THE ROLE OF INFRASTRUCTURE IN HOUSEHOLD RELOCATION DECISION AFTER DISASTERS: A CASE STUDY OF RELOCATION IN NEPAL AFTER THE 2015 EARTHQUAKE

A Thesis

by

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ABSTRACT

Social resilience after disasters is characterized by two key dimensions, reducing impacts and enhancing recovery. In that context, reducing the number of household that are either forced or choose to relocate due to damage to their homes or infrastructure disruption, can be considered a key resilience metric. The significance of relocation after disasters arises from two main aftereffects. First, relocation propagates in the community; as people leave their homes after a disaster, it becomes more likely that others will leave as well. Second, although relocation might start as a temporary movement, it can eventually evolve into permanent relocation. The more extensive the population dislocating and longer the duration of that relocation can jeopardize a community's long-term recovery. Whilst some studies have addressed the long-term repercussions of relocation, few focused on understanding the household relocation decision-making process itself and the factors that influence this decision as a group. Furthermore, the impacts of infrastructure services' attributes before and after the disaster on the relocation decision have not been well studied in the engineering research context. Empirical behavior models that examine the social impacts of infrastructure resilience are critical for proper investment in policies and measures directed to achieving infrastructure and community resilience. This study examined the impact of three infrastructure services on household relocation decision: piped water, government-provided electricity and vehicle-accessible roads. Logistic regression parsimonious models of the Yes/No relocation decision were developed using household survey data collected from Nepal after the 2015 earthquake. Different types of drivers that are expected to influence the relocation decision were used in the development of relocation models alongside with variables capturing aspects of infrastructure services. Examined drivers included demographic and socioeconomic characteristics of the household and the levels of damage to homes and neighborhoods. The consequences of infrastructure services for relocation was obtained by controlling for these other factors and then assessing the ceteris paribus impact of infrastructure disruption. The analysis in this study showed that the unique water service

situation in Nepal provides preliminary suggestions of the possible impacts of the pre-earthquake redundancies and the post-earthquake resourcefulness in providing sources of water in influencing the household relocation behavior. This unique water situation gave rise to a new hypothesis of the effect of piped water disruption, a hypothesis that does not necessarily conform with the general expectations in the literature. The failure and disruption in electricity, generally provided by the government, had the highest impact on the household's odds of relocation among all the investigated factors. This could be a result of the household's sole dependency on the government for providing electricity and the lack of backup sources of electricity in the house before the earthquake on one hand, and the unavailability of alternative sources of electricity after the earthquake on the other hand. Also, this study showed that vehicle-accessible roads had no significant impact on the Nepalese household relocation behavior, which could be attributed to the low percentage of car ownership in the community.

DEDICATION

To

My mother

For being the kindest and strongest woman I have ever seen and for having a scale always imbalanced with the heavy weight of our love. You are all my reasons, I am here because of you

My father

For always believing in me and for teaching me how to earn an honest living

My brother Humam

For always being there for me, no matter what

My sisters Rasha, Ghadeer and Raghad

For making my life a brighter and a warmer place

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1. INTRODUCTION[1*]

This section will provide an introduction to the societal problem that will be addressed in this study, a brief description of the point of departure of this research in the existing literature, the research question that will be investigated, and a description of the upcoming sections and thesis organization.

1.1 Problem Statement

Household displacement after disasters is an increasingly complex global phenomenon (Internal Displacement Monitoring Center, 2015a). Natural disasters are expected to increase in frequency and intensity (Masterson, Peacock, Van Zandt et al., 2014). At the same time, communities in disaster-prone areas are growing in size and their exposure to disaster risks is increasing as well (Nejat, Cong, & Liang, 2016). According to the latest historical models, displacement trends suggest that the likelihood of being displaced by a disaster is higher than it was four decades ago by 60 percent, even after adjusting for population growth (Internal Displacement Monitoring Center, 2015a).

Household displacement after disasters jeopardizes community recovery (Internal Displacement Monitoring Center, 2015a). The interest in displacement that occurs after a disaster arises primarily from the fact that it often propagates in the community and develops into permanent relocation. People behave collectively in disasters; as households start to relocate, more households tend to follow (Quarantelli, 1984; Storr & Haeffele-

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* Figure 1.1 System Resilience Concept in this section is adapted from Figure 1: Measure of seismic resilience—conceptual definition, with the permission from “A framework to quantitatively assess and enhance the seismic resilience of communities”, by Bruneau; Chang; Eguchi; Lee; O'Rourke; Reinhorn; Shinozuka; Tierney; Wallace; & von Winterfeldt. November 2003. *Earthquake spectra*, Volume 19, No. 4, pages 733–752, Copyright 2003 by Earthquake Engineering Research Institute.

Balch, 2012). Large numbers of displaced people can place local economies at risk and make it harder for governments to coordinate recovery plans with the displaced community. It can delay the restoration of services and discourage recovery efforts (Storr & Haeffele-Balch, 2012).

Longer durations of displacement often increase the eventuality of staying away (Esnard, 2017). Permanent relocation introduces major challenges to long-term community recovery processes. Permanent relocation can trigger and/or reinforce socioeconomic neighborhood decline. Large numbers of people leaving their homes increases the vacancy and abandonment in a neighborhood which ultimately decreases the tax base that funds long-term recovery efforts (Zhang, 2012).

At the same time, displacement adds to individuals' physical and psychological strains induced by disasters. Displacement usually results in the loss of the social capital and the surrounding community, and the destabilization of the sense of place attachment (Binder, Baker, & Barile, 2015; Erikson, 1976; Yzermans, Donker, Kerssens et al., 2005). Displacement threatens health on a communal level as well (Kessler, Galea, Gruber et al., 2008; Nejat et al., 2016). The wide spread and long durations of displacement are indicators of the weakness and fragility of a community in the face of disasters. A resilient community can be characterized through relatively low displacement numbers and quick return of its constituent populations (Chang & Shinozuka, 2004).

Currently, a gap exists in understanding the human behavior and the factors affecting decisions made in the different stages after a disaster (Miles, 2015). Understanding the decision-making process in the post-event evacuation during the response period, rather than the pre-disaster phase, is not being well studied (Miles, 2015; Wright & Johnston, 2010).

1.2 A Brief Overview of Relocation Drivers

Household relocation decision process can be perceived to go through sequential decisions as presented by Chang, Pasion, Yavari et al. (2009). The household first assesses the structural safety of their housing unit, followed by its functional habitability, their desire to leave, and lastly, its ability to relocate and the accessibility of likely places of relocation. Each of these decisions is influenced by physical, demographic and socioeconomic drivers.

Household decision at each stage can be influenced by the built environment as well as the social factors and economic situation. Many demographic and socioeconomic characteristics contributes to the household's physical and social vulnerability. The scholarly literature has discussed these different drivers. Socioeconomic characteristics addressed in the literature include drivers related to the household capacity, tenure, vulnerable demographic groups and socially vulnerable ethnic groups and linguistic minorities. Drivers related to the household capacity include income and education. Vulnerable demographic groups in the relocation context include women, children and elderlies.

Buildings' structural stability and its effect on displacement have been addressed in social science and engineering research (Girard & Peacock, 1997; Van de Lindt, Peacock, & Mitrani-Reiser, 2018). Relocation has been recognized to be one of the social consequences of lifelines losses disasters (Cavalieri, Franchin, Gehl et al., 2012; Chang, 2016; Chang et al., 2009; Peacock, Dash, & Zhang, 2007). However, the social science and engineering research addressing the effect of infrastructure disruption on dislocation is limited. Rather, infrastructure disruption has been addressed as a pure engineering problem in the engineering research context, while the social effect has been addressed in other research contexts such as emergency management, social vulnerability, and disaster recovery (Chang, 2016).

1.3 Terminology

1.3.1 Relocation

Many terms are used throughout the disaster and climate change literatures to describe human movements caused by environmental issues. There is no clear consensus on which terms to use to distinguish between voluntary and forced, short- and long-term, or internal and international human movements (Warner, Afifi, Kälin et al., 2013). Relocation, resettlement, displacement, and migration are all used to describe forms of human environmentally-induced mobility (Weerasinghe, 2014). Evacuation is also used to describe the rapid movement of a human population in response to either a potential threat, as in the context of hurricanes, or in the aftermath of a hazardous event (Dash & Gladwin, 2007; Sorensen & Sorensen, 2007). Studies, for example, have used the term evacuation to describe people's movement after an earthquake, a context in which pre-disaster warning does not exist, that is influenced by many reasons not restricted to property damage and life-threats (Khazai, Daniell, Franchin et al., 2012; Tai, Lee, & Yau, 2014; Wright & Johnston, 2010). People's perception of what constitutes an urgent reason for leaving or a serious threat varies, this variation produces common attributes between the definition of evacuation after disasters and other human movement terms.

Although no internationally accepted definition exists, the Council of the International Organization for Migration (IOM), in an attempt to capture the complexity of the matter of human movements driven by environmental issues, defined environmental migrants as "persons or groups of persons who, for reasons of sudden or progressive changes in the environment that adversely affect their lives or living conditions, are obliged to have to leave their habitual homes, or choose to do so, either temporarily or permanently, and who move either within their territory or abroad." (International Organization for Migration, 2008, pp. 1-2). The term migration, in this definition, captures displacement caused by acute environmental events as well as that set off by deteriorating environmental conditions, short- and long-term, forced and voluntary, and internal and international.

The conceptual confusion in distinguishing between voluntary and forced displacement is embedded in the spatial, temporal and socio-legal dimensions used for this distinction (Bansak, Hainmueller, & Hangartner, 2016; Esnard & Sapat, 2018). The significance of the terminology used rises in political and legal contexts. In determining who benefits from policies and how rights and expectations are determined, these terminologies are not semantically the same (Sapat & Esnard, 2017).

In this study, displacement, dislocation relocation and post-event evacuation will be the terms used to describe households' movement from their pre-earthquake home after the disaster. This study does not directly nor explicitly focus on the reasons, as expressed by households concerning why they decided to leave, nor does it account for the duration of this movement. Furthermore, household movement is not categorized based on the urgency of the reason/s driving the decision, temporal extent of the displacement, or where the household relocated to. Rather, this study focuses on the extent to which damage to a household's home, infrastructure disruption, and socio-economic and socio-demographic attributes predict household dislocation from their pre-event home.

1.3.2 Resilience

The use of the term resilience is expanding rapidly, especially in multidisciplinary fields (Herrman, Stewart, Diaz-Granados et al., 2011) including ecology, social sciences, and psychiatry and mental health. Although there is a lack of consensus on the subject of the operational definition of resilience, attributes used as evidence of resilience are similar in most definitions (Herrman et al., 2011). An overview of resilience in the various domains if scholarly publications suggest that resilience refers to the ability of a human being, a community or any type of a system, to withstand a shock or change, absorb it and maintain its function to a certain level, recover any losses and bounce back rapidly, learn from its past experiences and positively adapt to and mitigate for the new situations and challenges (see for example: Masterson et al., 2014).

Damage to the built environment cascades to generate social, physical, economic and psychological challenges on a community-wide scale. Community well-being in the context of disasters can be measured through community resilience. Community resilience is a community-wide state that maintains and restores the community health during and after disasters on the social, economic, physical and psychological levels. This resilience is achieved through mitigation of hazards exposure, minimizing the severity and extent of damage, maintaining functionality, rapidly restoring services, inclusiveness of recovery plans, and integrating past experiences in future plans (Gibbs, Harms, Howell-Meurs et al., 2015). For a community to be 'well', its resources should be robust and redundant, it should be rapid and flexible to counteract when it is faced with an extreme event, and it should be able to adapt to the new post-event environment to reduce its vulnerability and maintain its functionality (Norris, Stevens, Pfefferbaum et al., 2008).

To enhance the resilience of any community, it is fundamental to understand that a community is an urban system of systems, a network of networks (Bates & Pelanda, 1994; Peacock & Ragsdale, 1997). For these systems to function with resiliency in the face of disasters, a great deal of resilience-conscious design and engineering in the community is required (Boyd, Hokanson, Johnson et al., 2014). Policy makers and disaster researchers should work towards achieving resilient communities by carrying out well-informed recovery activities based on past experiences in a lesson-learning process aimed at mitigating future hazards and reducing future vulnerabilities (Chang & Shinozuka, 2004).

1.3.3 Resilience of Infrastructure Services

The functioning of interdependent complex infrastructure systems during and after a disaster determines cities' resilience (Chang, McDaniels, Fox et al., 2014; Godschalk, 2003). Although activities of emergency management in the short-term aftermath of a disaster are not directly related to community health, they are major contributors to well-being through protecting lives, minimizing damage to utilities and lifelines, and maintaining services that the community needs (Norris et al., 2008). Understanding the extent of infrastructure disruption on the impairment of household and community recovery is key to avoiding the unintended long-term consequences that could result from ill-informed infrastructure restoration decisions (Boyd et al., 2014).

Figure 1.1 shows a graphical representation of the concept of resilience that is applicable to social or physical systems, including the broader built environment and infrastructure networks. It is adapted from Bruneau, Chang, Eguchi et al. (2003); Chang et al. (2014); McAllister (2015); McDaniels, Chang, Cole et al. (2008). The figure indicated that the loss of the system's function, measured through a performance measure (the y-axis), due to the disaster requires time to reach a new steady state. The area of the system's function curve under the pre-disaster steady state curve/line represents the resilience loss in the system, also called the "Loss Triangle".

Infrastructure resilience could be reflected and monitored in four properties: robustness, rapidity, redundancy and resourcefulness (Norris et al., 2008). Figure 1.1 shows the amount of the system's function retained after the extreme event to be a measure of the system's robustness, the time from the loss of the system's function to its restoration to reflect the system's rapidity (Chang et al., 2014), and the behavior of the system's function curve in between to be a function of the redundancy and resourcefulness in the system. Enhancing the system's resilience reduces the area of the "Loss Triangle" in the figure. This could be achieved through ex ante and/or ex post approaches that would increase the system's ability to withstand and absorb stressors, minimize the duration of the function's loss (Chang et al., 2014), and accelerates the restoration of the system's function.

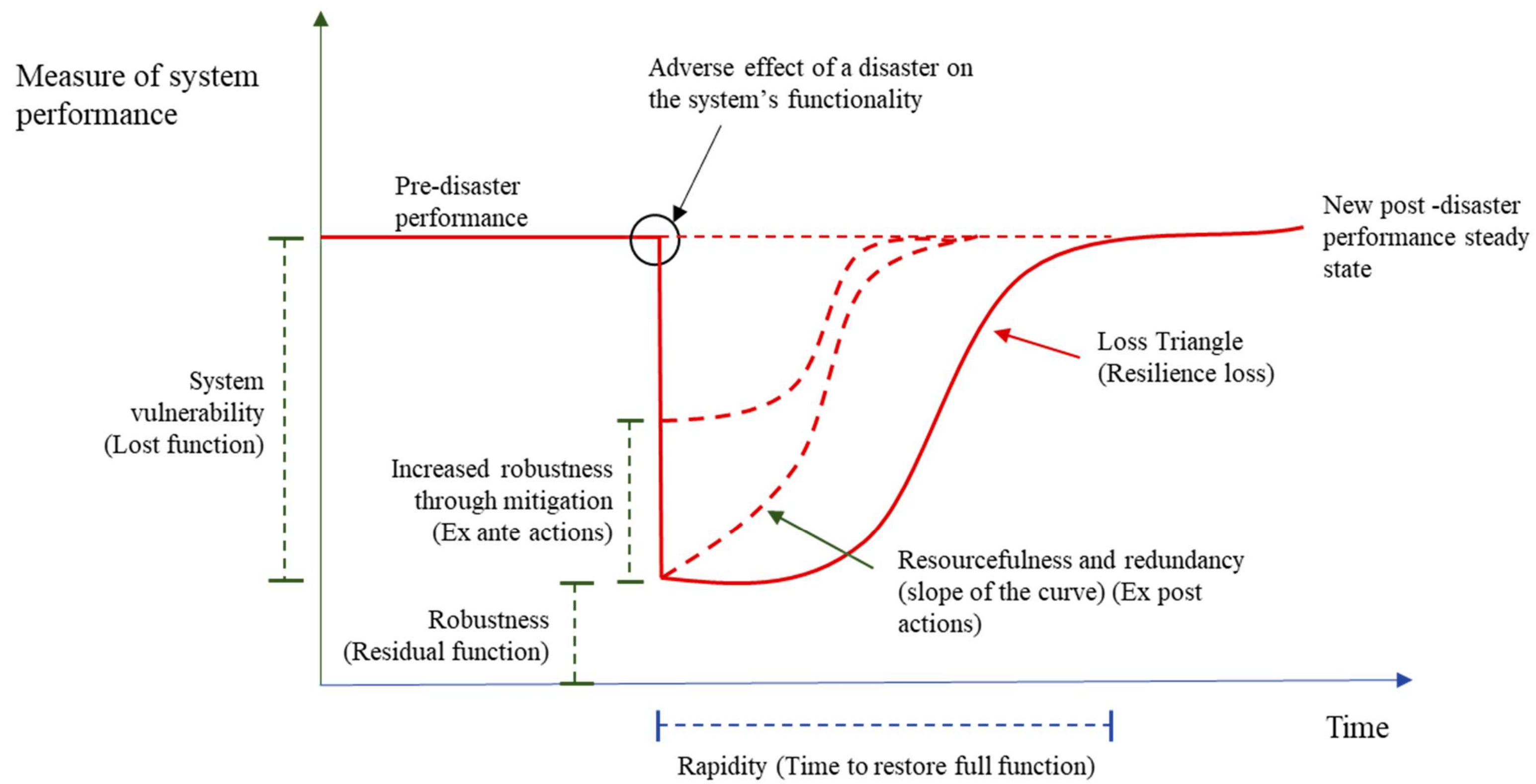

Figure 1.1 System Resilience Concept
adapted from from Figure 1: Measure of seismic resilience—conceptual definition, with the permission from "A framework to quantitatively assess and enhance the seismic resilience of communities", by Bruneau; Chang; Eguchi; Lee; O'Rourke; Reinhorn; Shinozuka; Tierney; Wallace; & von Winterfeldt. November 2003. Earthquake spectra, Volume 19, No. 4, pages 733–752, Copyright 2003 by Earthquake Engineering Research Institute; and Chang et al. (2014); McAllister (2015); McDaniels et al. (2008)

Again, as mentioned above, this resiliency curve can be applied to social systems, the built environment or its elements. Indeed, Chang and Shinozuka (2004) suggested using infrastructure services disruption to measure the organizational dimension of community resilience, and damage to infrastructure systems to measure the technical dimension of community resilience.

