expanded access to broadband and mobile networks could be justified on the grounds of a better prepared populous. Already, access is increasing rapidly with the adoption of smartphones.

Second, in locations that lack sufficient monitoring networks, social media provides an inexpensive way to track flood progression and map affected areas. Using people as sensors offers an interim solution for improved early warning, particularly in developing countries, ungauged basins, and highly complex urban environments. The usefulness of social media for describing earthquakes has been acknowledged in regions with insufficient instrumentation [Earle et al., 2012]. Yet, ensuring accuracy of crowdsourced information remains a challenge. Cross-checking could improve accuracy. Furthermore, aggregation of user updates could produce useful outputs such as user-generated flood maps. Efforts to develop web-based applications that can aggregate user updates posted on social media sites could be immensely useful for disaster preparedness, response, and recovery.

Overall, this study demonstrates the potential of social media for effective flood preparation. Disaster preparedness requires accurate, timely, and readily accessible information to guide household decisions. In developing urban areas with rapidly growing internet user bases, expanding the reach and functionality of social media applications offers promising opportunities to save lives and reduce impacts of future disasters.

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Figures and Tables

Figure 1. Difference in Flood Loss between Social Media and Comparison Households

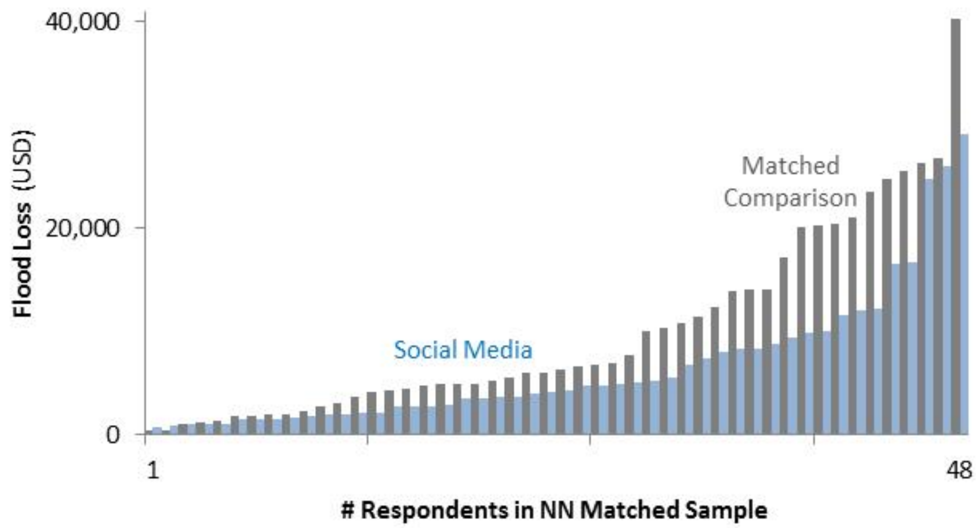

Table 1. Categories of Flood Information Source, before floodwater entered Bangkok

	# of households	% of sample
Social media	55	12%
Conventional internet (no social media)	98	21%
Offline information only	316	67%
Internet users in household (lapse in internet use before flood)	*105*	*22%*
No internet users in household	*211*	*45%*

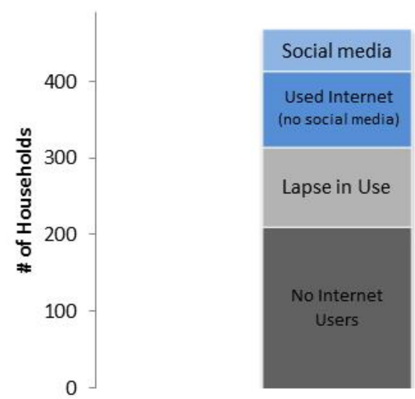

Table 3. Estimation of Average Treatment Effect on the Treated (ATT): Using regression analysis and PSM Matched Samples

	Nearest-Neighbor			**Kernel Matching**		
	Coeff.		Robust Std Error	Coeff.		Robust Std Error
Social media (dummy)	-3,708	**	1,626	-4,886	**	1,906
Annual Household Expenditure (USD)	-0.03		0.11	-0.06		0.11
Cars owned (number)	2,131	***	663	3,031	***	734
Household members (number)	1,833		1,958	2,879	*	1,537
Household members, squared	-106		206	-201		125
Size of property (sq. m)	2		4	2		4
One-story building	2,957		3,275	5,004	**	2,332
Low-income neighborhood	-4,812		3,748	-4,499		2,897
Age of Respondent	880		1,924	-93		101
Married	816		2,340	2,579		2,129
Education Level of Respondent						
High School or Vocational	3,952	*	2,194	-713		1,954
College or more	-13		89	3,028		2,407
Flood depth (on street in front of house)	97	***	24	62	***	22
Constant	-14,362		5,869	-10,363	**	5,153
Neighborhood controls (V_m)	yes			yes		
R^2	0.474			0.508		
Obs	96			393		

* Statistically significant at the 10% level. ** Statistically significant at the 5% level. *** Statistically significant at the 1% level

Table 2. Descriptive Statistics for Propensity Score Matching, Matched Sample

	Matched sample (N=96)				Social Media Households(N=48)				Households without social media (N=48)			
Variable	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Outcome Variable												
Total Flood Losses (USD)	8,278	8,066	413	40,330	6,594	6,591	780	29,180	9,961	9,071	413	40,330 †
Household Characteristics												
Annual Household Expenditure (USD)	13,122	7,471	2,990	36,112	12,976	7,245	2,990	33,126	13,269	7,765	3,305	36,112
Cars owned (number)	1.3	1.0	0	5	1.3	1.0	0	5	1.3	1.0	0	4
Household members (number)	3.9	1.7	1	9	3.9	1.7	1	9	4.0	1.8	1	8
Size of property (sq. m)	327	177	40	880	332	190	120	880	323	165	40	800
One-story building	0.1	0.3	0	1	0.1	0.3	0	1	0.1	0.2	0	1
Low-income neighborhood	0.2	0.4	0	1	0.1	0.4	0	1	0.2	0.4	0	1
Survey Respondent Characteristics												
Age of Respondent	42.5	9.8	19	70	43.2	10.0	19	70	41.8	9.8	24	69
Married	0.8	0.4	0	1	0.8	0.4	0	1	0.8	0.4	0	1
Education level												
High School or Vocational	0.28	0.45	0	1	0.23	0.42	0	1	0.33	0.48	0	1
College or higher	0.54	0.50	0	1	0.60	0.49	0	1	0.48	0.50	0	1

† denotes significant difference at the 5% level between households with and without social media use
Matched sample is created using nearest neighbor without replacement and common support.