A natural experiment of social network formation and dynamics

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Social networks affect many aspects of life, including the spread of diseases, the diffusion of information, the workers' productivity, and consumers' behavior. Little is known, however, about how these networks form and change. Estimating causal effects and mechanisms that drive social network formation and dynamics is challenging because of the complexity of engineering social relations in a controlled environment, endogeneity between network structure and individual characteristics, and the lack of time-resolved data about individuals' behavior. We leverage data from a sample of 1.5 million college students on Facebook, who wrote more than 630 million messages and 590 million posts over 4 years, to design a long-term natural experiment of friendship formation and social dynamics in the aftermath of a natural disaster. The analysis shows that affected individuals are more likely to strengthen interactions, while maintaining the same number of friends as unaffected individuals. Our findings suggest that the formation of social relationships may serve as a coping mechanism to deal with high-stress situations and build resilience in communities.

social networks | natural disasters | causal inference | natural experiment | propensity score matching

Social networks affect many aspects of life, including the spread of diseases (1), access to resources and information (2), the diffusion of knowledge (3, 4), productivity and stability of organizations (5, 6), and job prospects (7, 8). In this paper, we conceptualize a natural experiment[†] by taking advantage of the well-defined local impact of a hurricane to gain a quantitative understanding of how these networks form and evolve. Our analysis provides insights into how to leverage social dynamics for affecting outcomes of interest, such as how to design policies that can aid rescue and recovery efforts or influence behavior and the economy.

Establishing causal relationships in social network formation and dynamics has historically been difficult to study because of endogeneity between network structure and individual characteristics, and the cost of obtaining long time-series about individuals' behavior (16, 17). In addition, large-scale randomized experiments are often not feasible because of the complexity of engineering social relations in a controlled environment, and the multitude of incentives that influence human behavior (18–20), and often because of privacy and IRB related issues (e.g., see refs. 21 and 22). Recent research tackle these challenges by developing behavioral models of network formation (23) that can support what-if analyses, and by using automated services such as Amazon Mechanical Turk (aws.amazon.com/documentation/mturk) to carry out randomized human-subjects experiments of social dynamics in artificial environments, at scale (24–26). Related literature focuses on incentives, aiming at separating influence from selection effects, a task for which negative results exist in general (27, 28), using randomized experiments (29–32) and strategies tailored to specific applications (17, 33). The available empirical evidence indicates that social networks tend to display instability (34) due to temporal activities and volitional interest of the individuals (17). Here, we analyze social network adjustments to a large-scale natural disaster to quantify short- and long-term aspects of network formation and dynamics.

Disasters wreak havoc on individuals and communities and can result in deaths, disruptions to daily life, and jeopardized resources and future earnings (35–37). Although government agencies, such as the Community and Regional Resilience Initiative and the Red Cross, provide relief in the short term, immediate rescue and aid efforts heavily rely on ad hoc and grassroots undertakings (35, 38–41). Social mechanisms that facilitate adjustments to these shocks, however, are a matter of debate in the scientific community. On the one hand, communities can build resilience to future disasters by institutionalizing those initial grassroots efforts, strengthening social ties, and increasing embeddedness (38, 41). Often, disasters also have deep emotional and psychological impact, which promotes strong emotional bonding and consequently, leads to providing aid to kin types (35, 42). On the other hand, other researchers conjecture

Significance

This paper presents an empirical analysis of the short- and long-term causal effects of a hurricane on social structure. Establishing causal relationships in social network formation and dynamics has historically been difficult because of the complexity of engineering social relations in a controlled environment, and the lack of time-resolved data about individuals' behavior. In addition, large-scale interventions of network structure are not feasible in practice. Here, we design an observational study that enables the estimation of causal effects by leveraging the locally well-defined impact of a hurricane. This aspect allows us to conceptualize the analysis of individuals' behavior as a natural experiment, where the intervention is randomized by nature to locales, leaving only issues of balance to consider.

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[†]The conceptual construct of natural experiment aims to describe analysis settings "in which social and political processes, or clever research-design innovations, create situations that approximate true experiments" (9). These typically are observational settings in which causes are randomly, or as good as randomly, assigned among some set of units, such as individuals, towns, districts, or even countries. Simple comparisons across units exposed to the presence or absence of a cause can then provide credible evidence for causal effects, because random or as-if random assignment obviates confounding. Natural experiments can help overcome the substantial obstacles to drawing causal inferences from observational data, which is one reason why researchers from such varied disciplines increasingly use them to explore causal relationships (9). The technical issue is the need to assume, explicitly, that nature is randomizing the assignment of treatment, conditional on some covariates. Theory and applications of carefully framed natural experiments are discussed in refs. 10–15.