1.4 Point of Departure

Variables that are expected to influence the relocation decision have been discussed separately in the literature. Few studies have examined the expected influence of different types of relocation drivers as a group to eliminate the direct and indirect effects of these drivers on each other. A thoroughgoing and comprehensive analysis of the impact of infrastructure services' disruption on relocation should address infrastructure services along with house and neighborhood damage to capture the differential effects these different aspects of the built environment might have on relocation. Models also need to combine engineering and social impacts to be able to capture differences in household behavior across different groups (Chang & Shinozuka, 2004). Additionally, research has shown that relocation drivers are correlated and do not affect a household independently (McLeman & Smit, 2006). Therefore, integrating the socioeconomic characteristics with factors associated with the built environment will help in understanding the ceteris paribus effect of lifelines on household dislocation. Models developed in this study will utilize factors of physical damage to homes and neighborhoods, household's socioeconomic characteristics and infrastructure services attributes to predict household dislocation.

Evacuation decision-making process has been studied for the most part for disasters for which warning is possible, especially hurricanes and tsunamis evacuation in the worldwide research. Limited studies have addressed evacuation following earthquakes, a hazard for which there is no warning stage, and most of the existing post-earthquake research explores events in the United States (Wright & Johnston, 2010).

The decision to relocate or stay and the choice of whether to return and rebuild or relocate permanently are usually made on the household level (Chang et al., 2009; Khazai et al., 2012). Therefore, our understanding ought to begin at the household level. A behavioral model is required to measure social resilience by measuring the likelihood of a household to relocate in the case of infrastructure services disruptions (Chang & Shinozuka, 2004).

Both deductive and inductive approaches are required for disaster recovery research to advance (Lindell, 2013a; Miles, 2015). Connecting empirical observations and theory is required in the community disaster resilience methodology in order to produce robust research area in this field (Miles, 2015). Many studies recognized the interdependencies among the factors influencing household relocation and recovery behavior (McCarthy, 2006). Yet, empirically derived models that incorporate variables of house habitability, availability of basic infrastructure services and social vulnerability demographic and socioeconomic attributes are nascent at best. Lack of empirical data limits our understanding of human behavior. In 1991, the Federal Emergency Management Agency (Kessler et al., 2008) initiated a study to enhance the understanding of lifelines' disruption after earthquakes, help identify the priorities of the different policies and improve the national awareness of the importance of robustness, reliability and continued serviceability of lifelines after earthquakes (Applied Technology Council, 1991). Despite of FEMA's recognition of the importance of addressing these issues, the lack of empirical data that is required for in-depth studies excluded these lifelines from consideration in the study in that year (Applied Technology Council, 1991).

Displacement drivers, in addition to the relocation and rebuilding decision-making processes, have subtle differences among the different communities and places (Sapat & Esnard, 2017). Many studies have recognized the lack of sufficient community recovery studies conducted on international levels, especially in developing countries, and the need for these studies to support the theoretical evolution of models that are useful in divergent geographic regions (Kulig, Townshend, Lightfoot et al., 2013). Addressing the under-studied developing countries context helps in understanding the influence of contextual attributes on dislocation behavior: why different communities exhibit different resilience characteristics when threat occurs, which in turn can increase the depth of our understanding of the resilient human behavior and its universal predictors (Quarantelli, 1984).

1.4.1 The Scope of The Study

This study is directed at understanding the impact of infrastructure disruption on household relocation decision after disasters. This will be achieved by modeling the relocation decision of households in Nepal after the 2015 earthquake. Logistic regression will be used for the development of Yes/No relocation decision models incorporating attributes of infrastructure services.

To determine the significance of infrastructure, variables of competing explanations were employed as controls. Relocation after the 2015 earthquake is analyzed at the household level. It is modeled utilizing variables describing infrastructure services, physical damage to houses and neighborhoods, and household's demographic and socioeconomic characteristics. Demographic groups include females, children and the elderly composition of the household. Socioeconomic indicators include ethnicity/linguistic group, income, education level and tenure. These indicators cover the most relevant and influential indicators influencing relocation after earthquakes according to Khazai et al. (2012).

Although damage to the physical environment has been found to be the most significant determinant of relocation in this study, the inclusion of the demographic and socioeconomic factors that are expected to influence relocation along with infrastructure services provides a better understanding of the ceteris paribus impact of infrastructure on relocation, thus, improving our understanding of the role of infrastructure in the response and recovery phases.

The study considers the Nepalese context; a context of a developing country in a region of high seismic hazard. The same procedure can be used and expanded for other communities. Developed models can be utilized in anticipating the varying impact weights of lifeline services, which in turn can help lifeline utilities planners in prioritizing the repair and restoration of these services (Wright & Johnston, 2010) and capitalizing on the available resources, especially during the overwhelming response period. Relocation models are developed using empirical data. Empirical models contribute to the scholarship in complementary ways too, it can be used in the exploration of “what if” scenarios to study the impacts of proposed mitigation plans (Chang, 2016).

1.5 Research Question

The question this study addresses is:

What is the impact of infrastructure services, particularly: piped water, government-provided electricity and vehicle-accessible roads, on household’s relocation decision?

1.6 Thesis Organization

In this, the first section, a brief introduction of the societal problem this study addresses has been provided, gaps in existing literature have been pointed out, and terminologies that define the essence of this research have been discussed. The research question of this study was also introduced: understanding the role of infrastructure services in household relocation decision after disasters.

Section two will begin by discussing the importance of studying relocation after disasters and the socioeconomic, psychological and well-being consequences of relocation. Then, the section will provide a review of the literature related to the factors influencing relocation after disasters in the light of the available data. A conceptual model that captures the relocation decision-making process and the variables that influence it will be introduced as well.

Section three will describe the specifics of this study’s context: the Nepal 2015 earthquake. Figures and estimates of the damage caused by the earthquake will be provided followed by a description of the data and variables used in the analysis. The section will discuss how each variable was captured in the household survey, the variables types and coding, and the descriptive statistics of the sample surveyed.

Section four will present the analyses, utilizing logistic regression. Then the reader will be walked through the incremental steps performed and assumptions made during the development of the models estimating the relative consequences that damage, social, and infrastructural disruption have on the likelihood that a household would relocate.

Finally, section five will provide the conclusion of this research. The analytical results will be discussed along with the implications of these results. The section will finish with a discussion of the limitations of this research and offer suggestions for future research.

2. LITERATURE REVIEW*

In this section, there is no intention to provide a comprehensive review of existing theories of displacement after disasters, rather, this section presents a broad overview of theories and literature that can be related to the relocation behavior after disasters in the light of available predictors in the available data.

2.1 The Importance of Understanding Household Relocation Behavior

Displacement, for better or worse, has always been a survival strategy and a traditional response to destructive natural hazards (Hugo, 1996). Indeed, the number of households displaced is a traditional measure of a disaster's intensity and adverse effects, along with the number of casualties (Cavalieri et al., 2012; Comerio, 1997). This subsection, subsection 2.1, will discuss the fundamental consequences and repercussions of relocation that make it important to study and understand relocation.

2.1.1 Temporary Displacement Often Developing to Permanent Relocation

The destructive nature of disasters greatly increases the possibility of uprooting large numbers of people. When relocation happens on a community level, it has the potential of becoming a secondary disaster, generating the need for mass-care facilities and encampments, and it can make community recovery processes much more complex and precarious (Oliver-Smith, 2013).

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* Figure 2.1 Number of Nominations in this section is reproduced from Figure 4. Number of nominations found for indicators in the 18 studies surveyed, with the permission from the first author Bijan Khazai, from *A new approach to modeling post-earthquake shelter demand in the aftermath of earthquakes: Integrating social vulnerability in systemic seismic vulnerability analysis,* by Khazai; Daniell; Franchin; Cavalieri; Vangelsten; Iervolino; & Esposito. 2012. Paper presented at the Proceedings of the 15th WCEE 2102.

Households relocation starts as temporary post-event evacuation but often evolves into eventual and longer-term relocation (Esnard, 2017). The return of citizens permanently to their neighborhoods is a key to the success of community recovery processes (Boyd et al., 2014), and the speed of this return is important as well (Olshansky, 2005). When people relocate it can become much more difficult to motivate their desire or abilities to return and rebuild. The complexity of the human decision-making process is amplified by the multifaceted complications of the disasters and recovery processes.

Evacuation is a complex collectivistic behavior (Quarantelli, 1984). Likewise, people's return to their homes, which is one of the first steps in a community post-disaster recovery process, is a collective action process; as people start moving back, more people are likely to follow (Storr & Haeffele-Balch, 2012). This collective action drives people to wait and see what other people, especially what their social network, will do. The longer the return is delayed, the higher the probability of abandoning the hope of returning and deciding to resettle elsewhere (Storr & Haeffele-Balch, 2012).

Relocation can create a coordination problem in the recovery efforts between the relocated population and governmental and non-organizational agencies. When people are displaced, officials cannot gather all the knowledge to know which communities, or parts of a community, are most likely to rebuild because it is based on the decentralized decisions of multiple households, which could discourage the restoration of essential services and, consequently, could delay or even foreclose recovery (Storr & Haeffele-Balch, 2012). And even if the most generous aid and support were provided, returning home remains difficult to many (Sapat & Esnard, 2017).

2.1.2 Consequences of Permanent Relocation

Large population displacement, when it develops into permanent relocation, can result in psychological, social and economic challenges to individuals, community and governmental institutions on all levels. These challenges were evident in New Orleans after Hurricane Katrina (Boyd et al., 2014). McCarthy (2006) discussed how rebuilding

New Orleans after Hurricane Katrina was not a linear process in nature, nor was it comprised of independent processes. Rebuilding processes can go in positive virtuous cycles, or negative deleterious cycles. One negative cycle could be triggered by the people's abandonment of their homes and permanent relocation; more people will decide not to come back, the loss of social support network for those who did not leave increases the desire of relocation (Wright & Johnston, 2010) and the process continue in a reinforcing loop. And in the long run, relocation of a large proportion of the population results in high levels of property abandonment and vacancy, and, as a result, reduces the tax base that serves as one of the funding bases for long-term recovery efforts. The effect of people leaving their communities impedes the achievement of full recovery and it ripples through the different aspects of livelihood in a community (Zhang, 2012).

2.1.3 The Effects of Relocation on Individual's Psychology and Mental Health

Disaster survivors suffer from several mental and physical health strains caused by being away from their homes. Sense of loss, depression and the inability to adapt to the new environment are some of the disadvantages associated with displacement after a disaster (Binder et al., 2015; Yzermans et al., 2005). A study conducted by Erikson (1976) after the Buffalo Creek disaster, where traditional bonds of neighborliness and kindness drove human relationships in the community, revealed that survivors experienced disorientation, demoralization and loss of connection as a result of leaving their neighborhoods. People were considered to have suffered from a collective trauma because their feeling of well-being was fading as the surrounding community is torn out and no longer provides a source of support.

When people move away from their communities in which they are strongly rooted, their sense of place attachment is disrupted, threatening individual and communal self-definition (Fritz & Williams, 1957). Place attachment provides sense of stability, it implies an emotional connection, not only to people who live there, but also to one's neighborhood or city (Altman & Low, 1992). Place attachment is fundamental for community resilience as it often underlies residents' efforts to revitalize a community (Fritz & Williams, 1957).

When mental health is affected, a person's ability to use their qualifications is reduced in the time that it is mostly needed, the time to recover from a disaster (Herrman, 2012). Returning to homes and neighborhoods and rebuilding are most often the best option for the mental and social health on an individual level, and for wellbeing on a community level.

2.1.4 The Effects of Relocation on Community Well-Being

Community well-being goes beyond the individual well-being of its constituent population; a community is not simply the sum of its members, nor it is with community well-being (Norris et al., 2008). Therefore, studying the effect of relocation on community well-being is not achieved by solely addressing its effect on individuals. Community wellbeing research suggests that day to day interactions with family, friends and neighbors plays a critical role in maintaining a sense of community. Yet, sense of community is very fragile, and here come the potential critical consequences of a disaster on the communal health. Fine changes in the community can have a considerable impact on perceptions of community essence and consequently, community wellbeing (Hancock, 1993).

Relocation is an important decision for the household to make; it affects household's well-being in the short and long run and affects the community's well-being after the disaster on a collective level (Kessler et al., 2008; Nejat et al., 2016). The extent of displacement, along with the duration of displacement, could be used to measure the resilience and well-being of the community. Quantifying households who stayed at their houses is one of the performance measures and standards that could be used to measure community social resilience. Chang and Shinozuka (2004) suggested using the percentage of households displaced against a pre-established limit, less than 5% for example, as a standard to measure community social robustness, and the percentage of households that returned after a certain period, more than 99% after one week for example, as a standard to measure rapidity of the social system recovery in a community.

Comprehending migration, temporary and permanent, and its connection to the restoration of community health, is essential for a community context disaster recovery research, plans and policies. A focus on the role of emergency management and disaster response systems on the determinants and indicators of communal health is required because even though these systems are not directly responsible for community health and well-being, if it utilizes well-informed procedures and functions effectively, it could, not only protect lives, minimize injuries and reduce damage to facilities, but also, keep individuals distress and community well-being disruption to a minimum (Norris et al., 2008).

2.1.5 Policy Implications

High-impact, low-probability natural events are anticipated to increase exponentially in the future. This anticipation coupled with the growing size and increasing exposure of the at-risk communities in disaster-prone areas call for a pressing need for a better understanding of the drivers and dynamics of disaster response and recovery (Nejat et al., 2016) and the interactions between policy and society (Sapat & Esnard, 2017).

Any governmental and organizational efforts to incentivize rebuilding and recovery and organize the activities of thousands, hundreds of thousands, and maybe millions of affected people are severely weakened when residents are displaced (Storr & Haeffele-Balch, 2012). Effective planning for long-term recovery requires knowing which residents will be in the community to rebuild and recover to best allocate resources. Comprehensive and nuanced investigation and analysis of displacement drivers and the relationships among these drivers should inform how to respond to displacement (Internal Displacement Monitoring Center, 2015a, 2015b).

Relocation decision effects on household health, community recovery success, and community's well-being after a disaster attract policymakers' and the general public's attention, as well as the research community's attention (McCarthy, 2006). Acknowledging and addressing the complexity of displacement are the responsibility of the broad range of policy makers and community practitioners who work with displaced populations issues to enable and facilitate the desired outcomes (Sapat & Esnard, 2017).

When translating the concept of resilience into policies that could be implemented in the real world, communities' human dimension should be mindfully investigated and integrated into these policies. It should be examined in conjunction with the resilience of the built environment (O'Rourke, 2007). The role of physical environment in the household post-disaster decision-making process, including relocation decision, implies the importance of including physical environment resilience plans in the pre-disaster planning phase for the response and early recovery post-disaster phases. While these are significant motivators, analyses' and studies' results are more significant when variables are combined with socioeconomic complementary variables. Overlooking the social and economic consequences of lifelines losses result in underinvestment in mitigation efforts (Chang, 2016).

The severity of the socioeconomic impacts of infrastructure disruptions are not solely dependent on the occurrence and duration of the disruption, they are also determined by the preparedness and response measures assumed by governments and individuals (Chang, 2016). Existing policies and practices have shown inability to promptly implement effective response and recovery activities, including restoring of infrastructure, properties and other communal and commercial activities, even in the economically developed countries (Nejat et al., 2016). Public policy's recognition of the significance of recognizing and examining lifelines disruptions is growing. The growing attention on anticipating community's resilience is shedding a brighter light on the role of infrastructure systems in community resilience and our ability to foster it. Many reports and strategies in the United States have identified infrastructure as a strategic priority for research and application purposes (Chang, 2016).

In the direct aftermath of a disaster, the consideration of the long-term effects of procedures and policies long-term effects are often overwhelmed by the large quantities of urgent immediate needs of affected communities. Goals, priorities and patterns of redevelopment in the short- and long-term community recovery may be shaped by the details of infrastructure restoration in the community (Boyd et al., 2014). Planning for ex ante definition of priorities and options ensures that swift decisions made and procedures followed after a disaster are aligned with the long-term goals and visions of the community. At the same time, flexibility in the implementation of these plans after the disaster could turn adversity into opportunity (Boyd et al., 2014).

