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Patterns of Social Support and Trajectories of Household Recovery after Superstorm Sandy: Contrasting Influences of Bonding and Bridging Social Capital

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Abstract: Understanding how vulnerability conditions are related to disruptions in social support and trajectories of recovery after disasters is important for promoting resilience. Based on household survey data from New Jersey counties impacted by Superstorm Sandy, a hierarchical clustering method was utilized to classify recovery trajectories as well as common patterns of social support reflecting contrasting dimensions of social capital over time. Residents with a higher level of home damage relied largely on institutional sources for material and information support over the course of recovery. Younger and higher-income residents had a higher proportion of informal sources, particularly for emotional support. Patterns of social support were associated with recovery trajectories when vulnerability and disaster impact were controlled, where institutional sources for material and informational support combined with informal sources for emotional support were associated with quicker recovery trajectories. Results provide implications for bonding and bridging forms of social capital in recovery and motivate research and investments for assessing and cultivating both informal relations and institutional networks from which postdisaster social support can be mobilized. **DOI: 10.1061/(ASCE)NH.1527-6996.0000548.** *© 2022 American Society of Civil Engineers.*

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Introduction

Social capital, or value embedded within social structures (Woolcock and Narayan 2000), emerges as important for individuals and communities in the aftermath of natural disasters. Social capital influences economic and social activities after disasters as a function of the trust, norms, and relationships in networks (Nakagawa and Shaw 2004). The definition of social capital by Bourdieu (1985) addresses resources that result from a durable set of network relationships. Several elements comprise social capital and influence the extent and utilization of these resources, including the number and readiness of people to provide help, the available resources, and the density of the social network (Bourdieu 1985).

The operation of these elements of social capital is constrained in disaster situations. For example, the level of damage influences the motivation of impacted individuals to cooperate and coordinate social capital resources (Kawamoto and Kim 2015). Potential sources of aid, like personal contacts and institutionalized relief, tend to be limited in their ability to organize and assist. Likewise, in more impacted areas where residents are displaced, social capital can also be difficult to mobilize logistically (Aldrich 2011).

The exchange of social support in an individual's interpersonal and broader social ties is a behavioral manifestation of various elements of social capital. In other words, social support is a dynamic set of resources, like information sharing and esteem building, that can be derived from a person's network. Receiving social support is crucial to long-term coping with adverse situations including natural disasters (e.g., Kaniasty and Norris 1993). Theoretical models conceptualize recovery as a process (Kates et al. 2006; Quarantelli 1990), suggesting that the trajectory of recovery varies across individuals and social groups. Beyond physical and material factors such as the magnitude of damage and the restoration and reconstruction capacity of communities, vulnerability and protective factors impact the extent to which individuals can access recovery resources (Kates et al. 2006).

Prevalent vulnerabilities for disaster recovery include demographic factors like marginalized race or ethnicity and lower socioeconomic status and community attributes like higher population density (Cutter and Finch 2008), whereas examples of protective factors include better mental health and more social support (Hetherington et al. 2018). The loss of social networks is well-established as contributing to lower quality of life during long-term recovery (e.g., Stough et al. 2017). However, the extent to which social support and recovery move in tandem or in conflict with each other over time is less clear due to scant research empirically tracking received social support and recovery outcomes across multiple time points. In addition, it is important to examine how vulnerable populations may be disproportionately affected by disruptions in social support in an extended period of time. In other words, are there any identifiable patterns in which social support of

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certain types and from certain sources diminishes over time for households from different demographic and socioeconomic backgrounds? How do these changes in social support influence the course of recovery? Understanding the relationship among vulnerability conditions, social support, and recovery has implications for promoting long-term resilience and rebuilding outcomes.

Superstorm Sandy provides a useful context for examining long-term social support and recovery because it was one of the most damaging hurricanes in history and the recovery was, and continues to be, lengthy and arduous. Superstorm Sandy made landfall in the US on October 29, 2012, producing record high tide levels and powerful storm surges along the New Jersey and New York coastlines (Blake et al. 2013). Over 1 year later, only half of the survivors who requested assistance from the Federal Emergency Management Agency received it, leaving 30,000 residents of New York and New Jersey displaced (McGeehan and Palmer 2013). And 5 years after the hurricane, former residents still struggled to rebuild and remained displaced (Devecka-Rinear et al. 2017).

This study develops and predicts typologies of social support garnered in long-term recovery based on retrospective survey data collected from households impacted by Superstorm Sandy. The data capture three dimensions of social support (i.e., instrumental, emotional, and informational). In addition, three major sources (i.e., informal, institutional, and online ties) of received support are measured, which reflect contrasting forms of social capital. After discussing theoretical approaches to examining social support and social capital over time, we test and answer two exigent questions: (1) whether and how indicators of vulnerability conditions impacted the patterns of social support individuals accessed during long-term recovery; and (2) whether and how these typologies of social support influenced the reported trajectory of household recovery.

Literature

Recovery and Support as Long-Term Processes

The disaster recovery process evolves over time as households and communities move through various phases. Some definitions of recovery phases are based on time following the disaster (Drabek 1986), and others emphasize the specific actions undertaken (Dynes and Quarantelli 1989; Oloruntoba et al. 2018). These two aspects are sometimes blended, as by Kates et al. (2006), who identified a sequence that include the emergency phase (e.g., searching and rescuing, and emergency sheltering), restoration phase (e.g., returning and repairing), Reconstruction I (e.g., rebuilding and replacing), and Reconstruction II (e.g., commemorating and bettering, making improvements exceeding pre-event conditions, and ending the recovery process). These phases are not always distinct segments of similar durations but may overlap.

Further, both continuity and change characterize the pathways to recovery and resilience, directing attention to the ways in which communities may persist in a similar state or experience transformations in postdisaster periods (Masten and Obradović 2008). Due to these fluctuations that exist in the recovery process, measuring recovery at a particular point in time does not fully show the capacity of individuals and communities to move forward after a crisis (Marin et al. 2015). Adaptive capacity of households and communities, reflected in the length, patterns, and outcomes of the recovery phases, can be influenced by the background conditions (e.g., vulnerabilities) as well as actions carried out before the event (e.g., mitigation and preparation), during the event, and in earlier recovery phases (Neal 1997; Smith and Birkland 2012).

Protective factors such as social support provide a buffer against adverse impacts. Similar to recovery, social support constitutes a process over time. In long-term recovery, being able to receive sustained support is important but challenging. The community support fostered during the response and relief phases of natural disaster have been termed the honeymoon phase because volunteers are more likely to commit to restoration during this time (Silver and Grek-Martin 2015). Yet, community perceptions of togetherness felt initially dwindle after disasters (Moore et al. 2004), implying the difficulties of sustained support provision. Natural disasters have been referred to as a "double jeopardy" for victims; victims must have access to social support and yet the disaster likely weakens their networks of support (Kaniasty and Norris 1993).

Recent research suggests that bonding social capital (e.g., seeking resources from within one's immediate network) and bridging social capital (e.g., expanding efforts outside of one's local network) play different roles across disaster recovery phases (Nguyen-Trung et al. 2020). Some suggest that collectively oriented communities with close personal and family ties may have advantages in long-term recovery, whereas more individualized communities may perform better in short-term recovery (Hill and Hansen 1962). After a tsunami in Chile, an important factor in explaining if small-scale fishing organizations were able to achieve desirable outcomes was whether they were able to maintain their pre-existing level of social capital and gain access to potential resources (Marin et al. 2015). Similarly, it can be reasoned that variation in the types and sources of support provided to households over time likely influences recovery trajectories.

Empirical research observing the processes of social support and long-term recovery is rare. Due to challenges associated with gathering and analyzing data over long periods of time, studies have largely collapsed the level or patterns of recovery and social support into aggregate indicators (Lee et al. 2019). These approaches tend to assume a linear relation between social support and recovery outcomes. However, attention is needed to the temporal dimensions in studies of the recovery process, particularly the extent to which pre-event vulnerability conditions and postevent conditions of interest, like social support, contribute to long-term recovery trajectories.