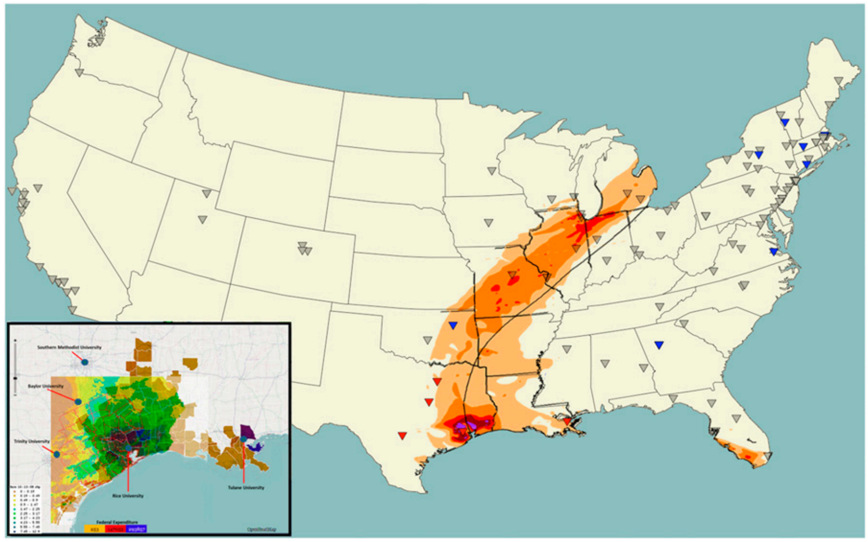

Fig. 1. Hurricane Ike's storm path by rainfall. Five universities (red) were severely affected by Hurricane Ike; 10 universities (blue) were used as the control group, and another 115 other universities (gray) were excluded from the main analysis. *Inset* shows the concentration of aid (green) for recovery from the Federal Emergency Management Agency.

that families mitigate the negative consequences by expanding their connections to outside communities, such as through marrying their daughters to distant farming villagers during periods of drought (43). Disasters can also have long-term divisive effects on communities (36). Despite national and international interest, a characterization of the causal mechanisms that support recovery remains elusive, and estimation of the effects of disasters on the social matrix remains challenging.

Here, we investigate the short-term and long-term causal effects of natural disasters on network formation and evolution by considering the effects of Hurricane Ike on a sample of 1.5 million college students enrolled in 130 universities in the United States. Our data span 4 years, and includes more than 630 million messages and 590 million posts. Because the path of the storm is plausibly "as good as random," we conceptualize the hurricane as a randomized intervention, and compare network-level outcomes for affected and unaffected universities. This natural experiment allows us to understand how interactions on Facebook are used to access resources and build a social support infrastructure in response to the hurricane, after 4 and 52 weeks.

From a statistical perspective, a natural experiment uses historical (observational) data as an effective means to identify causal mechanisms (44–47). Natural experiments (48) further qualify a subset of observational studies where plausible experiments can be conceptualized. According to Dunning (48), events that lead to settings that he terms natural experiments are accidental and allow for causal insight into interventions that would otherwise be not feasible. In addition, because Hurricane Ike was an unexpected event, we arguably avoid the selection bias often associated with artificial interventions, which may lead individuals to behave differently. In this sense, natural experiments are similar to randomized experiments. However, in a natural experiment, there is no control on the treatment assignment mechanism. Technically, we need to assume explicitly that nature is randomizing the assignment of treatment, conditional on some covariates (10–13). We conceptualize affected universities as the treatment group and compare them with similar but unaffected universities, conceptualized as the control group. Because Hurricane Ike is the key differentiator between these two groups, alternative explanations on network changes, such as seasonality effects, population-wide events, and changes in technology or platforms, are ruled out. Our statistical analysis examines the causal effects of Hurricane Ike on how students form relationships in the short term and the extent to which these relationships persist in the long term. Detailed balance checks are provided in *SI Text*.

From a substantive perspective, social media platforms offer users a medium to establish and maintain relationships, and as a result, they can shed light on the dynamics of offline relationships. In the event of disasters, social media platforms provide an efficient and effective communication medium for one-on-one interactions and broadcast calls (e.g., for assistance or dissemination and access to useful information).