Public policies, although established and implemented to overcome disasters adversities, are a double-edged weapon; it could either reduce risks and increase resilience or continue with the same mistakes and increase vulnerabilities (Sapat & Esnard, 2017). Uncoordinated responses can cause serious negative impacts, economically; socially and culturally, and increase the vulnerability of displaced people (Esnard & Sapat, 2018). Governments and organizations should utilize lessons learned from previous oversights, miscalculations and misunderstandings of the impacts and consequences of the implementation of, or the lack of, well-informed policies and procedures (Storr & Haeffele-Balch, 2012).

This study is directed at understanding and modeling the impact of infrastructure disruption, physical damage and socioeconomic characteristics on the relocation of people in Nepal after the 2015 earthquake. The same procedure can be used and expanded for other communities. Anticipating the varying weights of impact of lifeline services helps lifeline utility planners in prioritizing the repair and restoration of these services (Wright & Johnston, 2010) and capitalizing on the available resources, especially during the overwhelming response period. Empirical models contribute to the scholarship in complementary ways too, it can be used in the examination of “what if” scenarios to study the impacts of proposed mitigation plans (Chang, 2016).

The next subsection, subsection 2.2, will look at the details of the relocation decision-making process and the drivers that influence the household's decision to leave or stay in the literature.

2.2 Household Relocation Decision-Making Process

Households leave their residencies, and possibly neighborhoods and cities, after disasters for two main reasons: to avoid loss of life and physical harm to their members and/or assets (McLeman & Smit, 2006), and to achieve stability in daily routines that have been upended due to the loss of their homes, household assets, jobs, neighborhoods, and social capital (Chase-Dunn & Grimes, 1995; Khazai, Anhorn, Girard et al., 2015). Yet, displacement is not an automatic response when one of these reasons occur. In other words, relocation is rarely attributable to a singular reason; rather there are often multiple factors stemming from the event itself and the abilities of a household to make adjustments that will shape or determine dislocation (McLeman & Smit, 2006).

The decision by the household to evacuate or shelter in place can be perceived to go through a series of yes/no decisions as presented by Chang et al. (2009). Each decision is influenced by interacting and overlapping factors ranging from the physical environment stability, functionality and livability to the less tangible socioeconomic factors that determine the household's inclination and ability to leave.

This subsection, 2.2, will discuss each of the Yes/No decisions the household has to make for relocation and the different factors suggested by the literature to influence it. The literature reviewed will then be summarized in subsection 2.3 in a conceptual relocation decision-making model shown in Figure 2.4.

2.2.1 House Structural and Functional Habitability

Physical damage to a household's home is one of the primary reasons causing relocation after disasters (Build Change, 2015; Khazai, Anhorn, Brink et al., 2015; Peacock et al., 2007; Tai et al., 2014). Disasters damage and destruction to housing have been rising globally, increasing the numbers of displaced populations (Esnard & Sapat, 2018).

An additional and not unrelated issue will be access to critical infrastructure such as water and electricity. Many communities and households find infrastructure services essential to consider the building habitable (Chang, 2016; National Center for Research on Earthquake Engineering, 1994; Tai et al., 2014). Chang (2016) discussed how infrastructure disruption could result in households' displacement even when their houses are safe for living from a structural point of view because they considered it to be uninhabitable. A survey in the aftermath of the 1994 Northridge earthquake found that many people left their homes to the Red Cross shelters, accounting for 14% of people in the shelters, even though their house were found structurally safe after inspection (Chang, 2016; National Center for Research on Earthquake Engineering, 1994). Then, if the building is structurally safe, the loss of lifelines might make the building uninhabitable, in terms of its functional performance and usability (Chang et al., 2009; Wright & Johnston, 2010). Lifelines are necessary for sustaining health and safety of households and communities, minimizing the livelihood disruption (Wright & Johnston, 2010) and maintaining the building's usability (Cavalieri et al., 2012; Chang et al., 2009; Wright & Johnston, 2010). Weather condition is another factor that determines if the building is habitable after a disaster (Chien, Chen, Chang et al., 2002; Khazai et al., 2012).

Recognition of the dependence among and differences between building's structural habitability and usability has been addressed in some earthquake damage assessment studies (e.g. Cavalieri et al., 2012; Chang et al., 2009; Wright & Johnston, 2010). Habitability and usability in the short aftermath of disasters are usually assessed by quick observation (Wright & Johnston, 2010). The Italian Form for Damage during a

Seismic Emergency 'Agibilità e Danno nell'Emergenza Sismica’ used after the 2009 L’Aquila earthquake in Italy by the Italian Civil Engineers to record and classify the physical damage to structures included three classes for usability: fully usable, partially usable and non-usable, and two-class for habitability classification: habitable and uninhabitable. The classification of a structure’s usability is basically dependent on the level of residual utilities service in a structurally habitable building as well as the weather conditions (Cavalieri et al., 2012).

Structural habitability is solely a function of the level of structural damage and safety of the building. A building is classified as either habitable or uninhabitable, regardless of its usability. A structure’s functional habitability, or usability, on the other hand, is a function of the structural and non-structural elements damage. Usability depends on habitability, any structure that is not habitable is not usable.

In this study, the level of physical damage to houses, and neighborhoods, are not assessed by professional inspections. Rather, the survey respondent’s assessment or observation of their house damage is used. Separate questions for the level of house damage and the availability and residual services of water, electricity and roads were asked in the survey. Yet, that does not imply that a respondent’s assessment of the level of house damage was constrained to its structural damage. For the purpose of this study, a dummy variable was generated based on survey responses to capture homes that were significantly or completely damaged from those with no or slight damage.

2.2.2 Role of Infrastructure in House Functional Habitability

Relocation is one of the social impacts of lifelines losses in disasters (Cavalieri et al., 2012; Chang, 2016; Chang et al., 2009; Peacock et al., 2007). The significance of infrastructure systems to individuals, societies, and economy, and the physical vulnerability of these systems is evident in the disruption caused by almost all natural and human-induced disasters (Chang, 2016). The loss of lifelines services plays a significant role in driving people to leave their homes even if the building survived the disaster in good condition (Chang, 2016). The direct effect of infrastructure disruption on households' relocation decision and behavior in the aftermath of disasters have been addressed in some post-event evacuation and shelters capacity studies (Cavalieri et al., 2012; Chang et al., 2014; Chang et al., 2009; Wright & Johnston, 2010).

Three infrastructure systems will be addressed in this study: electricity, water and roads.

2.2.2.1 Effect of Infrastructure Disruption

Electricity has been found to be of the highest importance among the different lifelines in many communities (Chang et al., 2014). In an attempt to encourage residents to stay home when there is no major damage risk, officials and lawmakers ordered Texas Emergency Management Division to minimize power outage duration among other strategies to improve hurricane response plans following Hurricane Rita (Batheja, 2015). The impacts of electricity loss are aggravated by the reliance on electricity for food preparation, health equipment, heating, cooling and insulation, and the loss of other lifelines functionality like water and wastewater systems (Wright & Johnston, 2010). Electricity is not only important to people for direct use, it might also be a necessary input for other dependent infrastructure services that affect the household such as water pumps (Chang, 2016).

Water disruption, as well as electricity disruption, is part of the predictors that contribute to the uninhabitability of the building which triggers the relocation decision of the household after an earthquake (Chang et al., 2014; Chang et al., 2009; Tai et al., 2014). Transportation has been also found to be relatively significant (Chang et al., 2014; Tai et al., 2014). A study conducted following the 1999 Taiwan's 921 earthquake by Tai et al. (2014) showed that road disruption significantly increased the household's decision to evacuate.

2.2.2.2 Effect of Infrastructure Disruption Duration

Duration of infrastructure disruption is an important factor determining the criticality of the disruption impact. Disruptions for short durations could be perceived solely as inconvenience, while long durations cause serious disturbances to people's lives, reduce the tolerance for sheltering at home (Wright & Johnston, 2010) and makes it hard to rebuild and recover which leads to households' relocation and businesses closures (Chang, 2016). Communities, people and sectors vary in their tolerance to the different lifelines disruption, so what constitutes a tolerable "short" disruption duration is not constant. Weather condition is another factor influencing the tolerable limit of infrastructure services disruption (Chang, 2016).

2.2.2.3 Effect of Pre-Disaster Dependency and Services Alternatives

The high dependency on a lifeline source before the disaster and the lack of alternative sources after the disaster make people and communities more sensitive to the loss of services from that source. Social impacts of infrastructure disruption are caused by the disruption to the service not by the damage to the system that provided the service before the disaster. Redundant and alternative sources of infrastructure services could significantly prevent or reduce the adverse impacts caused by the damage to a specific infrastructure system (Chang, 2016). Functioning alternative roads, backup power generators and tanker trucks are examples of redundancy and resourcefulness in the systems that could prevent disruptions in people's lives or minimize its impacts. (Chang, 2016). This emphasizes the role of preparedness and response actions, performed by agencies and individuals, in determining the severity of the impact of lifelines disruption.

The nature of the pre-disaster infrastructure conditions in terms of redundancy, safety/quality, and other features are important to consider, for these may well have consequences for the potential impacts post-disaster disruptions may have on the likelihood of dislocation. Indeed, these pre-existing conditions juxtaposed with post-disaster disruptions and, most importantly, aid to address lifelines might be particularly important for whether or not households will feel the need to dislocate. Because of these issues, the particulars of the water supply situation in Nepal before the earthquake and the attributes of the aid provided after the earthquake will be examined and discussed.

Nepal faces a safe water scarcity crisis. The crisis expands and intensifies every day due to the rapid population growth and high rate of unplanned urbanization. As a consequence, Nepal is experiencing a drying up of conventional water sources and problems related to the operation and maintenance of water networks and treatment facilities. Furthermore, climate change is making the acquisition of sufficient clean water a daily struggle (International Centre for Integrated Mountain Development, 2014; International Union for Conservation of Nature, 2014; Shrestha & Maharjan, 2016). Kathmandu Valley, is densely populated. Population requiring water supply in Bhaktapur, one of the three administrative districts in Kathmandu Valley, is approximately 92,680, which includes the district's population of 81,748 (Central Bureau of Statistics of Nepal, 2011) and the estimated mobile population from tourists and foreigners of around 10,000 individuals (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015).

Bhaktapur is divided into three blocks; each block is supplied with water for one to three hours every three days (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015). Water supply volume depends on the monsoon, and therefore, varies considerable from the dry to rainy season. On average, based on supply and demand estimates for 2012, Bhaktapur municipality's supply deficit varies between 12,000 m^3/day in the dry season to 9,000 m^3/day in the rainy season (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015).

Residents of Bhaktapur make up for water shortage through the use of traditional water sources. Wells and stone spouts are the historical traditional water sources in the Kathmandu Valley, playing an important role in covering for the water supply-demand deficit (Shrestha & Maharjan, 2016). Bhaktapur had 153 stone spouts in 2008 (United Nations Human Settlements Programme UN-HABITAT, 2004), which once was the major water resource for citizens. Stone spouts were constructed to supply households with potable water and provide water to farm fields. Although the easy access to pipes water reduced the use of the spouts, residents of the Valley continue to use this source due to the fact that not all households have piped water supply, and for those who have access to it, the irregularity and deficit in supply from pipes maintained the dependence on it. Also, water from these spouts is free of cost; therefore, constituting the primary source of water for low-income households.

Newars', the largest and most influential ethnic group in Bhaktapur, traditional culture also supports the use of traditional water sources. This traditional practice is further established by the long founded Guthi, a social organization playing a key role in sustaining the traditional way of life of Newars. Women and female children hold the main responsibility of meeting household water needs through hours of laboriously collecting and bring water to the home. In addition, the relatively high illiteracy level among Newar women helps in the continuation of the traditional practices of using and cleaning stone water spouts, which is pushed even further by the limited and unreliable supply of piped water (Shrestha, Maharjan, & Rajbhandari, 2015).

Water quality is deteriorating rapidly in the Kathmandu Valley. Deterioration in these water spout, mostly detected by the change in water taste, in the past 15-20 years forced most citizens to pretreat the water to use it for drinking (Shrestha & Maharjan, 2016). In addition, rapid population growth increased the rate of urban environment deterioration in the Valley. Surface water is polluted with wastewater; most of the household generated wastewater is directly channeled to many surface water sources (Uprety, 2014). Water supply facilities are obsolete; it is not operated nor maintained appropriately, preventing the provision of sufficient supply of drinking water that satisfies minimum quality standards. Every year, water-borne diseases contribute to 22% of the deaths of children under five years-old (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015) Water tankers, bottled water and/or deep and shallow wells, in addition to stone spouts, are the significant sources of drinking water for many residents, even households supplied with piped water, as a result of the possible health hazards associated with the supplied water (Chapagain, 2014). Moreover, well's water quality worsens in dry seasons (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015), forcing many households to depend solely on bottled water and tanker water, at least for drinking purpose, despite the fact that tankers water is over five times more expensive than tap water (Hazama Ando Corporation & NJS Consultants Co. Ltd., 2015).

Following the Nepalese 2015 earthquake, water supply of up to 240,000 people was affected in the Kathmandu Valley (Thapa, Ishidaira, Bui et al., 2016). Water sufficiency and adequacy attracted immediate attention, especially in the response and early recovery phases (Uprety, Iwelunmor, Sadik et al., 2017). Water was supplied from public and private resources, and chlorine tablets were provided for treating drinking water. In a qualitative case study conducted by Uprety et al., (2017) after the earthquake, participants reported that water provided by the relief efforts was almost always sufficient, they did not run out of water because of the continuous supply. Also, they believed that the supplied water was pretreated by the city and was more reliable than the water they had before the earthquake. As well, the study showed that Nepali society compassion motivated neighbors to share their water with those experiencing water shortage after the quake.

Interestingly, governmental and nongovernmental organizations active involvement in aid efforts, to affected communities and households led to sufficient supply of higher quality water after the earthquake. People were satisfied with water quantity and quality after the quake, versus economic burden, dissatisfaction and worry associated with water insecurity that they suffered from before. Consequently, enhancing communities' ability to cope with the adverse effects of the earthquake (Uprety et al., 2017).

People's perception of the new water situation after the quake contradicts the impact expected in the general context in the literature. Piped water disruption and general shortage of safe, clean water was a normal expectation to daily routines prior to the earthquake. As a consequence, post event disruption of piped water might not have the expected consequence of forcing dislocation afterward, particularly when there was continuous availability of reliable water provided by governmental and non-governmental agencies after the earthquake. As a result of the Nepalese context unique situation, no hypothesis of the impact of piped water disruption could be developed, especially with the availability of piped water service data only and the lack of data regarding other traditional and aid water sources as will be shown in the next sections.

The impacts of the infrastructure services' disruption, disruption duration and the availability of alternative sources of the service on household relocation demonstrate the significance of infrastructure services' resilience in household relocation and community resilience. The loss of a service, the longer duration of the service loss, and the lack of alternative sources for the service, all could contribute to decreasing the house's habitability and could lead to relocation. Infrastructure resilience directly influences the attributes of the infrastructure service after the disaster. As shown in Figure 1.1, a robust system exhibits lower probability of losing its function and retain a higher level of remaining function, rapidity decreases the duration of the service loss, and the redundancy and resourcefulness provide alternative sources that allow the system's function to bounce back quicker.

2.2.3 Desire to Relocate

Relocation is not solely caused by the habitability, structural and functional, of the building itself. People's desire to leave goes beyond the safety and functionality of their home to whether they perceive it desirable to leave (Chang et al., 2009). The desirability of people to leave their homes and seek another shelter can be affected by demographic and socioeconomic characteristics of the household, risk perception, social capital and place attachment.

2.2.3.1 Neighborhood and Roads Damage

Neighborhood livability can be essential for household's well-being and ability to function. It affects the household's desire to stay in their home (Chang et al., 2009). Severe neighborhood damage affects the services and support systems households need, which makes it hard for the household to stay and increases the desire to relocate (Wright &

Johnston, 2010). Roads and public transportation can also be essential parts of making neighborhoods livable. In a world where households are highly dependent on other social units for products and services to meet the daily life needs from purchasing house supplies to visiting family and friends, the ability to access these other organizations and groups can be important. Hence, road closures and nonfunctioning public transportation negatively influence people's desire to stay. The longer the recovery takes, the harder people's daily lives and routines get and the more probable they would wish to leave (Wright & Johnston, 2010). Infrastructure system's interdependencies add another significance to operating road networks after disasters. Repairs and reconstruction require access to the to the damaged structures and systems. Rapid restoration of roads and removal of debris not only keeps the disruption to people's daily lives to a minimum, but also enables restoration and recovery activities of other infrastructure systems (Chang, 2016).

2.2.3.2 Effect of Demographic and Socioeconomic Characteristics on the Desire to Relocate

In addition to the build environment physical conditions, demographic and socioeconomic factors are included in human behavior research in the disaster response and recovery context. Studies addressing post-event evacuation, actual and modeled, indicate the complexity of this decision-making process and describe how it cannot be explained solely by the physical environment attributes (Wright & Johnston, 2010). Many past-earthquake events have been observed to have higher numbers of displaced people than the numbers calculated based on physical damage to building and utilities and external conditions (Khazai et al., 2012). Household's demographic and socioeconomic characteristics shape their experience in disasters (Zhang, 2012) and household response and recovery behavior are correlated with these characteristics (Lindell, 2013b; Peacock et al., 2007). The determinants and outcomes of relocation overlap in many ways, making it a multi-dimensional construct (Esnard & Sapat, 2018).