Linking Vulnerability with Types and Sources of Long-Term Social Support after Disasters

This study unpacks social support by paying attention to both the types and sources of social support. Social support is multidimensional in the sense that people need multiple types of support. Three differentiated types of support after disasters are typically identified: instrumental, emotional, and informational support (Norris et al. 2008). These types of support provide individuals with resources, such as financial assistance, cathartic conversations, and procedural clarification, that can facilitate their rebuilding and resilience. In addition, households affected by disasters typically have multiple types of support sources. Informal support may be received from kin networks, friends, and neighbors (Quarantelli 1990). Personal social networks are often viewed as greater sources of disaster relief than government agencies (Forgette et al. 2009; Lee et al. 2020). Support can also be received from institutionalized networks of agencies and programs offering disaster relief. Research is also progressively emphasizing social support organized through various online platforms after natural disasters (e.g., Taylor et al. 2012).

The ability to obtain social support depends on a variety of factors. Survivors generally report experiencing much less aid than they expected, with greater disaster exposure being associated with

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lower perceptions of support and social participation (Kaniasty et al. 1990). Household damage after a tornado positively predicted the receipt of instrumental support, like transportation, food, and shelter (Lee et al. 2019). Along with disaster characteristics, different types of support are subject to varying levels of demand and supply depending on individual's sociodemographic characteristics that may make them vulnerable. Vulnerability refers to external or contextual circumstances which make individuals or social groups more susceptible to damage when being exposed to disasters (Adger 2006; Cutter et al. 2003). Specific vulnerabilities in long-term recovery include household poverty, land holdings (i.e., rented or owned land), and ethnicity (Nguyen-Trung et al. 2020).

Some vulnerability conditions may preclude one from receiving instrumental support in particular, as in the case of retired residents having difficulty acquiring bank loans for rebuilding (Quarantelli 1999). Dimensions of support can also be differentiated by gender, with females being more likely to receive emotional and informational support (Lee et al. 2019). Similarly, findings indicate that informal support, or support originating from bonding ties that involve kin and friend relationships, are more likely to be experienced by people with low income and education (Marsden 1987; Nakagawa and Shaw 2004).

Although these studies provide helpful insights on the relationship between vulnerability conditions and social support, there is limited knowledge about how these findings apply to long-term recovery after disasters. In addition, disaggregating the concept of social support by types and sources can allow for a more nuanced understanding of households' postdisaster experiences. How does a household's access to social support over time depend on their vulnerabilities? Are there indicators of vulnerability conditions that lead to rapidly diminishing social support, particularly for certain types or sources of support? For example, the disaster situation may present a quicker decline of informal support provision for vulnerable populations. Hypothetically, the weakening of social networks may be observed to a greater extent among low-income populations due to a greater need to attend to immediate work and family concerns such as securing economic and material resources. Because examination of the full spectrum of social vulnerability conditions (e.g., Cutter et al. 2003) in the social and built environment is beyond the scope of the current study, the following hypothesis focuses on demographic and socioeconomic characteristics:

Hypothesis 1 (H1). Indicators of households' vulnerability conditions (i.e., respondents' age, sex, marital status, and household income) will influence the pattern of social support received during long-term recovery measured by changes in the types and sources of support after disaster impact is controlled.

Patterns of Social Support and Trajectories of Postdisaster Recovery

The strategies implemented throughout recovery are not always equitable across populations (Dynes and Quarantelli 1989) because pre-event conditions of a household impact recovery trajectories. The literature has suggested various factors that impact the recovery process. The effects of the disaster on a community, such as damage to retail facilities (Liu et al. 2012) and time taken to restore key utilities (Cimellaro et al. 2010), are important considerations for household recovery. Additionally, Smith and Birkland (2012) argued the extent to which a community has planned for recovery, as well as its funding and technical infrastructure, influence the progression of recovery. The presence of formal and informal organizations in the area postevent also has an impact (Bolin and Bolton 1986) because federal, state, and local resources vary in their distribution.

Along with these community-level characteristics, two key individual-level factors impact the process of recovery: conditions of vulnerability and protective factors such as social support. Vulnerability is often linked to disadvantaged demographic characteristics. Predisaster inequalities relate to varying trajectories of population return and recovery for different sociodemographic segments (Fussell 2015). Older populations and those of lower socioeconomic status have more difficulty returning to pre-event conditions (Quarantelli 1990). Older adults with higher vulnerability conditions (e.g., low levels of income, low functional ability, and more chronic medical conditions) and lower social support 4 to 6 years prior to Hurricane Sandy were more likely to have developed posttraumatic stress disorder syndrome after the storm (Heid et al. 2016). African American's perceived sense of recovery after Hurricane Katrina was predicted by their income and psychological distress (i.e., depression and anger), which was related to experiencing human loss and not having home insurance (Lee et al. 2009). Antecedent conditions of households such as adequate access to financial resources (Olshansky et al. 2012) and insurance also have an impact.

The ability to receive and mobilize social support is an important protective factor when responding to stressful situations such as disasters (e.g., Lee et al. 2020). Weak social support can cause greater levels of psychological distress and maladjustment (e.g., Holahan and Moss 1981). The quantity and quality of social support also has implications for effective and affective recovery. Recovery time is influenced by the strength of social support stemming from family, extended kin, and neighbors (Bolin and Bolton 1986). Kaniasty (2012) found that those people who received greater amounts of social support after a flood tended to more favorably appraise their communities and interpersonal networks; conversely, those who were dissatisfied with support reported lower levels of social psychological well-being (i.e., quality and quantity of their personal and communal bonds).

The amount and type of social support people need when dealing with a disaster change over time. An inverse relationship exists between social support received earlier in the year after a natural disaster and posttraumatic stress in later stages (Kaniasty and Norris 2008; Platt et al. 2016). When minimal community support develops after a disaster, communities may experience secondary trauma (Erikson 1976). Social networks of survivors from Hurricane Katrina decayed immediately after the storm and did not recover fully a year after, indicating social networks may lack resilience to natural disasters (Forgette et al. 2009). Because of secondary trauma, communities were unable to aggregate enough support to recover, ultimately leading to increased rates of crime and poverty (Gill 2007). Consequently, secondary trauma may be noticeable in recovery trajectories via a steep or sloping decline in perceived recovery. These studies suggest that the provision of social support earlier in recovery may have implications for earlier phases of recovery, as well as impacts in the long-term. When considering different types and sources of support, this study tests the following hypothesis:

Hypothesis 2 (H2). The patterns of received social support during long-term recovery measured by changes in the types and sources of support will influence the reported trajectory of household recovery, after indicators of vulnerability conditions and disaster impact are controlled.

Fig. 1 presents a summary of the relationships among variables tested in H1 and H2.

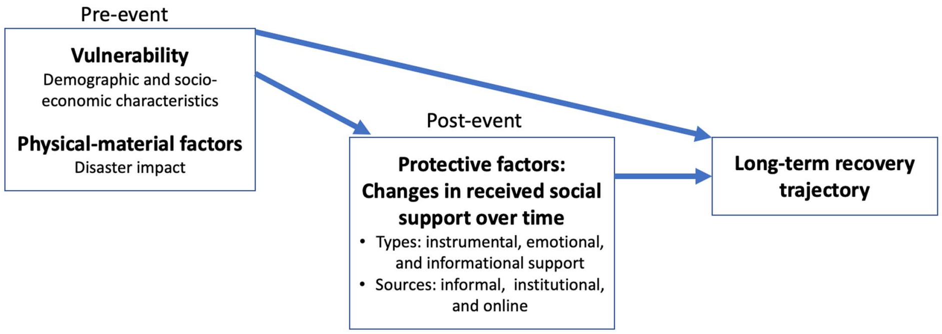

Fig. 1. Hypothesized relationships among vulnerability, patterns of received social support over time, and recovery trajectory tested in the study.