Each year, approximately six hurricanes form over the Atlantic Ocean, and up to five make landfall in the United States over 3 years (www.nhc.noaa.gov/). At its peak, Hurricane Ike had a diameter of 600 mi, with sustained winds exceeding 145 mph. Hurricane Ike made landfall in September of 2008, carving a path of destruction from Louisiana to Corpus Christie, TX and traveling up the Midwestern states until finally dying out in Michigan. Fig. 1 shows Hurricane Ike's path in terms of rainfall. Causing over $29 billion in damages and 195 deaths, Hurricane Ike became the second costliest hurricane in US history. Hurricane Ike was also unusual in that it affected communities less accustomed to hurricanes. Many of these communities were not directly hit by Hurricane Katrina 3 years earlier. Furthermore, unlike Hurricane Katrina, basic services and institutions resumed within weeks after Hurricane Ike made landfall, albeit with temporary and localized displacement of individuals and facilities. This fact is critical to our analysis, because access to Facebook and communication technology was not greatly affected. Furthermore, there was little relocation away from affected communities as a result of Hurricane Ike unlike in other cases of disasters, manmade or natural (35, 49).

Using Hurricane Ike as the context of our research, our study provides insight into how natural disasters affect the formation and dynamics of social relationships online as well as offline. Our findings suggests that humans may tighten social relationships as a behavioral response to cope with harsh environmental conditions. In this case study, such a collective response may help restore communities and increase resilience to future disasters. Policymakers should consider leveraging this organic behavioral response to effectively aid affected communities in the aftermath of natural disasters.

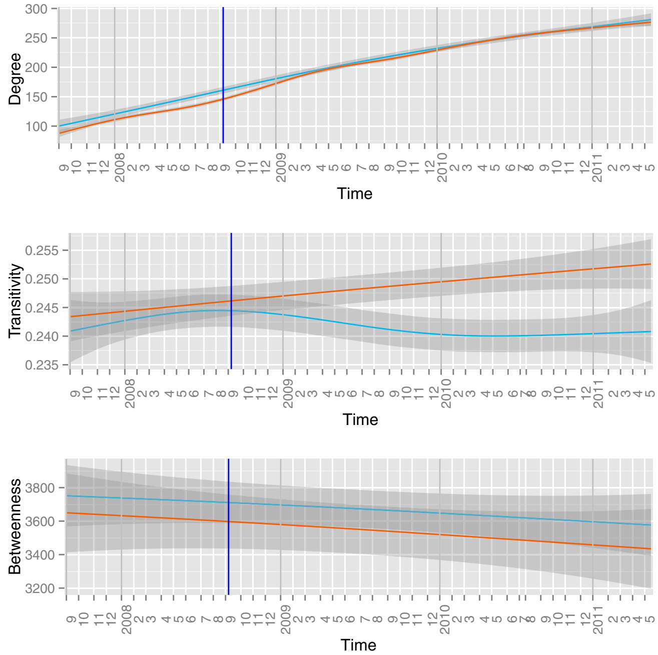

Fig. 2. We plot estimated outcomes (average degree in *Top*, transitivity in *Middle*, and average betweenness centrality in *Bottom*) for 64,957 students who attended 5 universities affected by the hurricane (treatment group; red) and 10 universities not affected by the hurricane (control group; blue) over a period of 192 wk (54 wk before the hurricane and 138 wk after the hurricane). The solid curves were fitted using locally weighted scatterplot smoothing, and the shaded gray regions show the 95% confidence bands for these curves. Hurricane Ike made landfall during week 0, which is marked by the blue vertical line. Details are in the text.

Data and Study Design

We sought to study the effects of the hurricane on affected universities, rather on individuals in affected and unaffected areas, in the spirit of (34). We started with a list of 130 universities in the United States and collected background characteristics for them. We identified affected universities based on geographic location, the amount of rainfall they suffered due to Ike, and the amount of Federal Emergence Management Agency (FEMA) claims made. Then, in collaboration with Facebook, we collected anonymized data on 1.5 million college students for these 130 universities and generated pairs of comparable universities. We carried out the analysis by identifying universities most affected by the hurricane as the treatment group and comparing it with similar but unaffected universities as the control group. Universities in the control group were identified using matching (45, 47, 50–54). The data have been archived at Facebook. This research was determined not human subject research by Harvard Institutional Review Board.