2.2.3.2.1 Social Vulnerability

Disaster vulnerability is socially constructed, i.e., it arises out of the social and economic circumstances of everyday living. (Morrow, 1999). Vulnerability explains why different people are at different levels of risk when subjected to equivalent force of disaster (National Research Council, 2006). Social vulnerability measures characteristics that influence the capacity of a person or a group to anticipate, resist, cope and recover from the impacts of natural disasters (Masterson et al., 2014; Zhang, 2012). Although the varying vulnerable social groups are not mutually exclusive, they overlap way too often resulting in higher risk and higher marginality. Yet, the identification of these groups is important if vulnerability issues are to be addressed (Morrow, 1999).

Khazai et al. (2012) provided 13 demographic and socioeconomic characteristics that influence post-earthquake evacuation decision based on eighteen key studies in this field, shown in Figure 2.1. Most nominations in these studies were to income, age, minority and occupancy statuses. Yet, vulnerability of households and communities change over time, the patterns of vulnerability cannot be categorized into absolute categories and characteristics, it is way too dynamic and complex (Wisner, 2016).

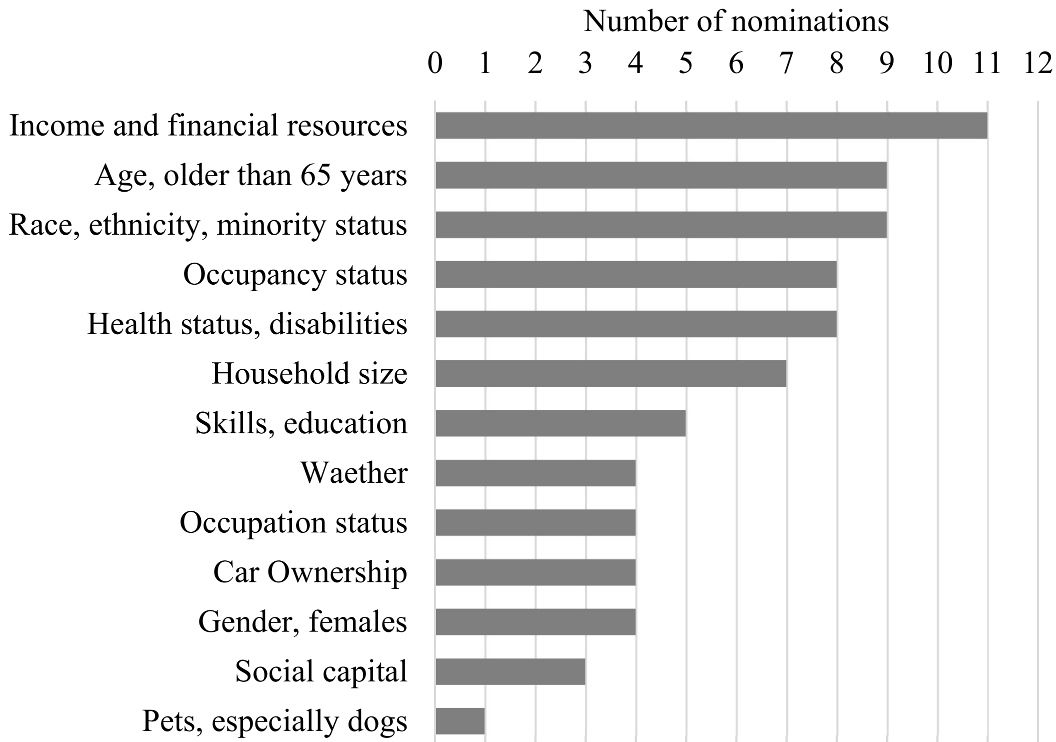

Figure 2.1 Number of Nominations Khazai et al. (2012) found for indicators in 18 studies
Reproduced from Figure 4. Number of nominations found for indicators in the 18 studies surveyed, with the permission from the first author Bijan Khazai, from *A new approach to modeling post-earthquake shelter demand in the aftermath of earthquakes: Integrating social vulnerability in systemic seismic vulnerability analysis*, by Khazai; Daniell; Franchin; Cavalieri; Vangelsten; Iervolino; & Esposito. 2012. Paper presented at the Proceedings of the 15th WCEE 2102.

Socially vulnerable households have less liquid financial assets (Morrow, 1999), lower quality of houses (Lindell, Prater, & Perry, 2006; Peacock, Van Zandt, Zhang et al., 2014), worse insurance coverage – if any (Peacock, 1997), and are in many cases located in areas at higher risk of natural hazards (Lindell et al., 2006).

2.2.3.2.1.1 Income

The association between poverty and vulnerability throughout the disaster response and recovery phases is easy to make. Households living in poverty suffer from disproportionate impacts of disasters from the beginning. They are disadvantaged before the disaster happens, and after the disaster, their material and economic losses, although is less in absolute terms, is more devastating. Reasonable financial resources, or insurance policies in some countries like the U.S., are necessary to pay for the interim living expenditures in order to find a sheltering substitute for the damaged house (Girard & Peacock, 1997). The insufficient financial reserves limit the options after the disaster for low-income households forcing them to stay and deprive them from buying services and material (Morrow, 1999) that could minimize the disaster impact on their livelihoods. More evidence points towards the fact that any impactful effort to reduce community vulnerability must essentially address economic stratification of the community and the issues related to poverty (Bolin & Stanford, 1998).

2.2.3.2.1.2 Education

As economic and material resources play a significant role in shaping individuals' and groups' experience after a disaster, these resources are extended to include a person's education (Morrow, 1999; Tierney, 2006). People with higher education can be safely assumed to have better work opportunities, better abilities to carry out self-protective actions and better skills in dealing with bureaucracies to obtain assistance in disasters (Morrow, 1999).

2.2.3.2.1.3 Race, Ethnicity and Linguistic Minorities

The mechanisms by which poverty, limited resources and marginal power and influence are associated with certain social characteristics of individuals and households introduce additional dimension for economic vulnerability in the disasters context (Morrow, 1999). Different racial and ethnic groups vary in their vulnerability to disasters (Tierney, 2006). The economic disadvantage that the constituents of racial or ethnic minorities suffer from in general is significantly contributed to their vulnerability. However, vulnerability is not the only reason for the higher risk; more critical impact and slower recovery they suffer from. Individual and group access to assets and political power is profoundly influenced by sociocultural background (Lynn, 2006).

A study by Perry and Mushkatel (1986) on ethnic groups evacuation in the face of pre-event warnings revealed that minority ethnic groups are less likely to evacuate even after controlling for income in the study's quantitative analysis and eliminating the direct and indirect effects of income. Girard and Peacock (1997) also found that ethnicity played a significant factor in the relocation of Blacks after Hurricane Andrew, even after controlling for the level of damage and housing characteristics. Blacks were found to be less likely to relocate when compared to other ethnic groups in the area because of the lack of alternative housing options and resources to find such housing (Girard & Peacock, 1997). The economic disadvantage that the constituents of racial or ethnic minorities suffer from, generally speaking, is usually accompanied by social and political marginality that limit their options even more in disaster response.

From the discussion above, it is clear that the ethnic status of households can have implications for response and potentially dislocation. However, it is also clear that the manner in which ethnicity might impact response, and indeed, the nature of ethnicity in different research settings can be quite different. Such is the case with Nepal and this research context. In Nepal, ethnicity has a particular relevance. Nepal's National Code, termed the Muluki Ain, specified a Nepalese caste hierarchy that identified four distinct ethnic groups based on cultural and language. These groups or castes are: the Parbatya, denoting the Nepali-speaking population; the Newar, comprising the Newari-speakers; the Bhote; and the Kirati. Each of the Parbatya and the Newar ethnic groups has its caste hierarchy, from the elite to the untouchable castes (Hofer, 1979). The caste system was a formal system, enforced and backed by the law until 1963 (Dani & de Haan, 2008).

One hundred and twenty-three languages were spoken as mother tongues in Nepal, as reports by the Nepal Central Bureau of Statistics (CBS) in the 2011 census report.

Nepali-speaking population constitutes the dominant proportion in all Nepal, as shown in Figure 2.2. The Nepalese linguistic classification does not reflect the socio-cultural typology in Nepal in full depth and details (Hofer, 1979). However, it provides sufficient base for the ethnic stratification for this study.

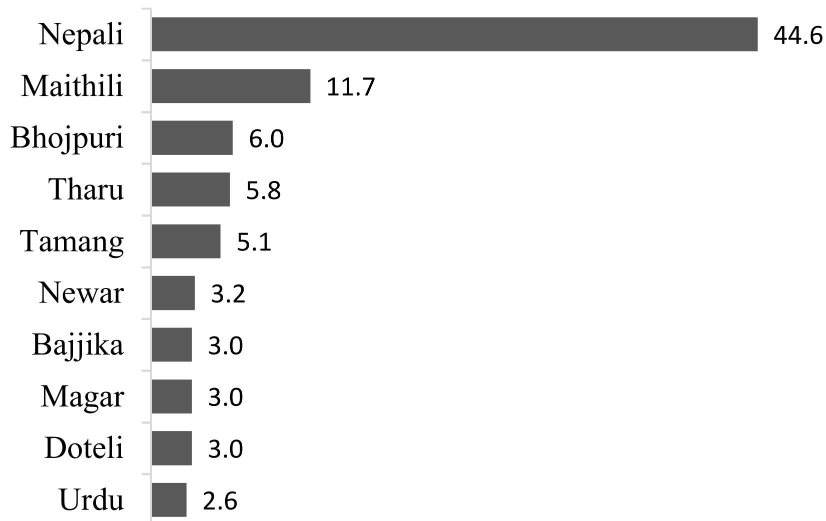

Figure 2.2 Top Languages Spoken as Mother Tongues in Nepal according to Alston, Whittenbury, and Haynes (2010)

Current laws and social policies in Nepal are following the increasingly shared global norms of social justice; it is even considered progressive. However, gender, caste, and ethnic discrimination have been rooted in Nepal for centuries. Ethnicity, to date, is a significant determinant of opportunities, social status, and life chance in Nepal (Bennett, Dahal, & Govindasamy, 2008). The caste system is one of the informal institutions that are deeply embedded in the Nepalese sociocultural context. Change through laws and policies requires attention to the mechanisms and incentive regimes used to change dominant groups' inequitable behavior and increase subordinate groups' access to opportunity (Dani & de Haan, 2008).

Newars are the dominate group in the area of Bhaktapur (von Fürer-Haimendorf, 1956). As mentioned earlier, the Newars are defined by the Newari-speaking population, therefore, Newars in the sample are defined as households who speak Newari language only.

The numerical dominance of the Newar population in Bhaktapur was reflected in this study where over 80% of the households in the sample surveyed were Newari-speaking, around 10% were Nepali-speaking, and less than 10% spoke both. That numerical dominance is also reflected in the social hierarchy of the area.

Dani and de Haan (2008) examined the links between poverty and social inclusion in Nepal and presented the persistence of caste, ethnic, and gender hierarchies. The Newar ethnical group has the lowest poverty headcounts, and the highest Human Development Index among the different ethnic groups in Nepal (Sharma, Guha-Khasnobis, & Khanal, 2014). Newars residing in Kathmandu Valley and its surrounding areas are considered influential, with social and economic leverage (Stash & Hannum, 2001; von Fürer-Haimendorf, 1956). In light of their higher status and greater access to scares resources, it will be expected that Newar households will have a higher likelihood of relocating when compared to other ethnic households that exhibit higher social vulnerability in the surveyed area of Bhaktapur.

2.2.3.2.1.4 Relationship of Social and Physical Vulnerabilities

Hazard exposure, social vulnerability and structural vulnerability have been found to be related (Lindell et al., 2006; Peacock et al., 2014). The impacts of disasters often appear to be arbitrary or determined exclusively by the disaster agent characteristics, however the literature has clearly shown that social and economic differences influence the likelihood of experiencing injury, damage, and hardship from a natural hazard event, and in many times, it even influences the quality of buildings and structures (Holand, 2014).

Peacock and Girard (1997) empirically examined the ethnic and racial inequities in houses damage and recovery process after Hurricane Andrew. Race and ethnicity played a significant role in neighborhood segregation, housing quality and homeowners' insurance that lead to differential damage of Hurricane Andrew on structures and households and differential resilience of households in the recovery process.

A study that included data from 207 countries found that a poor[2] person is 1.8 times more likely to live in a fragile building than the average person (Hallegatte, Vogt-Schilb, Bangalore et al., 2017), as shown in Figure 2.3. This physical vulnerability has been found to decrease as the individual's income increase.

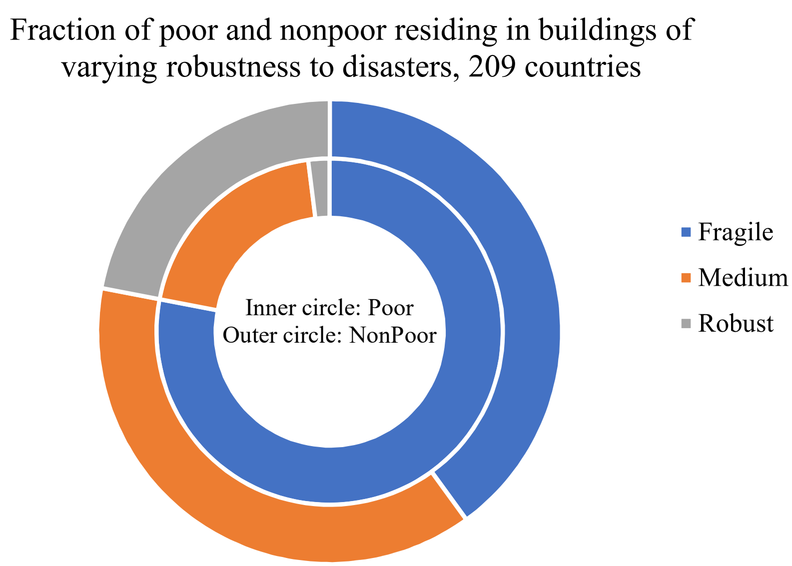

Figure 2.3 Physical and Social Vulnerabilities from Hallegatte et al. (2017)[3]

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[2] Within the poorest 20% in the population based on consumption.

[3] This is an adaptation of an original work by The World Bank. Views and opinions expressed in the adaptation are the sole responsibility of the author of the adaptation and are not endorsed by The World Bank.

Damage caused by disasters is not homogeneous over structures and households because structures and households are not homogeneous to begin with. The household's financial resources and social characteristics do not only control the physical vulnerability of the structure, but in many cases, its location too (Peacock & Girard, 1997). Many socially vulnerable groups live in neighborhoods located in disaster-prone areas (Lindell et al., 2006; Peacock & Girard, 1997).

Also, the criteria of what people consider suitable for living is not constant among different individuals, groups and communities. Indeed, the nature of the household (i.e., presence of children, the elderly, gender, etc.) may well shape their sensitivity to the level of damage to their residence and disruption to infrastructure services.

2.2.3.2.1.5 Social Vulnerability and Infrastructure Disruption

Research has found that different population groups vary in their vulnerability to infrastructure disruption (Hallegatte et al., 2017; Holand, 2014). Vulnerable groups usually have disparity in their access to emergency assistance and differential capacities and resources to get access to services alternatives resulting in differential capacity of these groups to withstand infrastructure disruptions. Although everybody depends to some extent on running water, electricity and operating roads, poorer people have less ability to protect themselves from the repercussions of infrastructure services disruption (Hallegatte et al., 2017). In return, infrastructure disruptions potentially contribute to the differential social vulnerability to disasters (Chang, 2016).

2.2.3.2.2 Home ownership

Tenure is also linked to the intention and ability to take measures directed towards protecting and repairing the property. Renters have little saying in what should happen to the house or building they live in, in terms of its structural soundness, protection and mitigation or the level of repair and maintenance after a disaster (Tierney, 2006). As a result, renters have less likelihood to stay in their pre-disaster homes (Wright & Johnston, 2010).

2.2.3.2.3 Demographic Groups

The relationship between income and vulnerability is evident in terms of finances, however, the link between age; gender; and race and ethnicity with limited economic resources and social and political influence is less apparent (Morrow, 1999). Disasters risk is concentrated in particular vulnerable demographic categories of the community. Age and gender attributes define some of these categories. Women, children, and the elderly are demographic groups that are at higher risk during the response process (Morrow, 1999).

Many studies have addressed the high vulnerability of the elderly (Chang, 2016). Although the vulnerability of the elderly is dependent on other factors including health, age, family and economic conditions, the elderly demographic category as a group can be safely assumed to suffer health-related repercussions and be short of the resources required for effective response, physically and economically (Bolin & Klenow, 1988; Bolin & Stanford, 1998; Friedsam, 1962; Morrow, 1999). Old residents often times need more assistance after a disaster. Information about the locations, the conditions and the availability of programs targeting their concerns are required for providing effectual sheltering options for the evacuation of old people (Morrow, 1999). Moreover, older people show higher unwillingness to leave their homes (Gladwin & Peacock, 1997).

Gender inequality in power, access to resources, as well as cultural barriers can have profound consequences, often negative, on the ability of women and girls to overcome the hardships introduced by disasters. Societies have different social environments among genders. Power, privilege, expected social behavior and roles in the community are not the same for both genders (Tierney, 2006). This gendered dimension rises from the complexities of culture and social structures resulting in gendered experience, response and impact of any social event, especially significant events like disasters (Morrow & Enarson, 1994). The gender stratification during disasters is evident from the higher likelihood of women dying in climate disasters (Alston, 2013; Neumayer & Plümper, 2007; Tierney, 2006). The differences in casualties and injuries between men and women are higher in developing countries because these disparities are caused by power unbalance that restricts women behavior and decision-making leverage (Tierney, 2006).