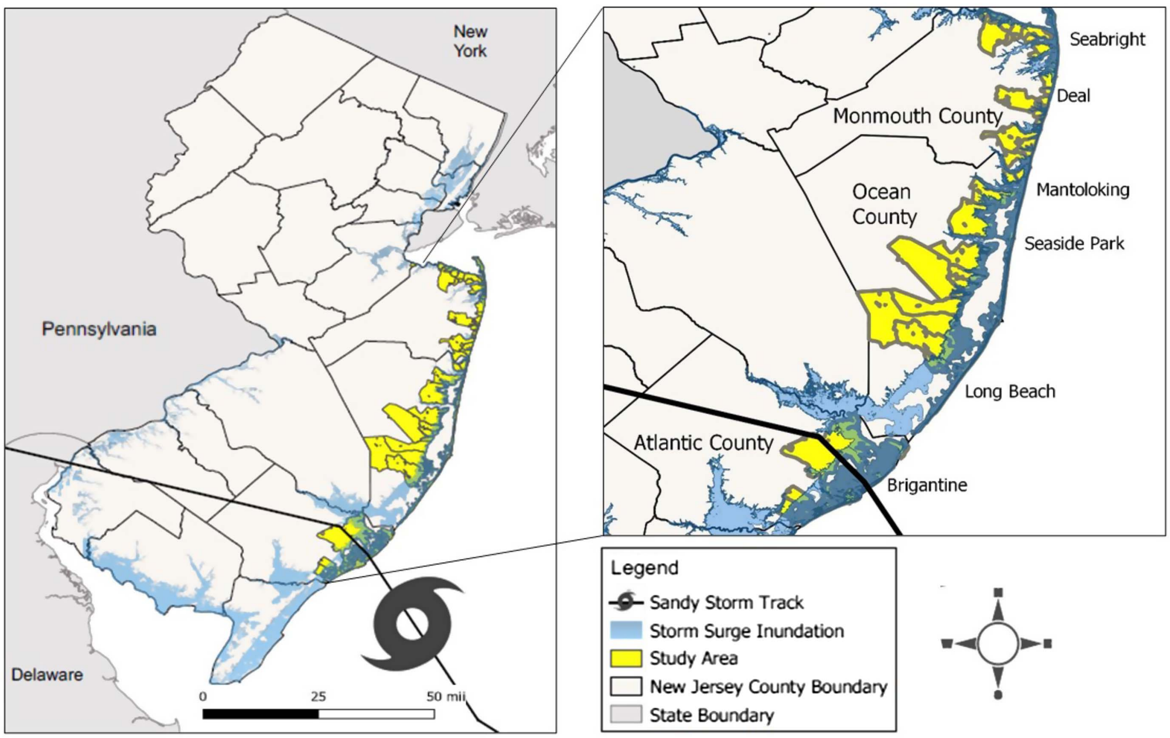

Fig. 2. Map of the study area from which household survey data were collected, Superstorm Sandy's track, and storm surge inundation. (Shapefile data courtesy of FEMA Modelling Task Force 2013; National Hurricane Center 2013; NJFloodMapper 2013.)

Methods

Data Collection and Sample Description

This study is based on a survey of New Jersey households' recovery experiences throughout the 5 years following Superstorm Sandy. Guided by information gathered through a series of focus group interviews of residents within Ocean and Monmouth Counties undergoing the household recovery process following the storm (Lee et al. 2020; Siebeneck et al. 2020), the survey included questions pertaining to the respondents' experiences during their initial and permanent return home, the restoration of key utilities and services in their home and township, their household's recovery, and their sources of instrumental, emotional, and informational support since the storm. To gather data about the recovery process, survey packets were mailed in March 2018 to 8,000 households located in Monmouth, Ocean, and Atlantic Counties in New Jersey. The sampling strategy focused on surveying households located within ZIP codes that reported damage to residential structures due to storm surge, inland flooding, and high winds (Blaikie et al. 1994; Blinski et al. 2015; Halpin 2013). In all, 46 ZIP codes, as shown in Fig. 2, were included in the study area.

Additionally, because the focus of this study is to examine household recovery, the sample was limited to only homeowners who lived at the same address during both Superstorm Sandy (2012) and at the time of the survey mailing. Guided by the previously stated criteria, a random stratified sample was utilized to solicit responses from residents within the study area.

Applying a modified version of Dillman's (1999) Tailored Design Method, participants were first mailed a survey packet in which they were introduced to the study and with provided a consent form to participate, a copy of the survey, and a preaddressed and stamped return envelope. Next, each household was sent a follow-up postcard reminder at 2 and 4 weeks after the initial mailing. Included in the survey packet and on the postcard reminders was a survey URL and QR code so the participants could opt to take

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Table 1. Comparison of sampled and County demographic characteristics

Demographic characteristics	Atlantic County		Ocean County		Monmouth County	
	Sample	Census	Sample	Census	Sample	Census
Female (%)	46.2	51.6	48.7	51.8	48.5	51.4
Median age (years)	63	41.5	62	42.9	60	43.2
Population over 65 (%)	41.3	16.9	43.1	22.3	32.9	16.6
White (%)	81.5	69.2	96	92.6	90.4	84.1
Median income (USD)	65,000–79,999	55,998	80,000–94,500	68,021	Over 95,000	95,699
Home ownership (%)	—	67.4	—	80	—	73.7

Source: Data from US Census Bureau (2019).

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the survey online. The first wave of surveys resulted in 438 completed responses, primarily from older households. To increase the number of completed surveys and to gain more data from younger households, a second wave of surveys were mailed out to 4,000 households selected at random from the original address list. These surveys were only mailed to prospective participants under the age of 50. The second wave yielded another 102 returned surveys. In all, 556 surveys were returned, achieving a response rate of 6.95%. The final data set for analysis includes 544 responses, which had an acceptable rate of completion.

In all, 280 respondents (51.6%) were male and 263 (48.4%) were female. The average age was 61.2 years [standard deviation (SD) = 12.1, median = 61] and participants were primarily Caucasian (92.2%) with annual household incomes over $95,000 (48.5%). Out of 544 respondents, 189 (34.7%) evacuated and 353 (64.9%) did not evacuate. Most respondents were homeowners (95.6%), with only 6 (1.6%) renters and 19 (3.4%) missing responses. The analysis excluded the six respondents who identified themselves as renters to focus on homeowners' recovery. In comparison with the population demographics of Atlantic, Monmouth, and Ocean Counties (Table 1), the sample was somewhat older and wealthier, possibly because the sample only included homeowners who were living at their current address during Superstorm Sandy and 5 years after. Although demographic data specific to homeowners were not available for the study area, homeowners in the US are generally older and have higher annual household incomes than renters (US Census Bureau 2020), providing evidence that the older age and higher household income of respondents by and large aligns with what would be expected for homeowners.

Variables and Measures

Respondents were asked to report about the people or groups that were the most important in helping with their return and recovery for three types of support. The three types included instrumental support (i.e., resources such as shelter, food, and help fixing home), emotional support, and informational support (i.e., information about which resources were available and whom to contact). For sources of support, respondents were given nine options regarding people or groups they received support from. The sources were classified into three categories in the analysis: informal ties (family and friend, coworker, or neighbor), institutional ties (relief groups or charity, FEMA, private insurance company, church or other faith-based groups, and local government and services), and online ties (people or groups known through social media or online). These questions about types and sources of support were asked for six time points: up to 1 week after Superstorm Sandy; up to 3 months; up to 1 year; up to 2 years; up to 3 years; and more than 4 years after Superstorm Sandy.