Prior studies have used propensity score matching (PSM) successfully in distinguishing between homophily-driven contagion and influence using micro-level data (55, 56). In the absence of assumptions such as those underlying PSM, it might not be possible to disaggregate network formation effects from correlated behavior using observational data alone (27). Our analysis on the other hand utilizes uses coarser university-level data to understand how individuals within organizations respond to disasters.

We identified the 5 universities most affected by Hurricane Ike as the treatment group (Baylor University, Rice University, Southern Methodist University, Trinity University, and Tulane University) and compared the network dynamics of their students with those in a control group of 10 universities (Colgate University, The College of William and Mary, Georgia Institute of Technology, Middlebury College, Smith University, Tufts University, University of Pennsylvania, University of Tulsa, University of Utah, and Yale University) with similar aggregate characteristics according to PSM analysis. We matched on the number of registered users before Hurricane Ike (Table 1). We did consider other factors, such as college ranking according to *USNews*, whether these colleges are public or private institutions, tuition fees, and other regional factors. We focused on the number of students, because our network-based response variables are most sensitive to the number of nodes; *SI Text* contains details on the PSM analysis and additional balance checks. We analyzed each university separately; membership was assigned to students whose birth year was between 1985 and 1990—the birth years of the average college students during the time window that we analyze—using self-reported attendance at each university. We analyzed the dynamic network structure and evolution in each university as well as the level of activities in terms of the number of posts and private messages. The level of peer-to-peer messaging is an indicator of social interactions and social tie strength (34).

Social media platforms have increasingly replaced other means of communication, such as telephone and emails, especially among college students and thus, can shed light on the complexity of social behavior (30, 34, 57). The focus on college students comes with the benefit that college years represent a critical stage of development and growth when lifelong social ties and communities are formed.

Empirical Analyses

We considered five quantitative aspects of friendship formation and dynamics in the treatment and control groups. First, we investigated whether there is a difference between the number of friends (i.e., average degree) among the two groups. Second, we examined with whom individuals make friends (whether it is with others close to them or not). Third, we looked at the volume and type of communication in the treatment and control groups. Fourth, we characterized the range of communication between individuals. Fifth, we investigated the extent to which affected and unaffected individuals engage in preferential attachment behavior. Code to reproduce the analyses is available upon request.

Size of Personal Networks. We analyzed friendship data over time to quantify how tight-knit communities emerged in the aftermath of Hurricane Ike. First, we compared the number of friends (namely, the average degree) of individuals in the treatment and control groups before and after Hurricane Ike. Fig. 2 shows that

Table 1. Number of students in the affected and unaffected universities who registered before Hurricane Ike

Universities	No. of Users
Affected universities	
Baylor University	8,462
Rice University	2,355
Southern Methodist University	4,324
Trinity University	1,882
Tulane University	4,505
Unaffected universities	
Colgate University	2,359
The College of William and Mary	4,446
Georgia Institute of Technology	8,703
Middlebury College	2,374
Smith University	1,874
Tufts University	4,337
University of Pennsylvania	8,644
University of Tulsa	1,877
University of Utah	4,296
Yale University	4,519

Table 2. Paired *t* tests using a 4-wk window before and after Hurricane Ike

Quantity	Treatment	SE	Control	SE	*P* value	*t* Statistic
Messaging	0.2654	15.5189	0.3470	32.1653	0.3628	−0.9100
Posting	−0.0871	8.6791	0.1209	9.3832	0.0000	−5.8176
No. of recipients	0.0196	3.4011	0.0597	3.7235	0.0044	−2.8498

individuals maintained similar numbers of friends over time in both the treatment and control groups. This result supports the notion that humans are able to maintain a fixed number of relationships based on their cognitive abilities (58). Individuals' ability to maintain relationships is also limited by other constraints.

Second, we analyzed the amount of social interactions and the number of messages passed between users.