Emergency response often times assumes a gender-neutral behavior of women and men, which unintentionally strengthens the existing inequities between genders (Alston, 2013). The lack of adequate facilities for women in shelters often makes staying home more preferable (Alston, 2013). Alston (2012) highlighted women's experiences about shelters in Bangladesh. Women reported that the isolated areas in which sanitation facilities were established by NGO exposed them to violent attacks and that some did not have separate female toilets. Besides, women vulnerability is demonstrated by the limited access to resources caused in part by the gender-specific responsibilities and constraints in most societies (Morrow, 1999) increasing their vulnerability and their desire to stay at home.

The unique experience of men and women in disasters is further amplified when combined with other social dimensions such as poverty, race and ethnicity, age, and culture (Enarson, 2012; Gladwin & Peacock, 1997). Poor people are more likely to be females, on average, their representation among the poor is higher than would be expected based on their proport in the population, which results in the adverse effect of a disaster disproportionally impacting on females (Neumayer & Plümper, 2007). The vulnerability caused by poverty associated with gender is not limited to developing nations (Neumayer & Plümper, 2007). Poor women from minority ethnic groups or vulnerable races are more likely to experience higher risk and higher damage, yet, are expected to have less resources and financial capacities. And in terms of living arrangements, female-headed households face higher risks of poverty and lower capacities and resources (United Nations, 2015).

On the other hand, women are more risk-averse than men (Tierney, 2006). Women in disasters are among the earliest to act, in what is interpreted as "panic" by men in some studies (Enarson, 2011), as they possess a stronger perception of risk and danger (Bateman & Edwards, 2002). Also, the presence of children makes the evacuation behavior of women even more likely (Gladwin & Peacock, 1997), yet, resources may actually inhibit their abilities to act. Vulnerability of children is self-evident (Sapir, 1993), children make the need for moving to a safer and more convenient place all important. The presence of children has been found to be positively correlated to pre-hurricane evacuation (Quarantelli, 1980; Wright & Johnston, 2010), except for single-parent households which is less likely to evacuate (Wright & Johnston, 2010), and since caregiving is traditionally a primary responsibility of women, women go with them (Enarson, 2011).

Yet, women's shortage of finances and power to make decisions in the household undermines the impact of their desire on the final decision of the whole household. Even if women would like to leave, their movement is tied to men's decisions way too often. Men make evacuation decisions, women's wishes to leave are often overruled by men in the household (Drabek, 1969). Nevertheless, women usually wait for men's decisions even when they are physically absent from the house (Enarson, 2011).

The body of knowledge shows a pull-push impact of women on household relocation decision. Domestic labor patterns, women's weight in the household decision-making process (Gladwin & Peacock, 1997), social norms and expectations of women (Alston, 2013), violence against women (Morrow, 1999) and the level of inclusion of women in the policy-making and planning for disaster response and recovery (Alston, 2013; Gladwin & Peacock, 1997) should be analyzed to have an accurate understanding of the eventual influence of women on household relocation decision in a community.

2.2.3.3 Effects of Risk Perception, Place Attachment, and Social Capital and Community Collective Action

Other factors influencing the desire of leaving that has been discussed in the literature include risk perception and safety concerns (Chang et al., 2009; Khazai et al., 2012; Riad, Norris, & Ruback, 1999), place attachment (Altman & Low, 1992; Jamali & Nejat, 2016), and social capital and community collective action effect (Henry, 2013; Khazai et al., 2012; Mawson, 2005; Nejat et al., 2016; Wright & Johnston, 2010).

2.2.4 Ability to Relocate

If the household decides that it is desirable to leave, the actual relocation then depends on their physical ability to relocate and accessibility to a place to shelter. The household's members should be able to move, locate a shelter and have means of transport to get there (Chang et al., 2009; Morrow, 1999; Serulle & Cirillo, 2014; Vogt & Sorensen, 1992) to be able to leave their home.

2.2.4.1 Mobility

2.2.4.1.1 Women

Cultural and social norms, that are usually derived from the unequal distribution of power between men and women (Neumayer & Plümper, 2007), can impose restrictions on women's movement during disasters. Male-escort maybe required by local customs for a woman to be able to leave her house (Alston, 2013), which limits women's ability to relocate in the absence of men. Women may remain in their homes unless they are escorted to leave (Alston, 2012). Women's compliance with the social norms and expected roles often seems voluntary, however, these norms and roles are a result of the inequitable distribution of power between men and women in many communities (Neumayer & Plümper, 2007).

2.2.4.1.2 The Elderly, Children and Injured Members

Human resources of the household, i.e., health and physical ability, play a leading role in determining the ability of people to move and the amount of assistance they need for it (Morrow, 1999; Vogt & Sorensen, 1992). Children, the elderly and disabled household members reduce the household's mobility and viable sheltering options (Morrow, 1999). Household's mobility is significantly reduced by people with age over 65 (Tai et al., 2014). Health issues reduce the household's ability to leave (Wright & Johnston, 2010). Household mobility is also influenced by the size of the household, smaller households are more transportable and have fewer constraints preventing them from leaving their homes. Households with many dependents face a higher potential of coming upon obstacles when responding to disasters (Morrow, 1999; Vogt & Sorensen, 1992).

2.2.4.2 Shelter and Transportation Availability

Availability of a place to shelter and having the appropriate means of transport are required to make the post-event evacuation trip a viable option (Chang et al., 2009; Vogt & Sorensen, 1992; Wright & Johnston, 2010) and make it more probable (Vogt & Sorensen, 1992). People with special health needs require transportation that can meet their needs, which could result in hesitance to evacuate if the suitable transport was not available (Stough, Sharp, Resch et al., 2016). Access to transportation systems to get to the shelter has been found to be related to income, households with low-income have differential access to transport systems (Serulle & Cirillo, 2014), lowering their ability to relocate even further.

The previous subsection provided an overview of the literature addressing the relocation decision-making processes and the built environment, social and economic drivers that are expected to influence them on a household level. The next subsection will summarize these processes and their drivers, and the hypotheses provided in the literature about the impact of these drivers on each process. It will also breakdown the conceptual model per process to provide a visualization of each process and the expected impact of its drivers.

2.3 Relocation Hypotheses

Summing up, the household’s relocation decision after a disaster depends on the level of damage to the physical environment as well as the household’s attributes. The literature discussed above provided hypotheses of the expected impact of the different factors on household relocation. These hypotheses will be later used in the development of relocation models in this study. In this subsection, 2.3, the relocation decision-making process, the variables that are expected to influence it and the expected impact of these variables will be summarized and a relocation decision-making conceptual model will be presented.

The relocation decision-making process adapted from Chang et al. (2009) and expanded according to the reviewed literature can be envisioned in the conceptual model shown in Figure 2.4. The conceptual model has four ordered decisions the household is expected to make when deciding whether to relocate or stay at their home. These appear in the model as diamonds flowing through the center of Figure 2.4 and are concerned with the household: assessing the structural and functional habitability of the house, deciding whether they desire to leave, and lastly, determining whether they can leave. A household is expected to stay if the house is habitable, both structurally and functionally, and they desire to stay, or if they can't relocate despite any need or desire to. The following discussion will walk the reader through the figure.

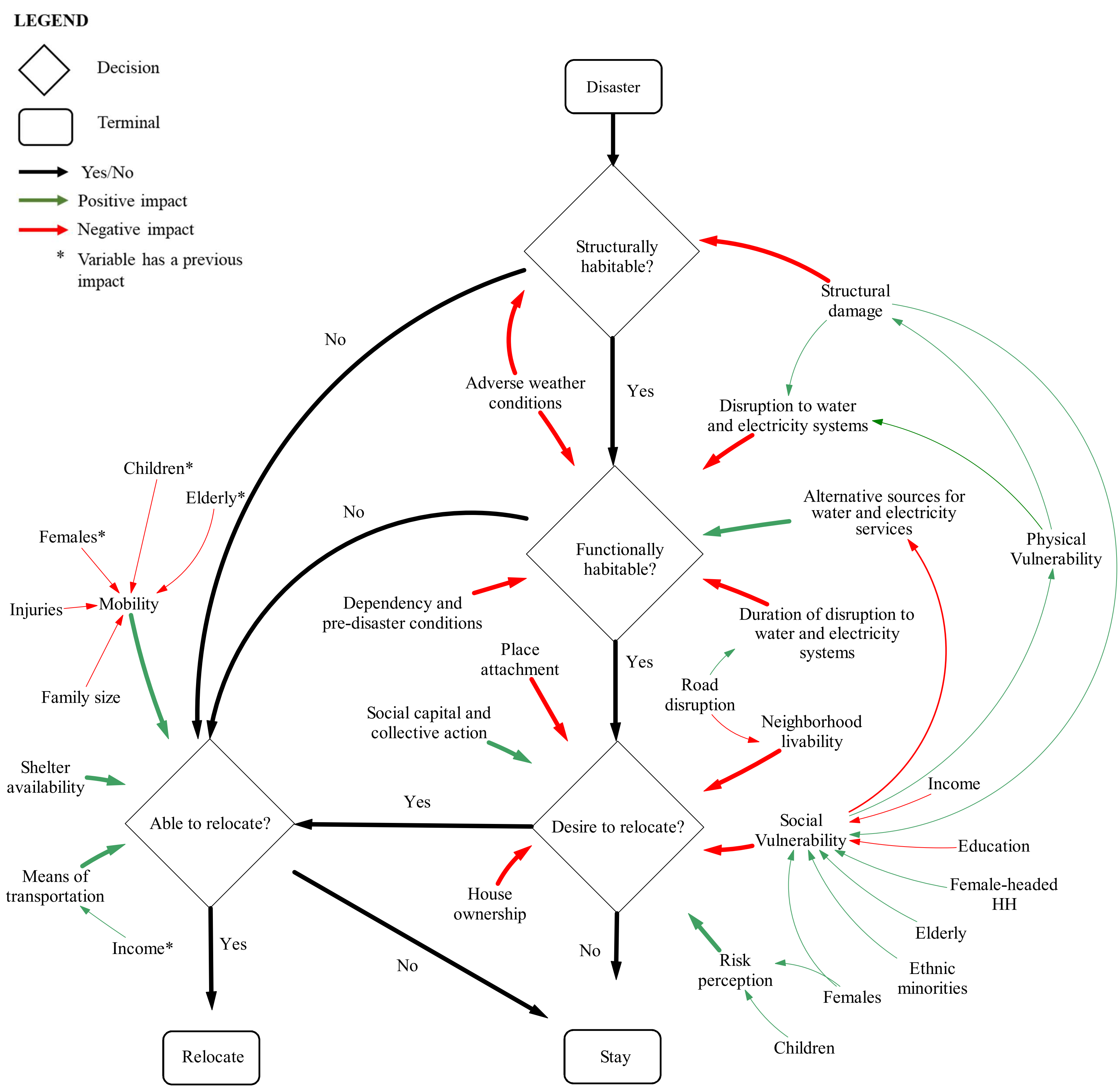

Figure 2.4 Relocation Decision-Making Process
adapted from Chang et al. (2009) and expanded according to the reviewed literature

* A colored arrow reflects the impact of a variable on a decision or on another variable. A positive impact on a decision means that an increase in the variable is expected to increase the probability of deciding “Yes” in that particular decision, and a negative impact means that an increase in the variable is expected to decrease the probability of deciding “Yes”. Similarly, in the cases where a variable is impacting another variable (not a yes/no decision), a positive impact implies that an increase in the variable at the tail of an arrow results in an increase in the impacted or dependent variable at the head of this same arrow, while a negative impact implies that as the “tail” variable increases the impacted or dependent variable decrease.

Relocation is at first a function of the physical condition of the household's home, i.e., the structural and functional habitability (Chang et al., 2009). Figure 2.5 focuses on these first two primary decisions.

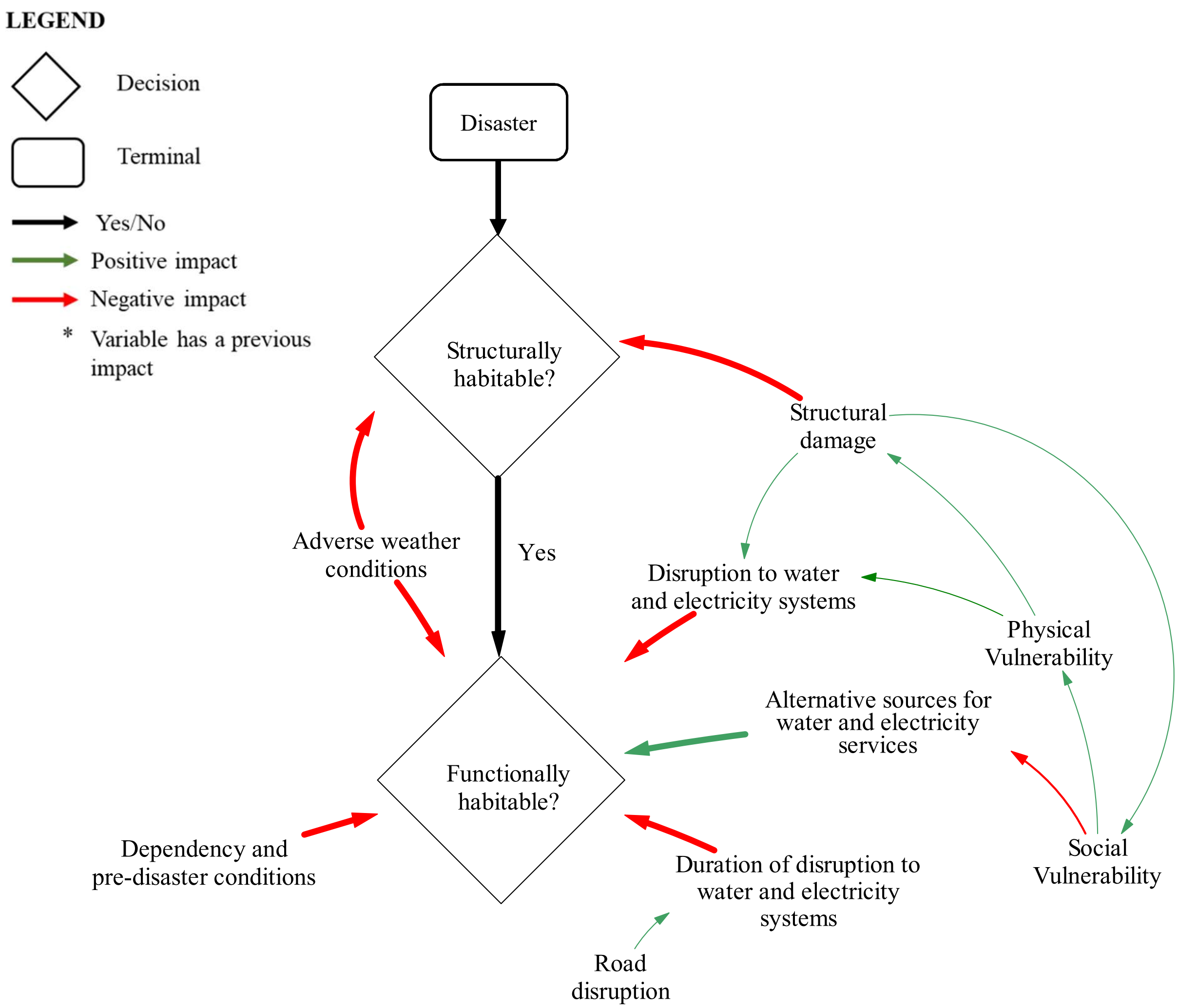

Figure 2.5 Assessing the Structural and Functional Habitability of The House

The house should be stable and safe to begin with for the household to be able to stay in it (Build Change, 2015; Khazai, Anhorn, Brink, et al., 2015; Peacock et al., 2007; Tai et al., 2014). The level of damage to the structure is not solely dependent on the intensity of the disaster. The level of destruction to the built environment is also conditioned on the its physical vulnerability.

Lifelines are essential for the house to be considered habitable in many communities, even if it was structurally stable (Chang, 2016; National Center for Research on Earthquake Engineering, 1994; Tai et al., 2014). Figure 2.5 shows the significance of water and electricity services in determining the functional habitability of the house. Disruption of utilities reduces the house's functional habitability and drives people to leave their homes (Cavalieri et al., 2012; Chang, 2016; Chang et al., 2009; Peacock et al., 2007). Communities, individuals and sectors vary in their tolerance for losses of utilities. Longer disruption durations make it harder to rebuild and recover and increases the likelihood of relocation (Chang, 2016). The high dependency on a certain source of service, especially with the lack of alternative sources, increases the impact of disruption and increase the likelihood of leaving. On the other hand, alternative sources of lifeline services could reduce the adverse impacts of lifelines systems services losses and could increase the likelihood of staying (Chang, 2016). Adverse weather conditions have also been found to reduce the house's habitability (Chien et al., 2002; Khazai et al., 2012).

Damage to homes and utilities losses cannot solely explain and model households' post-event evacuation behavior (Khazai et al., 2012). Figure 2.6 shows the variables that influence the household's desire to leave their house.