Respondents were also asked to rate the level of their household recovery at the same six time points, as well as at the time of their response. Respondents were provided a five-point scale of very good, good, fair, poor, and very poor for reporting their recovery, giving them the autonomy to self-identify what recovery meant to their household, as well as what the differences among good, fair, and poor recovery might be. In addition, respondents reported when they returned home initially, started rebuilding their home, returned home permanently, and completed rebuilding.

Demographic variables included age, sex, race/ethnicity, marital status, and income. Home location based on ZIP code was used to derive the distance from coast. For disaster impact, level of damage sustained by the home and by the town was self-reported, with damage being defined at the respondents' discretion. The following ordinal categories are used for home damage and town damage: none (0%), minor (1%–10%), moderate (11%–49%), major (50%–99%), and destroyed (100%).

Analysis

Studying how individuals access social support and evaluate their recovery over time involves the consideration of several dimensions. First, magnitude can be examined by observing the beginning level as well as the average level of support and recovery. Second, the overall trend (i.e., decrease, increase, or stay constant in the magnitude) as well as the rate of change (i.e., how fast the magnitude increases or decreases per unit of time) can be examined.

To consider magnitude, trend, and rate, the longitudinal patterns were grouped by similarity using a hierarchical clustering method. An agglomerative clustering method was used where the algorithm initially treats each observation as its own group (i.e., cluster), and merges similar groups into a bigger group based on similarity metrics Rokach and Maimon 2005). This bottom-up process is recursively performed until the total within-cluster variance is minimized, which is also known as the Ward's Method (Kaufman and Roussew 1990). Hierarchical clustering was adopted in this study given its advantage over other methods such as k-means, including not requiring assumptions about the distributions of the data and not requiring a predefined number of clusters.

To determine the number of clusters in each data set, the elbow method was used. The elbow method plots the explained variance as a function of the number of clusters and picks the elbow of the curve (i.e., a change of slope from steep to shallow) as the appropriate number of clusters to use. The algorithms were implemented in Python, by using functions implemented in the scikit-learn library (Pedregosa et al. 2011) which utilizes NumPy, Pandas, and SciPy libraries. Then, multinomial logistic regression was run to predict factors that explain respondents' membership in clusters of social support patterns and recovery trajectories.

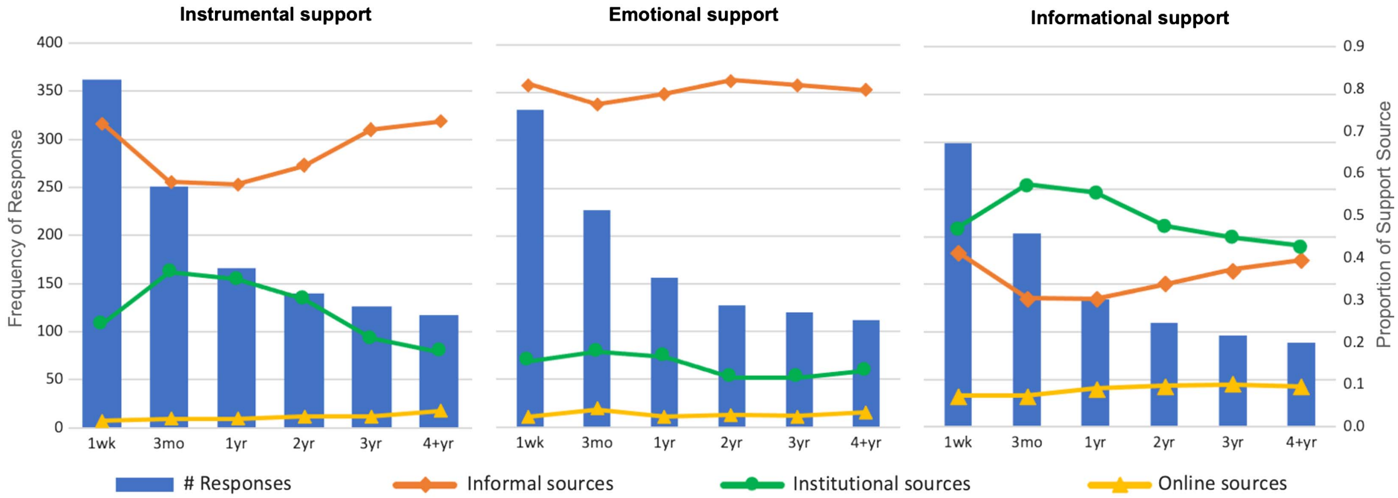

Fig. 3. Changes in the overall number of support sources (bar graph) and the proportion of each support source (line graph) for the three types of support over time. The number of support sources is measured as the frequency of support cases reported by the respondents. The proportion of each of the three support sources is measured as a percentage out of the total number of support cases.

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Results

Predicting Social Support Patterns (H1)

Fig. 3 shows changes in the pattern of the three types of support over the six time points. The bar graph shows the total number of support sources, which represents the frequency of support cases reported by all respondents. The total number of support cases decreases over time for all three types of support. Therefore, to examine the relative role each support source played over time, the line graphs were created. Each of the three lines display the proportion of each support source. For example, the line for informal sources shows the number of reported support cases from informal sources divided by the total number of support cases.

For instrumental support, informal sources played the biggest role. The proportion of support from informal sources was high immediately after the disaster, decreased slightly at 3-month and 1-year time points, and increased again in the longer-term recovery phase as shown for the 2-year time point and after. Institutional sources, on the other hand, had the largest role in the 3-month to 2-year time frame after the hurricane.

For emotional support, informal sources remained as the most frequently reported source by a large margin and remained stable over time. There were far fewer instances of institutional sources and online sources providing emotional support.

For informational support, institutional sources occupied the highest proportion of support sources for all time periods, with informal sources also playing a large role. Although the proportion of reported online sources was low across all three support types, it was relatively higher for informational support than in the cases of instrumental or emotional support.

Based on the hierarchical clustering method, we identified four clusters of residents for the pattern of received social support. A total of nine graphs displaying the combinations of each of the three support types and three support sources are shown in Fig. 4. The Y-axis of each graph in Fig. 4 indicates the frequency of reported support cases. The X-axis indicates six time points after the disaster. Based on observing the patterns extracted from the data, the name of each cluster is labeled as follows to improve our understanding and readability of the results:

- The cluster labeled the Minimal Support Cluster ($n = 178$) includes the largest number of respondents. Respondents in this cluster reported receiving overall little support from all sources throughout the six time periods for all three support types.
- The next largest is the Descending Support Cluster ($n = 93$). This cluster shows a moderate amount of support for all three support types and from all sources initially, but the support quickly decreases after the 3-month posthurricane time frame.
- Respondents in the Partial Support Cluster ($n = 66$) reported a large number of informal support sources in general. However, this cluster shows very few institutional sources, which distinguishes it from other clusters. The contrast between these two types of sources reflects the two differing forms of social capital, e.g., a stronger role of bonding social capital compared with bridging social capital.
- The cluster labeled Sustained Support Cluster ($n = 47$) is characterized by many cases of support from all sources for all types of support. In particular, this cluster indicates a distinctively high and stable level of support from institutional sources and online sources for all three support types. It reveals a lower number of informal sources for instrumental and informational support, yet a slightly higher number of informal sources for emotional support compared with the Partial Support Cluster.

Table 2 presents results from a multinomial logistic regression for predicting respondents' membership in one of the four clusters (H1). The table presents all independent variables included in the model. The Partial Support Cluster was selected as the base outcome in the model because this cluster is the most representative of respondents having bonding social capital (i.e., the key theoretical focus of this study), rather than bridging social capital. As mentioned previously, the Partial Support Cluster is comprised of people who received support from many informal sources and very few institutional sources.