Connecting with Friends of Friends and Bridging Relations. We focused on a measure of transitivity (59), which captures the proportion of triadic relationships among all of the possible triadic relationships for a given number of friends. Although students in the treatment group are making the same numbers of connections as those in the control group, we see a statistically significant difference with respect to with whom they connect. Students in the treatment group were more likely to connect with friends of friends, thereby boosting their transitivity measure (2), than those in the control group. Fig. 2 shows the extent to which transitivity diverged after the hurricane. Although students in the treatment group increased transitivity, students in the control group decreased transitivity in both the short term and after 2.5 y. The control group provides a reasonable baseline for the overall Facebook use, which may be affected by global confounders, such as factors that affect the adoption and use of the site, outside events, and the natural behavior of students using the service throughout the academic calendar. We find that students in both groups tend to decrease their transitivity in the autumn months as new students arrive on the university campus. However, transitivity generally increases soon after as the students' networks stabilize (34, 60). In the context of generally increasing friendships as suggested by the previous analysis, comparing the trend lines after Hurricane Ike suggests that students at unaffected universities used Facebook to reach outward to individuals in other circles rather than to friends of friends. This type of behavior has been associated with decreasing social segregation (61). However, affected students tended to connect with friends of friends substantially more than students in unaffected universities, increasing triadic closure and transitivity. Furthermore but to a lesser extent, betweenness, a measure of the extent to which an individual plays a role in connecting others, decreased more among affected students than among nonaffected students in both the short and long terms (Fig. 2). We speculate that these bonds persist well beyond the occurrence of the natural disaster because of psychological effects. People who contemplate the possibility of their own death often cope by spending more time with their friends and family (42, 62, 63). This decrease in betweenness also result in increased collaboration when affected individuals contribute to the group (24, 64). Indeed, we find that students who experienced the hurricane formed more tightly knit relationships with each other.

Posting and Messaging Behavior. We examined the wall posting and student-to-student messaging behavior in the treatment and control groups. Examining the 4-wk window before and after Hurricane Ike, in Table 2, we find that, on average, affected individuals produced 2.99 posts per week before Hurricane Ike and 2.90 posts per week after Hurricane Ike, a 3% (−0.0871) reduction in the short term. In contrast, individuals in the control group produced 3.65 and 3.77 posts per week before and after Hurricane Ike, respectively, a 3.3% (0.1209) increase. The treatment group wrote, on average, 2.82 messages per week before Hurricane Ike and 3.09 messages per week after Hurricane Ike, a 9% (0.2654) increase in the short term. Similarly, the control group wrote, on average, 3.89 messages per week before Hurricane Ike and 4.34 messages per week after Hurricane Ike, a 9% (0.3470) increase. Contrary to the work by Gao et al. (65), our short-term finding suggests that affected individuals continue to use Facebook and private messaging features at similar rates, but they decrease their posting behavior. These posting and messaging patterns persist in the long term (Table 3).

Number of Unique Recipients. We examined the number of unique recipients of the messages. A higher number indicates that individuals interact with a wider range of others, while a smaller number indicates that individuals focus their attention on a smaller, possibly more intimate, group. Students affected by the hurricane sent messages, on average, to 0.97 recipients per week before Ike, and to 1.0 recipients per week after Ike, a 2% (0.0196) increase as reported in Table 2. Unaffected students sent messages, on average, to 1.22 and 1.29 recipients per week, before and after Ike, respectively, a 4.9% (0.0597) increase. Table 2 reports the summary statistics using a four-week window before and four-week window after Ike. These effects persist in long-term as shown in Table 3, where the same statistics are computed over a 52-week window before Ike and 52-week window after Ike. In the context of the equal level of communication established in the previous section, for both groups, before and after the hurricane, these results suggest that affected students were communicating within their established networks, focusing their interactions on fewer people, while unaffected students engaged in a broader communication outreach.

Preferential Attachment Dynamics. We investigated the extent to which Hurricane Ike affects preferential attachment dynamics in friendship formation (66); that is, the fact that friendships are chosen proportional to degree (59, 67). Preferential attachment leads to scale-free social structure, which in turn, helps spread information efficiently and provides quick access to knowledge and resources (68). We compared the treatment and control groups in our matched design using a fixed effects model, where we used the degree of student i in week t as the dependent variable $D_i^{(t)}$. The model is as follows for 64,957 students in 15 matched universities over 192 wk:

$$\begin{aligned} D_i^{(t)} = {} & \alpha_i + \beta_1 D_i^{(t-1)} + \beta_2 I_{\text{after}}^{(t)} + \beta_3 I_{\text{after}}^{(t)} Z_i \\ & + \beta_4 D_i^{(t-1)} I_{\text{after}}^{(t)} + \beta_5 D_i^{(t-1)} Z_i \\ & + \beta_6 I_{\text{after}}^{(t)} Z_i D_i^{(t-1)} + \epsilon_i^{(t)}, \end{aligned} \quad [1]$$

where $D_i^{(t-1)}$ denotes the degree of student i in week $t-1$, Z_i indicates whether student i is in the treatment group, and $I_{\text{after}}^{(t)}$ indicates whether week t is after the hurricane. Table 4 reports the results of this analysis. We find that preferential attachment in friendship formation describes the behavior of all students well and that the behavior gets more pronounced after