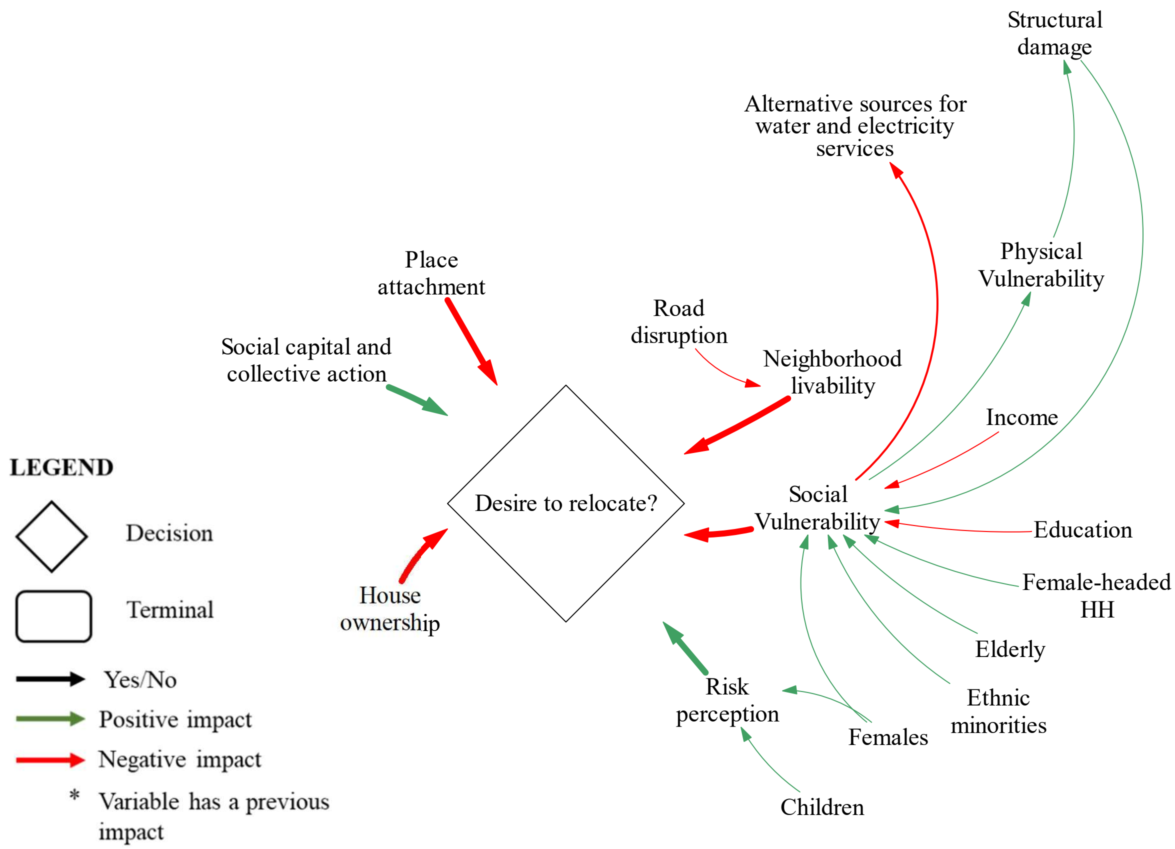

Figure 2.6 Desire to Relocate

Neighborhood livability and household's characteristics influence the household's desire to relocate (Chang et al., 2009). High neighborhood damage levels impede the household's ability to meet their daily living requirements and increases the inclination to relocate (Wright & Johnston, 2010). Open roads and functioning transportation positively influence the neighborhood livability and the desire to stay (Wright & Johnston, 2010).

Households demographic and socioeconomic characteristics shape their response behavior after disasters (Lindell, 2013b; Peacock et al., 2007). Vulnerable groups experience higher risks of disasters, more severe impacts of disasters and exhibit less ability to cope and recover after disasters. Socially vulnerable groups have less capacity caused by less economic resources and less social and political influence reducing their options after disasters and decreasing their capacity to relocate as shown in Figure 2.6

(Morrow, 1999). Income, age, minority and occupancy statuses were found to be of significant influence in many relocation studies (Khazai et al., 2012).

Social vulnerability is positively correlated with income and education (Morrow, 1999). Race, ethnicity and linguistic minorities have been found to be more vulnerable after disasters and less likely to relocate, even after controlling for income (Perry & Mushkatel, 1986), house damage and house characteristics (Girard & Peacock, 1997). Home ownership has been found to influence the household's desire to relocate as well. Home owners have less likelihood to leave their homes (Wright & Johnston, 2010).

Women, children and the elderly are demographic groups at higher risk during the response phase (Morrow, 1999). The elderly is less likely to leave because they require more assistance and more information about the conditions and services provided in the available sheltering options to be able to leave (Morrow, 1999). Also, they exhibit less willingness to leave (Gladwin & Peacock, 1997). Children vulnerability in the response period increases the need to leave to a safer and more livable place (Quarantelli, 1980; Wright & Johnston, 2010).

Women have higher risk perception and are more risk-averse (Tierney, 2006). They act quickly, especially with the presence of children (Gladwin & Peacock, 1997) as women are traditionally the main caregiver in the household (Enarson, 2011). These factors make women more likely to relocate. However, women's vulnerability in the response period caused by the limited access to resources (Morrow, 1999), lack of shelters with adequate facilities for women and violence (Alston, 2013) makes relocation less favorable. However, power and privilege to make decision for the household combined with women's limited resources weaken the impact of women's wishes on household decisions (Drabek, 1969).

Risk perception (Chang et al., 2009; Khazai et al., 2012; Riad et al., 1999), place attachment (Altman & Low, 1992; Jamali & Nejat, 2016), and social support system and collective action (Henry, 2013; Khazai et al., 2012; Mawson, 2005; Nejat et al., 2016; Wright & Johnston, 2010) have also been discussed in the literature to be positively, negatively and positively correlated with the desire to relocate, respectively. Figure 2.6 summarizes the variables that are expected to affect the household's relocation desire along with the hypothesized impact of each of these drivers.

If the household wanted to relocate, their physical relocation depends on their ability to relocate. Figure 2.7 shows that the ability to relocate is dependent on the availability of shelter to go to, availability of appropriate means of transport to get there (Chang et al., 2009; Vogt & Sorensen, 1992; Wright & Johnston, 2010) and the household's mobility (Chang et al., 2009; Morrow, 1999; Serulle & Cirillo, 2014; Vogt & Sorensen, 1992).

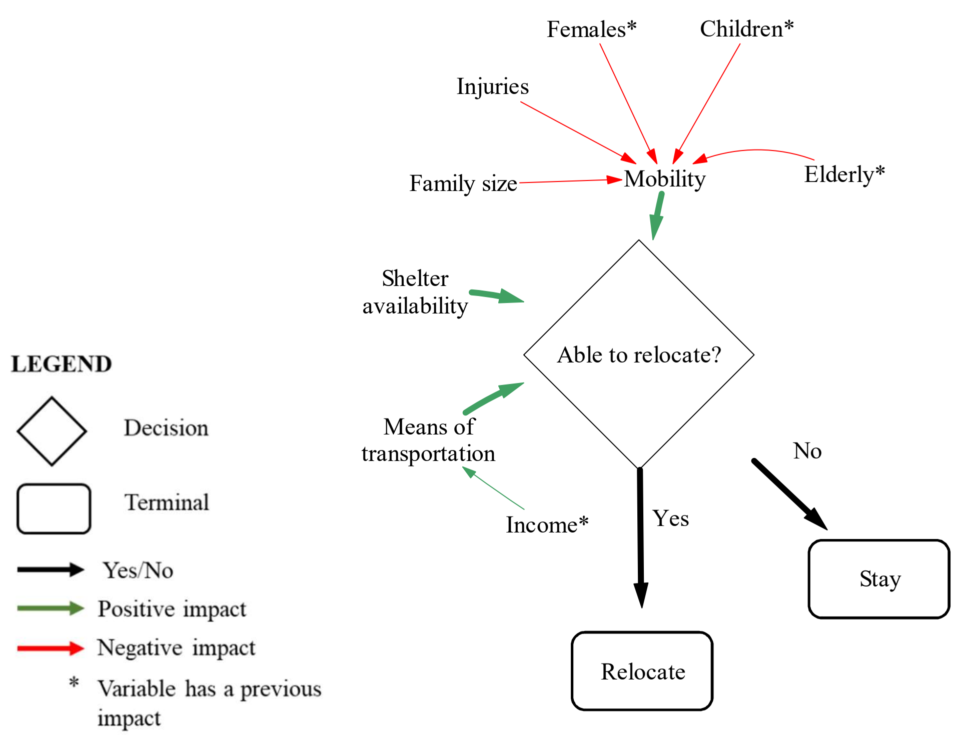

Figure 2.7 Ability to Relocate

The elderly (Morrow, 1999; Tai et al., 2014), children (Morrow, 1999), members with health issues (Wright & Johnston, 2010) and large household size (Morrow, 1999; Vogt & Sorensen, 1992) reduce the household's mobility. Women's mobility has also been found to be constraint by cultural and social norms in many societies reducing their ability to leave their homes (Alston, 2012). The effect of these variables on the ability to relocate is summarized in Figure 2.7.

The conflicting influences women have on relocation desire and their restricted mobility make women's ultimate role in household relocation not clear, therefore, no hypothesis was developed. The same goes for children; although they increase the household's desire to avoid risks, dependents reduce the household's ability to be movable.

The above discussion provides an overview of the many variables that the literature has found to potentially impact a household's decision to relocate, or more generally that might impact dislocation. In general, we have seen that a household's relocation decision is strongly determined by the level of damage to a household's home, and yet is potentially shaped by disruption to infrastructure/lifelines and can be shaped by household socio-economic and demographic attributes. Unfortunately, in this study, we do not have the possibility of modeling dislocation based on all of the possible factors discussed above, nor are all of these factors necessarily salient for the particular event. Nevertheless, we do have the ability to assess the degree to which specific factors determine dislocation. In this case, our focus will be on the consequences of damage to the housing unit, household socio-economic and demographic characteristics, and infrastructure disruption. Before specifying each of the factors to be examined, the following section will first discuss the disaster event and the data to be utilized in this study.

3. STUDY CONTEXT

The previous section presented the theoretical basis for a number of key drivers that are expected to influence relocation and their expected impact on relocation. This subsection will describe the context that will be used in this study to examine the relationship between relocation and its drivers and analyze these relationships.

To understand the role of infrastructure services' attributes in the household relocation decision, these relationships will be empirically analyzed using household survey data collected from Bhaktapur in Nepal after the 2015 earthquake. This section provides a brief description of the earthquake and the damage caused by it, followed by a description of the survey sample and collected data.

3.1 Disaster Event

3.1.1 Earthquake Figures

Nepal is located in a region of highly seismic risk (Chaulagain, Rodrigues, Silva et al., 2015). The 7.8 magnitude earthquake that has hit Nepal on April 25, 2015, also known as the Gorkha earthquake, is the most recent. The first shock was followed by more than 400 aftershocks (The World Bank, 2016). The earthquake triggered many landslides, avalanches and rock/boulder falls (Goda, Kiyota, Pokhrel et al., 2015; Khazai, Anhorn, Girard, et al., 2015).

Affected people reached about 8 million. The number includes 9,000 earthquake-related fatalities, 23,000 earthquake-related injuries (Simkhada, van Teijlingen, Pant et al., 2015), and 2.8 million displaced people (Goldberg, 2015). The earthquake was devastating and caused huge damage (Asokan & Vanitha, 2017). Damage cost was evaluated around 7 billion US dollars (Government of Nepal National Planning Commission, 2015).

The earthquake affected 31 districts, 14 of these districts were severely affected (United Nations Children's Fund UNICEF, 2015): Bhaktapur, Dhading, Dolakha, Gorkha, Kavrepalanchwok, Kathmandu, Lalitpur, Nuwakot, Ramechhap, Rasuwa, Sindhupalchwok, Makawanpur, Sindhuli and Okhaldhunga (United Nations Women, 2015). The household survey used in this study was collected in Bhaktapur.

3.1.2 Damage to Buildings

Despite the high seismic risk in Nepal, majority of structures were neither seismically designed nor seismically built (Goda et al., 2015). Majority of houses in Nepal are constructed using unreinforced masonry that is fundamentally brittle and weak. Consequently, structures are highly vulnerable to quakes (United Nations, 2015). Some structures are built using cement-mortared masonry and reinforced concrete (RC) frame. These buildings perform better during earthquakes, relatively speaking. However, deficiencies in design, detailing, material and craftsmanship reduce the seismic resilience features of these buildings resulting in serious damage to the structures during the earthquakes (United Nations, 2015).

Nepal's buildings typology resulted in widespread destruction to houses and human shelters during the 2015 earthquake (United Nations, 2015). After the earthquake, over 887,000 homes were partially or fully destroyed in Nepal (United Nations Children's Fund UNICEF, 2015). About 70% of the households in urban areas reported total collapse or severe damage to the buildings they lived in (Khazai, Anhorn, Brink, et al., 2015). The housing and shelters sector suffered from the greatest part of damage and losses among the different social and economic sectors (Government of Nepal National Planning Commission, 2015), see Figure 3.1.

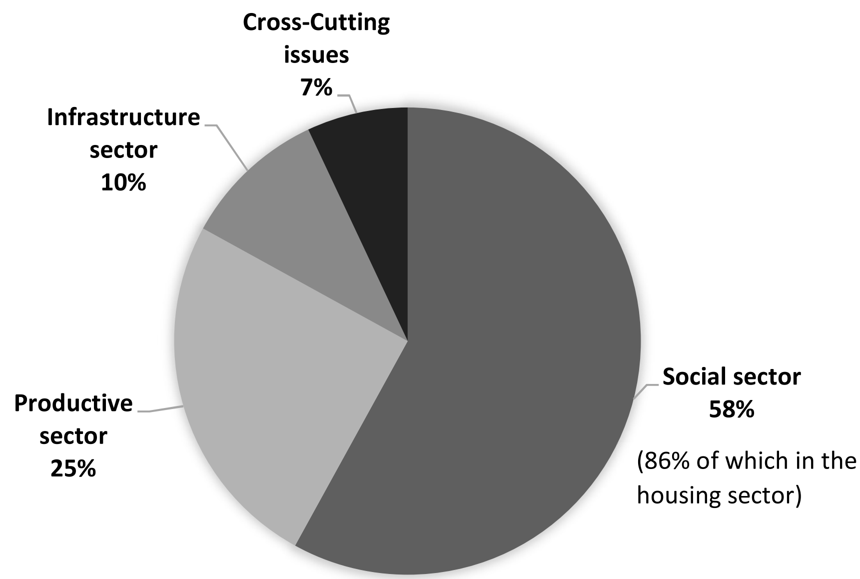

Figure 3.1 Share of Disaster Effects Across Sectors
estimated by Post Disaster Needs Assessment team in Government of Nepal National Planning Commission (2015)

3.1.3 Damage to Infrastructure

Utilities and roads were damaged in severely-affected districts (Government of Nepal National Planning Commission, 2015). About 50% of the water systems were destroyed in the districts affected by the quake. Damage to drinking water projects in Kathmandu only was estimated at 2 million US dollars (Rai, 2015). International relief and development programs focused on providing alternative water systems and distributing chlorine tablets among the urgent relief measures (Uprety et al., 2017). Also, over 600,000 households experienced electricity loss as a result of damage to buildings or to electricity supply facilities (Government of Nepal National Planning Commission, 2015).

Small portion of the roads network was fully damaged because of the earthquake (Government of Nepal National Planning Commission, 2015) Secondary effects of the earthquake such as landslides and avalanches contributed to the damage to the transportation network (Khazai, Anhorn, Girard, et al., 2015). More than 50% of roads in Bhaktapur were severely damaged (HRRP-Nepal, 2018).

This study utilizes data collected from Bhaktapur in Nepal after the 2015 earthquake. The next subsection concisely describes the source of the data that will be used and the data collection method.

3.2 Data Source

Household survey data were provided by a research team led by Dr. Ali Mostafavi. Data were collected as part of a reconnaissance study in the aftermath of the earthquake. The household survey sample was collected in the Bhaktapur municipality, in collaboration with the Khwopa College of Engineering (KCE), for the purpose of gathering data related to infrastructure services disruptions in different wards, post-disaster experiences of households, and public perceptions of post-disaster infrastructure service disruptions.

The research team who collected the data obtained a separate IRB exemption approval for the household survey at their college and from Florida International University's IRB. A sampling strategy was developed to ensure that households residing in both damaged and undamaged homes were interviewed. Specifically, the team first obtained data from the damage assessment reports undertaken by the municipality for wards or neighborhoods in the community. Then proportionate stratified random samples were drawn to ensure representative samples households residing in both damage and non-damaged houses. In total, data were collected from 222 of the households.

While a variety of different types of data were gathered as part of this survey, as described above, we utilized those data related to the household's decision to relocate, household characteristics, housing damage and infrastructure disruption. Many of these data were recoded and modified to more explicitly and appropriately assess household and house characteristics. The next subsection will describe the variables generated from the household survey that will be utilized for this study.

3.3 Variables Description

Table 3.1 displays basic information on the nature and coding of the key variables, both the dependent and independent, that will be employed in this study. These variables include demographic and socioeconomic characteristics of the household, damage levels of structures and neighborhoods, and measures of infrastructure services before and after the earthquake. Table 3.2 presents the descriptive statistics for each of the variables.