First, the level of disaster impact was associated with the support patterns. Larger home damage was associated with belonging to the Sustained Support Cluster, where respondents reported more institutional and online sources overall, and less informal sources for information and instrumental support. Once disaster impact was controlled, several demographic characteristics predicted respondents' membership in different clusters. Respondents who lived

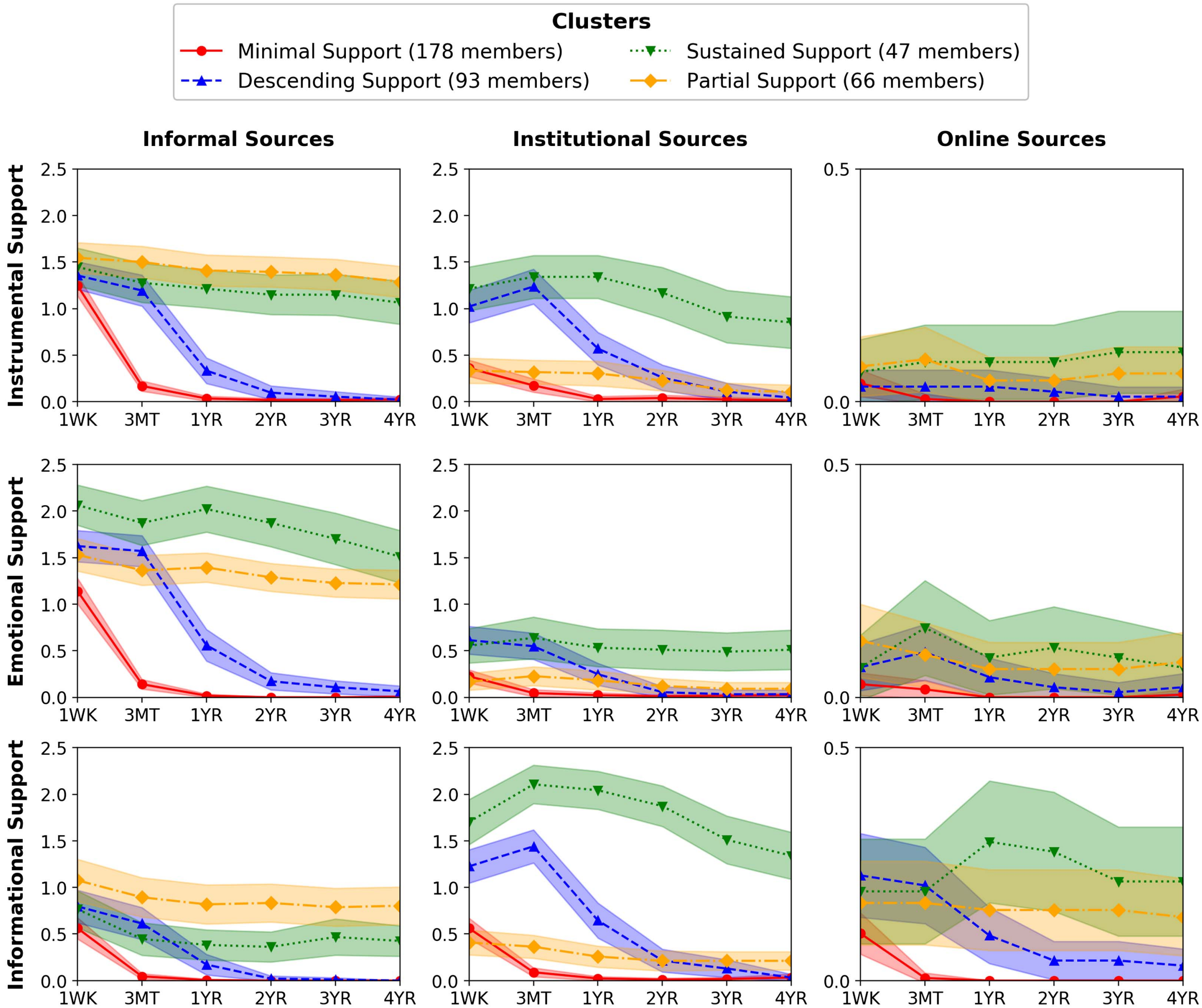

Fig. 4. Clustering results of patterns of social support over time, distinguished by the three sources (informal, institutional, and online, displayed as columns) and three support types (instrumental, emotional, and informational, displayed as rows).

longer in the impacted community had a higher likelihood of being in the Partial Support Cluster compared with the Minimal Support Cluster, indicating that they reported a more continued support from informal sources. Several variables significantly predicted a higher likelihood of being in the Partial Support Cluster compared with the Descending Support Cluster: being younger, living further from the coast, and being single or widowed rather than married. In other words, older residents, married residents, and residents living closer to the coast reported a larger number of institutional sources, especially immediately after the disaster. On the other hand, these residents experienced a quick drop of support received from informal sources over time. These residents also reported fewer cases of receiving support from online sources in general, compared with those in the Partial Support Cluster. In general, these results support the prediction of H1.

For an in-depth examination of how support sources vary across support types over time, a regression model was run to predict the proportion of informal sources in contrast to institutional and online sources (Table 3). Table 3 contains three columns for each of the three types of support. Although the same set of predictor variables as in Table 2 were included in the regression, Table 3 only presents the significant variables. The proportion of informal sources for instrumental support was predicted by the level of home damage (i.e., lower level of home damage was associated with higher proportion of informal sources), especially in the earlier time frame including up to 1 year after disaster. The proportion of informal sources for emotional support was associated largely with age and income (i.e., younger people and higher-income people having more informal sources). The proportion of informal sources for informational support was generally predicted by home damage (i.e., lower level of home damage predicted higher proportion of informal sources) and distance from the coast (i.e., larger distance predicted higher proportion of informal sources).

Predicting Recovery Trajectory (H2)

Four clusters were derived for household recovery over time, as shown in Fig. 5. The mean level of initial housing damage reported by respondents in each of the four clusters is indicated in Fig. 5(b).

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Table 2. Multinomial logistic regression results for variables hypothesized to predict individuals' membership in one of the social support clusters

Variables	Minimal support cluster β	Minimal support cluster SE	Descending support cluster β	Descending support cluster SE	Sustained support cluster β	Sustained support cluster SE
Age	$0.03^{\dagger}$	0.02	0.04^{*}	0.02	0.01	0.02
Sex (female)	0.29	0.36	0.38	0.41	0.36	0.46
Marital status[a]	—	—	—	—	—	—
Single	−0.34	0.56	-1.43^{*}	0.70	−0.30	0.67
Divorced	−0.12	0.55	$-1.31^{\dagger}$	0.75	−1.24	0.91
Widowed	−0.66	0.69	-1.89^{*}	0.81	−1.23	0.92
Income	0.04	0.11	−0.11	0.12	−0.03	0.13
Current town	-0.03^{**}	0.01	−0.02	0.01	$-0.02^{\dagger}$	0.01
Distance from coast	−0.08	0.08	-0.35^{**}	0.12	$-0.25^{\dagger}$	0.13
Home damage	−0.26	0.16	0.13	0.18	0.43^{*}	0.20
Constant	0.60	1.36	−0.17	1.56	−0.50	1.74

Note: β = regression coefficient; and SE = standard error. Partial Support Cluster served as the baseline comparison group for estimating the likelihood of individuals belonging to the other three cluster types, e.g., a one-unit increase in variable *Age* is associated with a 0.04 increase in the relative log odds of belonging to Descending Support Cluster versus Partial Support Cluster; $^{\dagger}p < 0.10$, $^{*}p < 0.05$, and $^{**}p < 0.01$. Model Pseudo R^2 = 0.0799, Log likelihood = −347.5697, and Number of observations = 296.
[a]Reference category for variable Marital Status is Married, e.g., the relative log odds of belonging to Descending Support Cluster versus Partial Support Cluster decreases by 1.43 for individuals who are Single versus Married.