Table 3. Paired *t* tests using a 52-wk window before and after Hurricane Ike

Quantity	Treatment	SE	Control	SE	*P* value	*t* Statistic
Messaging	0.0204	5.4548	0.0267	10.0864	0.4393	−0.7733
Posting	−0.0067	3.2523	0.0093	3.7682	0.0000	−4.1947
No. of recipients	0.0015	1.1383	0.0046	1.3107	0.0205	−2.3168

Table 4. Estimating a model of preferential attachment dynamics

Coefficient	Effect	Estimate	SE	t Value
β_1	$D_i^{(t-1)}$	0.9967	$2.4579 \times 10e-5$	40,552.3543
β_2	$I_{\text{after}}^{(t)}$	0.4769	$3.1256 \times 10e-3$	152.5746
β_3	$I_{\text{after}}^{(t)}\ Z_i$	0.1356	$5.4359 \times 10e-3$	24.9362
β_4	$D_i^{(t-1)} \times I_{\text{after}}^{(t)}$	−0.0027	$1.7402 \times 10e-5$	−154.0051
β_5	$D_i^{(t-1)} \times Z_i$	0.0026	$4.213 \times 10e-5$	59.8139
β_6	$D_i^{(t-1)} \times I_{\text{after}}^{(t)} \times Z_i$	−0.0014	$4.213 \times 10e-5$	−43.0399

$R^2 = 0.9988$, 64,957 students, and 13,577,088 effective observations (72). All reported coefficients are significant at P value $< 2.2 \times 10e-16$.

Hurricane Ike. However, the negative three-way interaction implies that students in the affected universities are less prone to this behavior than the control group after Hurricane Ike, likely reflecting a different set of priorities at play for them. Technically, we are using fixed effects to model serial autocorrelation; thus, there is a concern that the dependent variables do not satisfy the independent and identically distributed (IID) assumption empirically—they do not in theory. However, recent results suggest that regression analysis and mixed effects models on non-IID data (69, 70) may be valid depending on the amount of correlation between the units of analysis. We expect that IID violations for most of the responses that we consider will lead to negligible losses in efficiency on the estimates of interest.

Discussion

We presented a study of how college students adjust their social dynamics in response to a hurricane. Whether or not the main findings in this study hold in the affected communities along the Gulf Coast, more generally, is an open question. For instance, fishermen along the Gulf Coast of Louisiana are likely not heavy Facebook users, and most of them have never attended college. Thus additional studies should be carried out to characterize social dynamics among some of the most affected subpopulations during a hurricane. Such a line of research presents several challenges, however, as outlined in the introduction. Our study provides a starting point for future research along these lines by suggesting testable hypotheses about social dynamics in the larger population.

We find that individuals affected by the hurricane formed significantly more close-knit groups, both in the short term and in the long term, compared to unaffected individuals. Although students in both groups maintain a comparable number of friends within their social networks, over time, individuals who experienced the hurricane tend to form new relationships with friends of friends. This behavior results in higher triadic closure and transitivity when compared to unaffected individuals. Affected students also reduced their role in connecting others. These effects lasted up to three years after the hurricane. Community structure can provide a strong social medium for efficient information and resource flow, as well as psychological and emotional support. While students affected by the hurricane continue to use Facebook, they reduced public posting. And while affected students send messages to fewer people, they do increase the interactions with those they communicate with, strengthening existing social ties. Affected students also are less prone to preferential attachment dynamics than unaffected students, thus displaying a shift from a typical friendship formation pattern.

In this paper, we conceptualized a natural experiment to quantify the effects of Hurricane Ike on mechanisms driving the formation and dynamics of social relationships. Our results suggest that major disasters lead individuals to form close-knit groups and strengthen their social ties. In contrast to prior research, our findings show that these social effects can last up to several years after the event. Such a tighter and lasting social matrix has the potential to positively influence individuals' future outcomes, including job prospects, social status, and access to information (7, 71). We speculate that social network formation processes induced by traumatic events are more stable than those driven by individual volition, and may have developed as a social mechanism to cope with a hostile environment.

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