Table 3.1 Key Variables

Category	Variable	Type	Code
Relocation/Dislocation	Household vacated their neighborhood	Dummy	0: did not leave the house, 1: left the house
Household Demographic Characteristics	Number of females	Interval	-
	Members below 18-years	Interval	-
	Members over 65 years	Interval	-
Ethnic/Linguistic Group	Newari*	Dummy	0: others (Napali-speaking or others), 1: Newari-speaking
Socio-Economic Status	Income (Rs.) **	Indicator	Categories: income < 50,000 Rs., income 50,000-100,000 Rs., income > 100,000 Rs. (Reference category is income < 50,000 Rs.)
	House ownership*	Dummy	0: does not own the house, 1: owns the house
	Education (highest degree obtained by any of the household members) **	Indicator	Categories: tenth grade or less; high school, vocational training or bachelor's degree; graduate degree (Reference category is tenth grade or less)
	HH own a car prior to EQ	Dummy	0: no, 1: yes
Losses	Injury in the household	Dummy	0: no member injured, 1: one or more member/s injured
Structural Damage	House damage*	Dummy	0: no or somewhat damaged, 1: significant or complete damage
	Neighborhood damage*	Dummy	0: no or somewhat damaged, 1: significant or complete damage

Table 3.1 – Continued

Category	Variable	Type	Code
Piped water	Duration of water supply under normal conditions	Ordinal	1: less than 5 hours per week, 2: 6-15 hours per week, 3: 16-25 hours per week, 4: 26-35 hours per week, 5: more than 35 hours per week
	Piped water disruption after EQ	Dummy	0: no disruption, 1: piped water disrupted
	Duration of post-EQ piped water disruption	Ordinal	0: no disruption, 1: 1-3 days, 2: 4-6 days, 3: 1-2 weeks, 4: 3-4 weeks, 5: 5-12 weeks, 6: 13-24 weeks, 7: More than 24 weeks (6 months)
Government-Provided Electricity	Duration of electricity outage under normal conditions	Ordinal	0: Did not have any power outages, 1: less than 10 hours per week, 2: 11-40 hours per week, 3: 41-80 hours per week, 4: more than 81 hours per week
	Electricity disruption after EQ	Dummy	0: no disruption, 1: government-provided electricity disrupted
	Duration of post-EQ electricity disruption	Ordinal	0: no disruption, 1: 1-3 days, 2: 4-6 days, 3: 1-2 weeks, 4: 3-4 weeks, 5: 5-12 weeks, 6: 13-24 weeks, 7: More than 24 weeks (6 months)
Vehicle-Accessible Roads	Vehicle-accessible roads disruption after EQ	Dummy	0: no disruption, 1: vehicle-accessible roads disrupted
	Duration of post-EQ vehicle-accessible roads disruption	Ordinal	0: no disruption, 1: 1-3 days, 2: 4-6 days, 3: 1-2 weeks, 4: 3-4 weeks, 5: 5-12 weeks, 6: 13-24 weeks, 7: More than 24 weeks (6 months)

* There were originally more response categories, but these have been recoded into a binary response.

** There were more response categories, however many has sparse frequencies, so categories were collapsed.

Table 3.2 Sample Descriptive Statistics

Category	Variable	No. Obs.	Mean/Percentage	Standard Deviation
Relocation/Dislocation	Household vacated their neighborhood	222	32.88%	47.08%
Household Demographic Characteristics	Number of individuals*	212	6.00	3.21
	Number of females	212	2.90	1.85
	Females ratio to total number of individuals**	212	47.00%	13.79%
	Number of members below 18-years	208	1.29	1.76
	Number of members over 65 years	212	0.28	0.66
	HH with elderly members***	212	18.87%	39.22%
Ethnic/Linguistic Group	Newari	221	80.54%	39.68%
Socio-Economic Status	Income (Rs.)	206		-
	< 50,000 Rs.	54	26.21%	-
	50,000-100,000 Rs.	105	50.97%	-
	> 100,000 Rs	47	22.82%	-
	House ownership	221	95.02%	21.80%

Table 3.2 – Continued

Category	Variable	No. Obs.	Mean/Percentage	Standard Deviation
Socio-Economic Status	Education (highest degree obtained by any of the household members):	219		-
	10th Grade or Less	23	10.50%	-
	High School, VC, or Bachelor's Degree	174	79.45%	-
	Graduate Degree	22	10.05%	-
	HH own a car prior to EQ	221	0.90%	9.49%
Losses	Injury in the household	215	7.44%	26.31%
Structural Damage	Houses significantly or completely damaged	221	49.32%	50.11%
	Households in neighborhoods significantly or completely damaged	219	65.75%	47.56%
Piped water	Household with access to piped water	221	71.49%	45.25%
	Duration of water supply under normal conditions (hr/week) for households who had access to it	155	6-15 hours per week	-
	Households experienced disruption to piped water after EQ	155	42.58%	49.61%
	Duration of post-EQ piped water disruption(day) for households who experienced disruption	151	1-2 weeks	-

Table 3.2 – Continued

Category	Variable	No. Obs.	Mean/Percentage	Standard Deviation
Government-Provided Electricity	Household with access to government-provided electricity	222	100.00%	0.00%
	Duration of electricity outage under normal conditions (hr/week) for households who had access to it	175	41-80 hours per week	-
	Households experienced electricity disruption after EQ	218	78.44%	41.22%
	Duration of post-EQ electricity disruption (day) for households who experienced disruption	216	1-2 weeks	-
Vehicle-Accessible Roads	Household with access to vehicle-accessible roads	222	71.17%	45.40%
	Household experienced vehicle-accessible roads disruption after EQ	156	58.97%	49.35%
	Duration of post-EQ vehicle-accessible roads disruption (day) for households who experienced disruption	155	weeks	-

* Number of individuals variable was generated by summing the numbers of members in the different age categories: less than 18, 18-65, older than 65.

** Female ratio variable was generated by dividing the number of females by the total number of individuals in the household.

*** Households with elderly members variable is a dummy variable generated by assigning 1 to households who has at least on member over 65 years old and 0 to the households who do not have any member over 65 years old.

3.3.1 Household Relocation/Dislocation

The dependent variable in the study, i.e., the household's leaving decision, is dummy coded to represent households who left their neighborhoods in the short aftermath of the quake compared to the ones who did not. Household dislocation was assessed by a question in the survey of whether the household left their pre-disaster neighborhood after the earthquake. We are interpreting their response to the question of "did you leave your pre-earthquake neighborhood in the aftermath of the earthquake" to mean that they did, necessarily, leave their principle residence. However, it is conceivable that a household could have left their home but still stayed in their neighborhood. So, we might be potentially underestimating the number of households that relocated after the earthquake. It In the sample, approximately 33%[4] of the households left their neighborhoods after the quake.

3.3.2 Household Demographic Composition

Respondents were asked a series of questions about the number household's members in each age category: less than 18, 18-65, and over 65 years old; and number of members from each gender. A variable of the total number of household members was generated by summing the numbers in the three age categories. Average household size in the sample was 6 members, with an average of 2.9 females. Surveyed households consisted of about 22% members less than 18 years-old, 15% elderlies and 73% aged between 18 and 65 years, on average. For the purposes of the analysis, we also generated female ratio variable that was calculated by dividing the number of females in the household by the total number of the household's members. On average, 47% of the household composition were females. Also, a dummy variable of whether the household

[4] All numbers were rounded to the smallest digit presented.

had an elderly was generated. Around 19% of the households surveyed had at least one person above 65 years old.

3.3.3 Household Ethnicity/Linguistic Groupings

Over 80% of the households spoke Newari only, less than 10% spoke Nepali only and the rest spoke both. Nepali-speaking population are from the Parbatiya ethnic group, and the Newari-speaking are from the Newar ethnic group (Hofer, 1979). The numerical majority of the Newars in the surveyed area of Bhaktapur is expected because they have historically dominated the Kathmandu Valley, including the surveyed area of Bhaktapur (von Fürer-Haimendorf, 1956).

3.3.4 Socio-Economic Characteristics

As seen in Table 3.1, different socioeconomic characteristics were captured in the survey and used in this study: income, education, house ownership and the ownership of a motorized vehicle. These variables were used to reflect the household's capacity and social vulnerability. Household income categories were collapsed into three categories because some of the initial categories had spare frequencies. Income will be used in the development of the models as an indicator variable with is income < 50,000 Rs. as the reference category. Over 50% of the households in the sample had annual income of 50,000-100,000 Rs., about 26% below 50,000 Rs. and 22% over 100,000 Rs.. House ownership variable was recoded to a dummy variable to compare households who owned their pre-earthquake home to those who did not. Almost 95% of the households owned their house before the earthquake. Respondents were also asked if they owned a car before the earthquake, less than 1% said they did.

The level of education in the household was captured by asking the respondent about the highest level of education obtained by any of the household members. There actually were a variety of possible response categories ranging from less than an School Leaving Certificate (SLC), which is taken upon the completion of the 10^{th} grade, to graduate degree and even vocational training. These response categories have been collapsed due in part to very low responses to a simple indicator variable with three categories: tenth grade or less; high school, vocational training or bachelor's degree; and graduate degree. Reference category is: tenth grade or less. Only about 10% of the households had education less than high school, and about 10% had a graduate degree.

3.3.5 Losses/Injuries

Respondents were asked whether any member in the household have been injured. About 7% of the households surveyed reported at least one earthquake-related injured member.

3.3.6 House and Neighborhood Damage

Structures in the Bhaktapur area experienced severe damage. Damage levels were measured based on respondents' assessment. Specifically, respondents were asked about the level of damage to their pre-earthquake homes and neighborhoods. Response categories provided to the respondent, along with descriptors, were: completely damaged, significantly damaged (unsafe to live in); somewhat damaged (needing repairs before living in); no damage, or don't know. These responds categories were then recoded to a binary variable that compare the unsafe house damage levels (severely or completely damaged) to the other levels of house damage where the house is considered safe to live in although it might need repairs (no or somewhat damaged). Comparing the two distinctly different damage states better reflects the safety and structural stability of the house.

As explained previously, structural habitability of the house is mainly influenced by the structural stability of the building and weather conditions, see Figure 3.2. Since there were no extreme adverse weather conditions after the 2015 earthquake, structural habitability can probably be easily estimated to be a function of the structural stability/damage. Therefore, the house damage variable captures the role of structural habitability in driving the household relocation decision with higher accuracy.

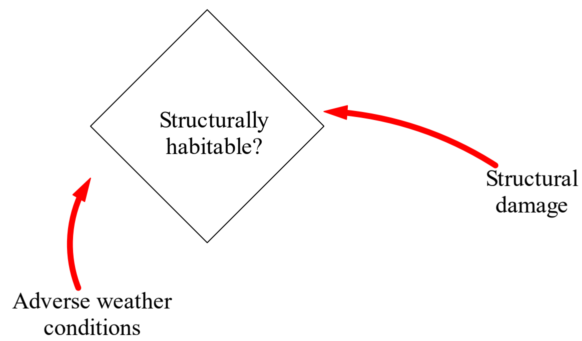

Figure 3.2 Factors Affecting Structural Habitability

A similar coding scheme was employed to assess neighborhood damage. Specifically, respondents were asked to estimate the overall levels of damage to their neighborhoods with the response categories again reflecting: completely, significantly, somewhat or no damage. These again were recoded to a binary variable as shown in Table 3.1, reflecting complete or significant damage and somewhat or no damage. The binary variable reflects the difference between neighborhoods with low damage levels where households might well have access to the services and support systems their neighborhoods provide, versus neighborhoods with high levels of damage that reduces the availability and efficiency of these services and systems.

About 49% of the households surveyed reported that their homes were severely or completely damaged, and about 66% of households reported high levels of damage to their neighborhoods.

3.3.7 Infrastructure

Different infrastructure-related variables were used in the development of relocation models to reflect the various attributes of infrastructure services that can influence relocation as shown in Figure 3.3.

To capture and assess a household's access to and disruption of infrastructure lifelines, respondents were generally asked several questions. First, respondents were asked whether or not the household had access to piped water, government-provided electricity and vehicle-accessible roads before the earthquake to determine their access to these infrastructure lifelines.

Respondents who had access to any of these services were asked if they experienced any disruption in it after the earthquake in a binary-response question. And if the household have experienced disruption in that service, they were asked about the duration of this disruption in a categorical response variable as shown in Table 3.1.

Respondents were also asked about the levels of piped water and government-provided electricity services before the earthquake. Again, respondents were asked about having access to specific infrastructure lifelines as well as their experiences with respect to normal disruptions that are quite routine in Nepal. As noted above, the degree to which a household is likely to assess post-earthquake habitability is likely to be a function of their relative experience with disruptions prior to the earthquake. Hence, these data will be employed to assess relative disruption or inconvenience. In other words, pre-disaster conditions can influence what a household considers habitable conditions in their home; consequently, it can influence the household relocation decision as discussed in the previous section. See Figure 3.3.

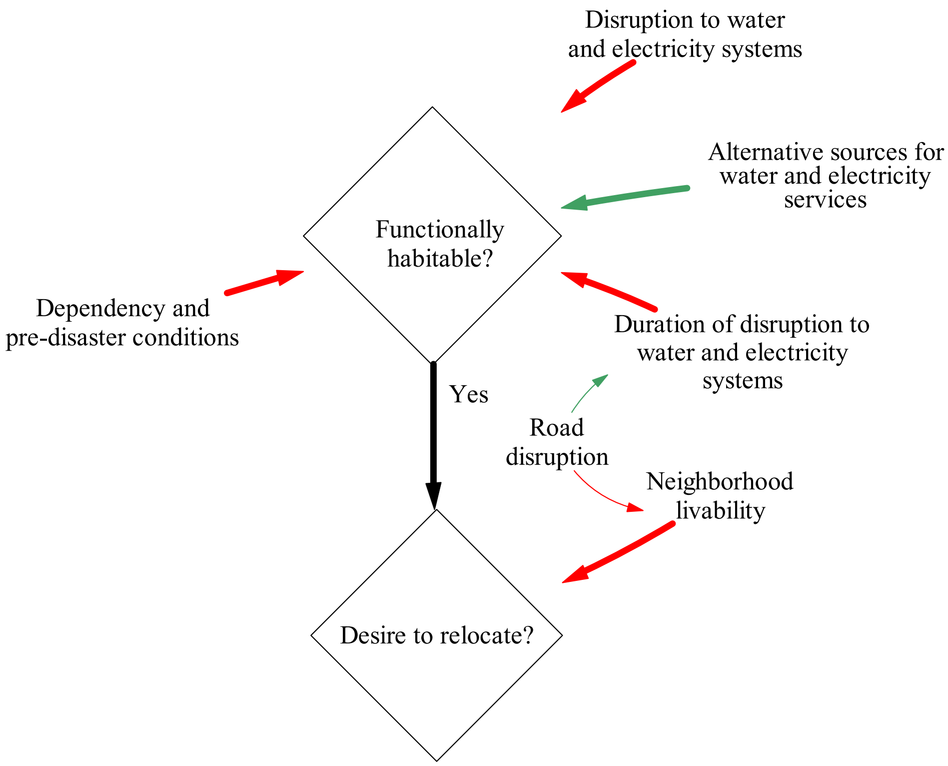

Figure 3.3 Role of Water, Electricity and Roads Services in the Relocation Decision-Making Process

3.3.7.1 Piped Water

About 30% of the households in the sample did not have access to piped water before the earthquake, which is not unexpected in Nepal as explained in the previous section. Additionally, households reported that they had water supply for about 6-15 hours per week on average.

Additionally, less than 50% of people who had access to it experienced disruption in the service after the earthquake. The post-event disruption lasted for about 1-2 weeks on average.

3.3.7.2 Government-Provided Electricity

Unlike with piped water, households in the sample were highly dependent on government-provided electricity as their primary source of electricity. All households reported that they had access to government-provided electricity before the earthquake. Yet, many respondents reported that they experienced frequent outages in electricity before the earthquake of about 41-80 hours per week on average.

Over 78% of the households reported experiencing disruption in the electricity after the earthquake. The disruption was reported to have lasted for 1-2 weeks on average.

3.3.7.3 Vehicle-Accessible Roads

Although less than 1% of the households had a car, about 70% of households reported that they had access to vehicle-accessible roads. Over 50% of the households that had access to these roads experienced disruptions to it. The duration of the disruption was about 3-4 weeks on average.

This section provided a background about the context of the study: Nepal 2015 earthquake. The variables extracted from the data collected after the earthquake was described and coded. In the next section, these variables will be used in the development of relocation empirical models and results of these models will be presented.

4. ANALYSIS AND RESULTS

In the previous section, variables capturing demographic and socioeconomic household characteristics, damage to structure and infrastructure services' attributes were derived from the household survey collected from Nepal after the 2015 earthquake. In this section, household relocation models will be developed to empirically examine the relationship between these variables and relocation in an attempt to capture and understand the role of infrastructure services play in influencing household relocation. In the following subsection, the methodology used for the development of the models will be explained.

4.1 Methodology – Logistic Regression

To empirically model the relationship between the dependent variable and the predictors discussed in the previous section, regression analysis will be used. The dependent variable in this study, whether a household relocated after the earthquake, is binary (dichotomous). There are a variety of approaches that might be employed to model this binary outcome variable. Following the general approach taken in the literature, logistic regression will be used to establish the influence household characteristics, damage levels and infrastructure services as independent variables have on the dependent variable, dislocation. The logistic predictive models will help in answering the questions of this study: Does infrastructure attributes affect the household relocation decision? If so, what is the extent of this effect?

In logistic regression, the dependent variable is the probability of the occurrence of a certain event. Logistic regression predicts the probability that a person will shift from state 0 to state 1 based on the change in the predictor *X* (Menard, 1995; Peacock, 2018; Wooldridge, 2015).

$$\frac{P_i}{1-P_i} = e^{\beta_0+\beta_1 x_1+\ldots+\beta_k x_k}$$

The dependent variable, the probability of the success, is constraint between 0 and 1 for all possible values of *X* (Agresti & Finlay, 2009) and the probability conforms to an S-curve, as shown in Figure 4.1.