Table 3. Variables predicting a larger proportion of informal sources for each of the three types of support

Time points	Instrumental support	Emotional support	Informational support
1 week	Home damage (−)	Age (−) ($p < 0.10$), female (−)	Distance from coast (+), home damage (−), single (+) ($p < 0.10$), marital status[a]: divorced (+)
3 months	Home damage (−), marital status[a]: widowed (+)	Age (−), income (+)	Age (−) ($p < 0.10$), female (−) ($p < 0.10$)
1 year	Home damage (−)	Age (−)	Distance from coast (+), home damage (−) ($p < 0.10$)
2 years	—	Income (+)	Female (−) ($p < 0.10$)
3 years	—	Age (−), income (+), home damage (+)	Distance from coast (+), home damage (−)
4+ years	—	Age (−) ($p < 0.10$), income (+)	Female (−) ($p < 0.10$)

Note: Significant variables from each of the regression models for support types and time points are listed; $p < 0.05$ except when otherwise noted.
[a]Reference category for variable Marital Status is Married.

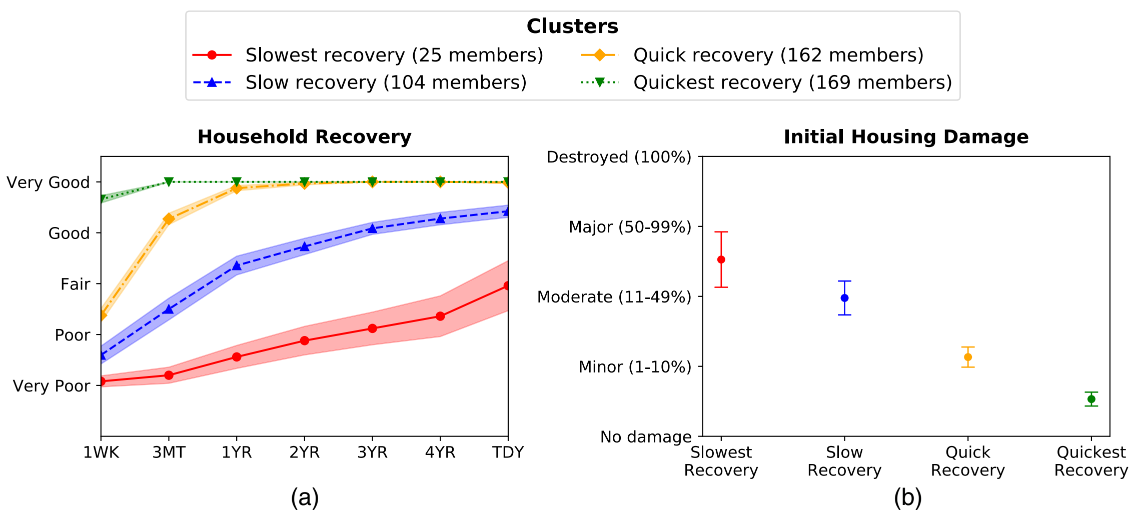

Fig. 5. (a) Clustering results of recovery trajectories over time, based on respondents' perception of household recovery rated on a five-point scale; and (b) reported level of initial housing damage for the four clusters derived.

The four clusters are labeled according to the speed of the recovery trajectory. The Slowest Recovery Cluster has the largest housing damage ($n = 25$). The Slow Recovery Cluster ($n = 104$) experienced moderate levels of housing damage and slower recovery compared with the Quick Recovery Cluster ($n = 162$). The Quickest Recovery Cluster, which experienced minimal initial housing damage, included the largest number of respondents ($n = 169$).

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Table 4. Multinomial logistic regression results for variables hypothesized to predict individuals' membership in one of the recovery trajectory clusters

Variables	Slow recovery cluster β	Slow recovery cluster SE	Quick recovery cluster β	Quick recovery cluster SE	Quickest recovery cluster β	Quickest recovery cluster SE
Age	0.05	0.04	0.04	0.04	0.05	0.04
Sex (female)	−0.33	0.78	−0.41	0.83	−0.68	0.79
Marital status[a]	—	—	—	—	—	—
Single	−0.98	1.10	−1.49	1.20	−1.88	1.17
Divorced	−0.14	1.32	−0.67	1.39	−0.14	1.32
Widowed	15.03	2730.31	14.05	2730.31	14.50	2730.31
Income	−0.38	0.27	−0.32	0.28	−0.28	0.27
Current town	−0.02	0.03	−0.02	0.03	−0.01	0.03
Distance from coast	−0.19	0.23	0.17	0.24	−0.02	0.23
Home damage	-1.03^{*}	0.47	-2.26^{**}	0.51	-1.75^{**}	0.48
Town damage	−1.06	0.71	−1.38	0.74	−0.78	0.72
Support pattern cluster[b]	—	—	—	—	—	—
Minimal support	17.09	1214.66	18.78	1214.66	18.16	1214.66
Descending support	$1.78^{\dagger}$	0.93	$1.90^{\dagger}$	1.05	2.06^{*}	0.95
Sustained support	1.95^{*}	0.93	2.25^{*}	1.07	$1.72^{\dagger}$	0.97
Constant	8.04	4.74	11.22	4.91	8.21	4.76

Note: β = regression coefficient; and SE = standard error; Slowest Recovery Cluster served as the baseline comparison group for estimating the likelihood of individuals belonging to the other three cluster types; $^{\dagger}p < 0.10$, $^{*}p < 0.05$, and $^{**}p < 0.001$. Model Pseudo $R^2 = 0.2418$, Log likelihood = −240.71734, and Number of observations = 257.

[a]Reference category for variable Marital Status is Married.

[b]Reference category for variable Support Pattern Cluster is Partial Support Cluster.

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Table 4 presents results from a multinominal logistic regression model predicting respondents' membership in one of the four clusters derived for household recovery trajectory. All of the predictor variables included in the model are presented in the table. To identify factors that explain a high level of delay in recovery, the Slowest Recovery Cluster was used as the base outcome in the model. Results show that those with less home damage were more likely to be in the Slow Recovery Cluster compared with the Slowest Recovery Cluster. In addition, unsurprisingly, less home damage explained membership in the Quickest Recovery Cluster.

The results address H2, which predicts the effect of social support pattern on recovery trajectories when demographic and disaster impact variables are controlled for. The Partial Support Cluster was specified as the reference group in the model. Respondents who belong to the Sustained Support Cluster, compared with the Partial Support Cluster, was more likely to be a member of the Slow Recovery Cluster. In other words, those who received social support more from institutional sources tend to show an overall quicker recovery than the base condition, which is the Slowest Recovery Cluster. This effect was significant for the likelihood of belonging to either the Slow Recovery Cluster or Quick Recovery Cluster, and was marginally significant for predicting the likelihood of being in the Quickest Recovery Cluster compared with the base condition. Belonging to the Descending Support Cluster was associated with a higher likelihood of being in the Quick Recovery Cluster, showing that having a higher level of institutional sources initially, even when combined with a quick decrease of social support from informal sources, predicted a quicker recovery. Overall, the results support the prediction in H2 that social support patterns can explain the different trajectories of recovery.

In addition to overall perceptions of household recovery, the timing of four key activities in the phases of recovery was examined to gain a detailed understanding of recovery trajectories. Hierarchical clustering process yielded four clusters (Fig. 6), which map closely to the overall recovery trajectories as shown.

The number of complete responses for the timing of activities was small ($n = 141$), likely due to the questions being open-ended and some respondents' having difficulty remembering specific dates, so these clusters only represent a subset of the respondents. The Slowest Recovery Cluster had a prolonged timeline for all four key activities. The Slow Recovery and Quick Recovery clusters in Fig. 6 are differentiated by the level of initial housing damage. The largest contrast in the timing of the four key activities exists in the permanent return timing. In other words, quicker recovery was particularly linked with quicker permanent return to home among the four key activities. The Quickest Recovery Cluster reported all activities being completed in less than a week after the hurricane.

Discussion

Individuals go through various stages of adaptation and recovery after adverse or stressful events, with differing psychological, social, and logistical experiences (Harms et al. 2018). By measuring the differing sequences in these trajectories, this study provided an empirical test of both pre-event and postevent factors influencing the progression of long-term recovery.

Results show the large and sustained role played by informal sources for both instrumental and emotional support compared with institutional and online sources. In particular, when support from institutional sources (i.e., government, private insurance, relief groups, and religious groups) declined in the long-term recovery, informal sources appeared to fill the gap, particularly by providing instrumental resources to affected residents. This tendency is shown in all three types of social support, as reflected in the inverse patterns in which the proportion of institutional sources and informal sources change over time (Fig. 3).

The clustering results show noticeable contrast in patterns of support over time. The Minimal and Descending Support Clusters are primarily residents who did not require much support given a low level of home damage (Table 2). The Partial and Sustained Support Clusters show meaningful contrasts. The Partial Support

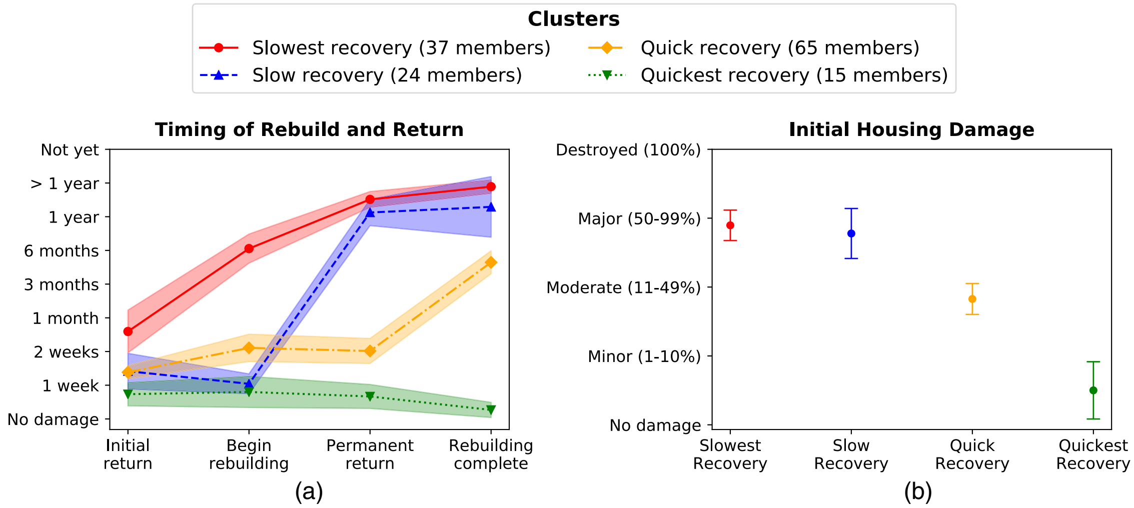

Fig. 6. (a) Clustering results of recovery trajectories over time, based on reported timing of return and rebuilding; and (b) reported level of initial housing damage for the four clusters derived.

Cluster relies largely on informal sources for support and much less on institutional sources, implying a high reliance on bonding social capital over the course of recovery. Residents in the Sustained Support Cluster, in contrast, draw support from institutional sources, but also nominate informal sources to a considerable degree. A significant variable predicting these contrasts was disaster impact. The primary contrast between the Partial and Sustained Support Clusters lies in the level of reliance on informal versus institutional sources, and this contrast was associated with differing levels of home damage. In other words, experiencing more home damage explained receiving a large proportion of institutional support, indicating that utilizing informal sources of support may be challenging for those experiencing severe disaster impacts. Yet, the effect could also be due to support from institutional sources being less likely to be directed to households with less severe disaster damage, therefore seemingly inflating the relatively proportion of support from informal sources.

Existing literature from routine contexts suggests that conditions of vulnerability, such as lower income and education, are associated with a stronger reliance on close-knit and bonding ties. These conditions likely limit individuals in taking advantage of certain network positions that in particular offer brokering or bridging opportunities (Burt 2000). Findings from the current study differ from this general idea that vulnerable people tend to rely more on bonding social capital than on bridging social capital. The findings also suggest that younger and higher-income respondents, in general, had a higher proportion of informal sources for support, particularly in the case of emotional support.

In addition, a high level of bonding social capital, reflected in having a membership in the Partial Support Cluster, was predicted by living in the impacted community longer, younger age, and not being married. In disaster contexts, elderly and lower-income populations might not have sufficient capacity to mobilize close social circles. Subsequently, the limited capacity of pooling or buffering of resources among informal ties, some of which may be local (e.g., family, friends, or neighbors), could lead to a higher reliance on external support resources.

Residents with high demand for support relied on official and institutional relief and, at the same time, did not rely as much on support from informal sources in terms of material and information support. The effect of home damage on the low proportion of support from informal sources was pronounced in the early time points, whereas the effect extended to the 3-year-after time point for informational support. On one hand, the result may be explained by institutional support being channeled into residents with much need. On the other hand, the lighter role of informal sources could be a function of the limited capacity of their personal ties. Overall, the results show the effect of households' demographic and socioeconomic vulnerability conditions on patterns of social support received over time (H1).

In predicting recovery, the initial condition measured by housing damage had a significant effect. Yet, the progress of recovery phase was predicted by several additional factors, which include postevent conditions involving social support. Although informal support occupies a substantial portion of overall support, a consistent predictor of quicker household recovery was receiving support from institutional sources, as shown in the effect of the Sustained Support Cluster and the Descending Support Cluster compared with the Partial Support Cluster. These findings may imply that even when informal sources of support are sustained, if they are not accompanied by institutional sources of support, the positive impact on recovery is limited. In sum, the Sustained Support Cluster appears to represent an ideal condition in which institutional sources operate for providing material and informational resources, and yet individuals can also turn to informal sources for emotional support. Further, given that pre-event demographic variables did not directly predict recovery, it may be reasoned that the impact of vulnerability conditions on recovery operates through postdisaster conditions such as social support.

Disaster recovery necessitates instrumental support in all phases. The short-term recovery phase involves activities such as meeting the immediate needs of citizens including temporary shelter or housing, restoring utilities, and clearing debris from roads. Moving into the long-term recovery phase includes rebuilding and restoring homes, business, and infrastructure. Although institutional support takes a central responsibility in relief planning, the capacity for response becomes strained, especially when multiple disasters occur in quick succession. As a result, residents who need sustained support beyond the immediate phase of disaster need to rely on alternative sources. Results from this study show that identifying ways to facilitate informal support in communities affected by disasters can play an important role in recovery.

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The relationship among home damage, perceived recovery, and rebuilding and return patterns (Fig. 6) followed previously suggested return-entry patterns (Siebeneck et al. 2020). Most households with minor to moderate home damage started their rebuilding efforts within the first couple of weeks. Conversely, for households with larger home damage, independent of when they began their rebuilding efforts, their permanent returns occurred around a year after the hurricane. Given that permanent return timing is a key distinguishing factor of recovery speed, community infrastructure and support that allow residents to complete rebuilding at their home may facilitate the overall recovery process.

Theoretical and Methodological Implications

This study examined how social support, a function of social capital, and recovery unfold over time in a postdisaster situation. A common assumption in network, disaster, and communication theorizing is that people heavily utilize bonding social capital, relying on their strong ties for social support, when encountering difficult life events. However, evacuation, relocation, and physical damages disrupt people's routines and can inhibit their ability to mobilize social support (Solomon 2014). These disruptions likely impact both providers and recipients of social support. With the accessibility of ties predicting incidental and spontaneous activation of ties (Small and Sukhu 2016), this finding addresses the challenges of utilizing strong ties after natural disasters. Social support from informal sources is sharply decreased at the 3-month time point for all three kinds of support, whereas institutional sources have an increase. The results comport with recent findings (Nguyen-Trung et al. 2020) in highlighting the importance of bridging social support in long-term recovery. Nonetheless, this study sheds light on the nuances of these findings by illustrating the continued role of informal sources in offering instrumental and emotional support.

Recent research found that quality, but not quantity, of social support can be an important mediator in reducing posttraumatic stress during recovery (Shang et al. 2019). Evaluating the patterns of social support through multiple dimensions (i.e., types, sources, and change over time), like in this study, provides a richer picture of social support provision. For example, sustained social support from a given sources is likely evaluated as more high quality than social support that is fleeting. A quick decline in emotional support from informal ties may have a strong impact on residents who are in vulnerable conditions. Continuing to evaluate multiple sources and types of social support (e.g., Lee et al. 2020) together and changes in social support over time to detect such patterns is important for understanding disaster recovery trajectories.

Resilience is increasingly theorized a process rather than a fixed trait of individuals (Buzzanell 2018). As this study illustrated, individuals recovering from natural disaster undergo a range of nonlinear experiences in the process of recovery, often coordinating both bonding and bridging forms of social capital in the immanent and prolonged aftermath of a hurricane. Although there is a wealth of research within natural hazards scholarship that addresses resilience, it is frequently conceptualized as an ability to return to normal levels of functioning through capacity and adaption (Pelling 2003). Through analyzing long-term recovery, the results support the conceptualization of resilience as a process, one which draws on various networked sources and types of social support to work toward an often-indefinite recovery. The findings suggest that understanding long-term recovery and resilience from disasters require an examination of both pre-event conditions of vulnerabilities and postevent factors such as social support, which can protect individuals and households from adversities. Both the conceptual and methodological frameworks utilized in the study for investigating over-time patterns of social support and recovery can inform future studies.

This study applies a temporal clustering approach to classify and understand social support patterns as well as trajectories toward recovery, instead of examining each of the support and recovery states in time step independently. Consequently, this study could unravel how important factors, like vulnerabilities and social support, sway individuals to follow certain recovery trajectories. Future studies should address the influence of wide-ranging factors on recovery trajectory. For example, the measurement of vulnerability in this study was focused on demographics and disaster impacts. Examination of the full spectrum of social vulnerability conditions (e.g., Cutter et al. 2003) including the built environment (e.g., infrastructure and commercial and industrial development) and the broader society (e.g., population growth and medical services) accompanied by a larger scale data set will provide a more comprehensive understanding of long-term support and recovery.

Practical Implications

Proactively building future resilience by addressing the causes of their vulnerabilities is important to rehabilitating disadvantaged communities after a natural disaster (Pomeroy et al. 2006). Practically, the results support the notion that lack of sustained social support can be detrimental to recovery. One method to extend the honeymoon phase of recovery, where support is abundant, is through focusing rebuilding efforts on restoring degraded places (Silver and Grek-Martin 2015). Communities may consider focusing their energy on gathering spaces or cornerstones of their communities, like public libraries and parks or long-standing local businesses. In addition, when people who have great recovery needs might not be able to receive sufficient institutional support, local efforts to facilitate informal support across neighbors and communities can be helpful. Given impacted residents' high reliance on informal sources, policy makers should note that cooperative and supportive relations are also influenced by the presence of social capital in the larger social structure including norms, trust, and reciprocity (Putnam 1993). Cultivating these durable relations requires a long-term horizon, which should be incorporated in communities in the predisaster phase.

The rate of decay of social support increases notably after the 3-month time point. Agencies should use this narrow time window to create policies that will help communities rebuild and return. In addition, in spite of recent usage of online tools and social media platforms, this study showed that online sources were not a source of major support except for a modest level of informational support. New ways to make these tools more relevant in the disaster context should be identified at the community level.

Limitations

This study relied on retrospective data instead of longitudinal panel data collected at multiple time points. Although the approach taken in this study is favorable in terms of cost and response rate, estimating the extent to which biases might have been introduced due to the inaccuracy of recall is difficult. Further, in limiting the survey's length, respondents were not provided with formal definitions of recovery, damage, household, and township, leaving them to evaluate their experiences based on their personal understandings of these terms. Data based on individuals' recall can be combined in future research with other data sources to improve the granularity and scale of the recovery analysis.

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First, recovery trajectories have been studied in spatial and temporal detail using novel data sources, including mobile phone location data and social media data (Hasan et al. 2013). These data can allow us to understand the varying dimensions of heterogeneity in recovery outcomes. For example, a recent study shows that inequality in mobility capacities across socioeconomic population groups accounts for spatial segregation after disasters (Yabe and Ukkusuri 2020), suggesting that identifying and satisfying needs for instrumental support, such as mobility, can impact larger-scale outcomes related to recovery.

Second, Kaniasty et al. (2020) argued investigations of social support after natural disaster would benefit from a combined quantitative and qualitative analysis. Future research should focus on scaling and enriching data collected from small sample sizes to offer additional understandings of the variability in recovery processes.

Third, another limitation of this study stems from the low response rate achieved through the mail surveys. Although studies such as this one benefit from the ability of mail surveys to target participants meeting various disaster experience, geographic parameters, and demographic parameters, the overall trend in response rates has declined dramatically over the last decade (Stedman et al. 2019). This can lead to concerns about the extent to which the sample is representative of the study area. As mentioned previously, our sample was limited to homeowners who were residing at their current address both during Superstorm Sandy and 5 years after. We believe this condition may be one reason our data are skewed more toward individuals that are older and have higher incomes, which aligns with national-level trends (i.e., older and higher-income population being more likely to own a home) identified in a recent Census report (US Census Bureau 2020). However, it is also possible that participants in our study area who completed the rebuilding and recovery of their home in the 5 years following the storm or who were currently still in the process of recovering are those who had the financial means and resources to do so.

Additionally, it is important to note that this study is limited to residents who either permanently returned home or at the time of the survey were in the process of rebuilding and returning home following Superstorm Sandy. Similarly, the survey excluded renters and many younger residents who were not homeowners during the storm. Future studies may benefit from examining these populations who relocated or were unable to rebuild their homes, and more specifically, the role social networks have in facilitating recovery at a different location as well as the constraints or limitations of social networks that may lead to homeowners not being able to recover disaster-damaged properties.

Another limitation concerns generalizability. Although this study provides meaningful findings about social support and recovery for Superstorm Sandy, the transferability of these insights to other communities or disaster contexts should be explored so that a coherent national policy can be developed regarding the facilitation of social support.

Conclusion

Following natural disasters, social capital is frequently argued to be a key component of resilience (Aldrich 2011; Eller et al. 2018). How do different indicators of vulnerability conditions explain constraints of social capital after disasters, which make it difficult for households to access social support? The current study suggests theoretical implications for how the different forms of social capital relate to vulnerability conditions and recovery trajectories, assisted by an analytic framework for classifying common patterns of social support and recovery trajectories at multiple time points. Overall, respondents reported a decay in social support starting 3 months after the storm. Residents with high demand for support relied largely on institutional sources as opposed to informal sources for material and information support over the course of recovery. Younger and higher-income residents had a higher proportion of informal sources for support, particularly in the case of emotional support. Patterns of social support predicted recovery trajectories when pre-existing vulnerability and disaster impact were controlled, indicating that the postevent conditions of receiving support serve as a protective factor. In particular, beyond the initial condition of housing damage, utilization of institutional sources for material and informational resources combined with informal sources for emotional support predicted quicker recovery trajectories.

In sum, this study draws attention to policies that consider not only infrastructure recovery but also more sustainable and long-lasting mechanisms to enable social support after disasters. Continued research and investments are needed for assessing and cultivating both informal relations and institutional networks from which postdisaster social support can be quickly mobilized.

Data Availability Statement

Some or all data from household survey without individual identifying information that support the findings of this study are available from the corresponding author upon reasonable request and upon completion of the authors' use of the data. Some or all models or code for hierarchical clustering and regression analyses that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

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