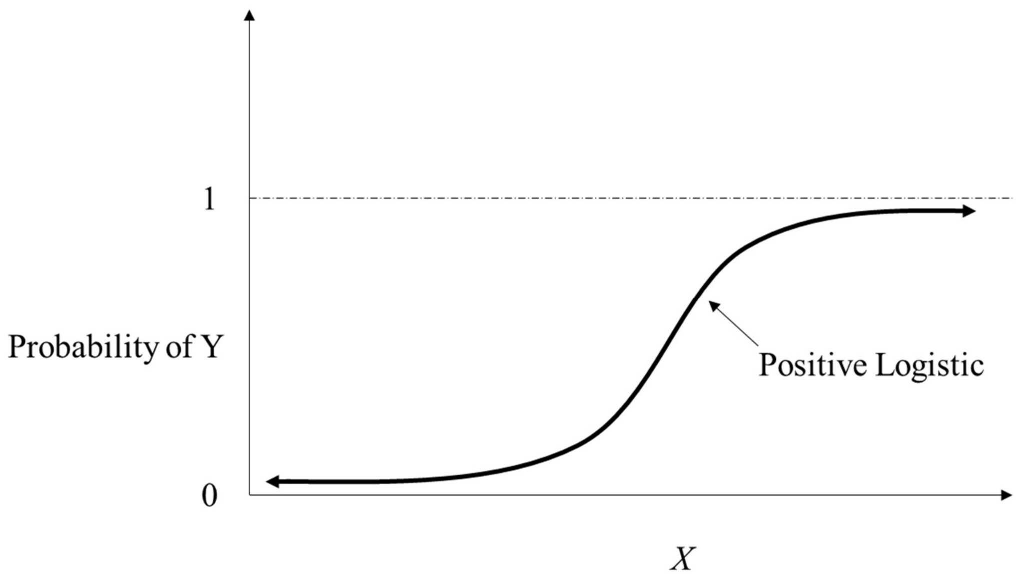

Figure 4.1 Logistic Regression Model
(Peacock, 2018)

The logistic model is a non-linear model. Variables' parameters will be estimated using Maximum-likelihood Estimation (MLE). Parameters are estimated in an iterative procedure to choose estimates that are most likely to give rise to the pattern of observations in the sample data (Peacock, 2018).

The variables' parameters reported in the different models in this study represent the ceteris paribus change in the odds of relocation corresponding with a unit change in the predictor. Parsimonious best-fit logistic models were developed to show the effect of the change in infrastructure services' characteristics on relocation while controlling for other factors that significantly influence relocation as well.

Logistic regression has a couple of assumptions. First, the nature of the dependent variable should be dichotomous, and it is assumed to be a stochastic event. Second, there should be no high multicollinearity among the predictors to avoid standard error inflation. In this study, the dependent variable is binary. We did encounter problematic levels of multicollinearity for some combinations of independent variables. Unfortunately, there were no possibilities of collecting additional observations and hence increasing the sample size that would potentially mitigate against multicollinearity. Hence, less than optimal solutions of partially specified models will be employed. Following sections will discuss these issues more completely.

In the next subsection, logistic regression will be used in the development of relocation models.

4.2 Development of Models

As noted above, the maximum available data included 222 surveys. In order to estimate the parameters in the logistic models, only observations/surveys that have a complete data set among all the variables in the model could be used. The number of missing observations varied considerably across the variables being employed in our analyses (see Table 3.2). Consequently, the number of observations available to specific analyses attempting to address the consequences of damage, household characteristics and infrastructure varied considerably. These differences were particularly evident when attempting to assess the consequences of infrastructure disruption.

For each infrastructure service, only surveys of households who had access to that service have data related to the service's variables. Consequently, infrastructure variables have more missing data than other variables used in this study, considerably reducing the number of useful observations. Therefore, to maximize the utilization of available data, a two-step process was introduced for model development.

The first step will be the development of parsimonious model from variables not related to infrastructure. In another word, variables associated with damage and household characteristics have the largest number of observations with complete data among the variables. Hence, step one will focus on the development of dislocation models making use of damage and household characteristics. The focus will be on maximizing our ability to account for dislocation utilizing these variables and then these models will be employed to assess the consequences of disruption to infrastructure services for dislocation.

Three infrastructure services are considered in this study: piped water, government-provided electricity and vehicle-accessible roads. If we want to use all three infrastructure services in the same model, the sub-sample. of households would that had access to all three services would be reduced from 222 to only 66. Unfortunately, multi-collinearity and other estimation issues arose with this small sample size. The only real solution to this issue would be to collect more data increasing our sample size which would ameliorate these issues (Wooldridge, 2015). This solution was, of course, not practicable. As a result, the less than optimal solution of developing infrastructure models will be undertaken separately for each infrastructure service. This will provide the largest possible number of observations in the sub-sample used for the model development of each service, but also introduces specification issues.

The research work related to relocation after disasters reviewed in Section Two along with the specifics of the Nepalese context and the 2015 quake discussed in Section Two and Three provided the opportunity to generate informed hypotheses of the impact for most of the variables in this study. The hypothesized expectations with respect to independent variables are specified in Table 4.1. One-tail tests were used for the development of the significance levels for the variables for which we have hypotheses of their impact. On the other hand, no hypotheses were developed for couple of variables: females, underage members and piped water service variables. For these variables, two-tail tests were used for reporting the significance level. A minima significance level of 0.1 will be used in this study as the significant level required to reject the null hypothesis in all models.

For all models developed, Pearson correlation coefficients and Variance Inflation Factors have been inspected among all variables in the different models in order to maintain the no-high-multicollinearity assumption of logistic regression. No high multicollinearity issues were found between the variables combinations used in the development of the models. Pearson correlation coefficients have been reported in this document as will be shown below. Variance inflation factors will not be reported here within.

4.2.1 Development of Base Model

The observations employed in the development of the base model were restricted to those having complete data for all the variables related to damage and household characteristics used in the model development. Out of the total potential observations of 222, complete data were available for a total of 177 of the sampled households. As a result, observations used will be the same among the different models. This will give us the ability to nest the models and directly compare the goodness of fit measures along the different models. Table 4.1 shows the descriptive statistics of the sub-sample used for the development of the base model.

Table 4.1 Base Model Sub-Sample Descriptive Statistics (n=177)

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Relocation/Dislocation	Household vacated their neighborhood	31.64%	46.64%	-
Household Demographic Characteristics	Number of individuals	5.83	2.94	Negative
	Number of females	2.74	1.61	No hypothesis
	Females ratio to total number of individuals	46.14%	13.16%	No hypothesis
	Number of members below 18-years	1.31	1.78	No hypothesis
	Number of members over 65 years	0.31	0.88	Negative
	HH with elderly members	19.21%	39.51%	Negative
Ethnic/Linguistic Group	Newari	81.36%	39.06%	Positive
Socio-Economic Status	Income (Rs.)		-	Positive
	< 50,000 Rs.	28.81%	-	-
	50,000-100,000 Rs.	52.54%	-	-
	> 100,000 Rs	18.64%	-	-
	House ownership	94.92%	22.03%	Negative
	Education (highest degree obtained by any of the household members):		-	Positive
	10th Grade or Less	11.30%	-	-
	High School, VC, or Bachelor's Degree	79.10%	-	-
	Graduate Degree	9.60%	-	-
	HH own a car prior to EQ	1.13%	10.60%	Positive

Table 4.1 – Continued

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Losses	Injury in the household	7.91%	27.07%	Negative
Structural Damage	Houses significantly or completely damaged	47.46%	50.08%	Positive
	Households in neighborhoods significantly or completely damaged	64.97%	47.84%	Positive

* A positive impact implies that an increase in the variable results in an increase in the impacted or dependent variable (household dislocation), while a negative impact implies that as the variable increases the dependent variable decrease.

As discussed previously, the literature and the Nepalese context provided the following hypotheses: house damage reduces the habitability of the house and is expected to increase relocation. Neighborhood damage reduces neighborhood livability and increases desire to leave and, consequently, it is expected to increase relocation as well. Socially vulnerable groups are expected to have lower likelihoods of leaving. Socially vulnerable groups include linguistic minorities - which are represented by the non-Newari population in Bhaktapur in this study, low-income households, and households with lower levels of education. Renters usually have less control over mitigation measures and repairs and, therefore, are expected to have higher likelihood of relocation. It is anticipated that injured members, large households and people older than 65 years-old will impede the household's mobility and decrease their ability of relocation. One-tail test will be used to report the significance level of these variables.

On the other hand, no expected effect of females and underage members could be developed. Therefore, two-tail tests will be used to report the significance level of these variables and any variables that are generated from them. Two-tail tests p-values in the table will be indicated.

The fourteen regressors shown in Table 4.1 were used in the development of the best-fit parsimonious base model. Table 4.2 shows the correlation coefficients between these variables and the dependent variable. It shows no indication of any multicollinearity issues.

Based on the literature and the preliminary analysis, house damage is most probably the main factor driving displacement. Therefore, the development of the model is initiated with house damage. Variables are then added singly to the model. Income and education are ordinal variables and will be added as indicator level variables[5] to the model. The variable's significance in the model and its contribution to improving the model's goodness of fit measures, i.e., Pseudo R-square and AIC, are the criteria set for keeping or removing the variable.

Many permutations of the variables were used for the development of the final parsimonious best-fit base model. In these permutations, different orders of adding the variables were considered as well. In each permutation one regressor is added, it is retained in the model for the next permutation if it had a significant parameter and/or improved the model's goodness of fit. Otherwise, the regressor is removed. Income and education variables were added to the models as indicator variables. Same criteria were used for retaining or removing these variables: the significance of any category of the variable and the goodness of fit of the overall model.

Variables of the household's demographic composition were not significant in any model, nor was education. The car ownership variable was dropped from all the models during the analysis because it predicted the failure in the model perfectly.

Due to the large number of permutations performed, only the variables retained in the final base model will be presented. Table 4.3 shows the variables retained in the final base model and how the addition of each variable to the model enhanced the overall model. All models show significant increase in the variance accounted for above the base model at a significance level less than 0.001. Model 6 in Table 4.3 is the best-fit parsimonious base model.

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[5] Income and education variables have three classes each, the first class of each is the reference class. For income, the first class: income less than Rs. 50,000, is the reference class. For education, the first class: 10^{th} grade or less, is the reference class.

House and neighborhood damage, injuries, income level, house ownership and ethic group are the statistically significant factors, not related to infrastructure, that influence the relocation behavior of people in Bhaktapur after the 2015 earthquake. All predictors in the best-fit base model are statistically significant at a significance level of 0.1[6]. House damage, as anticipated, has the highest impact on household relocation behavior. People whose houses are significantly or completely damaged have higher relocation odds by over 3.7 times. In the same manner, high neighborhood damage is expected to increase relocation odds by about 2.25 times. Injured member/s in the household are expected to reduce the odds of relocating by about 58%.

Newars in the Bhaktapur area are considered more influential. This socioeconomic inequity is reflected in the higher odds of leaving. A Newari household odds of leaving are about 2.7 times higher than other ethnic groups in the area. Income played a significant role in relocation as well. The difference in odds between the lowest income category, the reference category: income less than 50,000 Rs., and the highest income category: income larger than 100,000 Rs., is statistically significant. People with income more than 100.000 Rs. have approximately 2.5 times higher odds of leaving than people with income less than 50,000 Rs. House ownership had a significant impact on household relocation behavior too. Home-owners odds ratio of leaving are expected to be lower by about 67%.

After we developed the best fit base model, we will use it in the development of relocation models that incorporate variables of the attributes of infrastructure services. Each set of variables of each infrastructure service will be used separately with the base model for the development of best fit models. In another word, piped water variables will be added to the base model to develop the best fit water model, then government-provided

[6] Using a one-tail test p-value since hypotheses exist for the effect of all the variables in the best fit base model on relocation.

electricity variables will be added to the base model then the variables of the vehicle-accessible roads, in this order. At the end of this subsection we expect to have three models: one for piped water, one for electricity, and one for roads.

Table 4.2 Correlation Matrix – Variables Used in The Development of The Base Model

	1	2	3	4	5	6	7	8
1 Household vacated their neighborhood	1.000							
2 Number of individuals	0.142*	1.000						
3 Number of females	0.185**	0.901***	1.000					
4 Females ratio to total number of individuals	0.103	0.166*	0.543***	1.000				
5 Number of members below 18-years	0.135	0.499***	0.454***	0.075	1.000			
6 Number of members over 65 years	0.139*	0.272***	0.296***	0.133	0.383***	1.000		
7 HH with elderly members	0.086	0.375***	0.441***	0.234***	0.255***	0.733***	1.000	
8 Newari	0.151*	0.145*	0.178**	0.124	0.026	0.119	0.147*	1.000
9 Income (Rs.)	0.003	0.166*	0.134	-0.016	0.169*	0.069	0.034	-0.080
10 House ownership	-0.060	0.108	0.103	0.053	0.103	0.034	0.060	0.045
11 Education (highest degree obtained by any of the household members)	-0.015	0.086	0.079	0.033	0.012	0.097	-0.038	-0.030
12 HH own a car prior to EQ	-0.067	0.045	0.005	-0.059	0.011	-0.035	-0.048	-0.074
13 Injury in the household	-0.016	-0.004	-0.009	-0.037	0.012	-0.031	-0.036	0.093
14 Houses significantly or completely damaged	0.366***	0.132	0.140*	0.043	0.217**	0.098	0.028	-0.039
15 Households in neighborhoods significantly or completely damaged	0.327***	0.120	0.088	-0.109	0.135	0.126	0.108	0.067

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.2 – Continued

	9	10	11	12	13	14
10 House ownership	-0.013	1.000				
11 Education (highest degree obtained by any of the household members)	0.112	-0.002	1.000			
12 HH own a car prior to EQ	0.148*	0.022	0.001	1.000		
13 Injury in the household	-0.057	-0.021	0.119	-0.027	1.000	
14 Houses significantly or completely damaged	-0.155*	-0.023	-0.031	-0.095	0.139*	1.000
15 Households in neighborhoods significantly or completely damaged	-0.203**	-0.018	-0.071	-0.134*	0.126	0.647***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.3 Development of Base Model - Variables Permutations

Household vacated their neighborhood	1	2	3	4	5	6
Houses significantly or completely damaged	4.375****	4.685****	3.362***	3.519***	3.788***	3.743***
	(1.536)	(1.673)	(1.447)	(1.537)	(1.676)	(1.659)
Newari		2.363**	2.279**	2.339**	2.576**	2.715**
		(1.147)	(1.116)	(1.147)	(1.282)	(1.384)
Households in neighborhoods significantly or completely damaged			1.890*	2.124*	2.187*	2.245*
			(0.940)	(1.073)	(1.106)	(1.145)
Income (Rs.)						
50k-100k				1.738*	1.685	1.578
				(0.721)	(0.704)	(0.663)
>100k				2.565**	2.647**	2.502**
				(1.376)	(1.427)	(1.347)
Injury in the household					0.429	0.418*
					(0.290)	(0.280)
House ownership						0.329*
						(0.253)
Observations	177	177	177	177	177	177
Pseudo R^2	0.087	0.103	0.110	0.126	0.133	0.143
AIC	205.653	204.215	204.564	205.139	205.470	205.364

Exponentiated coefficients; p-values in parentheses; One-tail tests

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.2.2 Development of Infrastructure Services' Models

The base model developed in the previous subsection reflects the importance of house and neighborhood damage, one aspect of damage to the physical environment, in the human decision-making process. In this subsection, the second step of the analysis, the role of infrastructure services will be addressed.

Each of piped water and government-provided electricity lifelines has three explanatory variables[7] describing the service before and after the earthquake: a measure of the service level before the earthquake, whether the service was disrupted, and if it was, for how long. Vehicle-accessible roads has two variables describing the situation after the earthquake. A variable capturing the occurrence of a disruption event and the second capturing the duration of it.

Disruption data addresses disruption of governmental sources only for water and electricity services. This data limitation gave rise to a couple of issues. First, the lack of data regarding the disruption of other sources of water after the earthquake introduced a complication in studying the impact of water disruption in the Nepalese context. As it was mentioned earlier in section three, not all households had access to piped water. This reduced the number of observations that could be used in the analysis by over 25%. Second, the water situation in Nepal cannot be properly assessed using piped water variables only, even for households who had access to it, because many people in Nepal rely on more than one source to obtain water. However, no data were available regarding the disruption of other water sources. Also, no data were available regarding the water provided for by the government and other international agencies for aid purposes. Aid water had a significant impact on the water availability and reliability after the quake as

[7] That could be used for the purpose of this study.

was discussed in section three. And since water models developed in this study include covariates of piped water service only, the degree of confidence in its outcomes is limited.

Available data best captures the electricity service situation. People in Bhaktapur relied mainly on the government for providing electricity. That being the case, the available data of government-provided electricity captures the electricity service situation in Bhaktapur after the earthquake.

Roads data were also constrained to vehicle-accessible roads. However, almost 99% of the households surveyed in the study did not have a car. No data were available regarding other types of roads. Therefore, the outcomes of the roads model may not capture the role of roads in general on relocation.

Missing data varied among the different lifelines' covariates. It reduced the number of usable observations by about 60% when all lifelines' variables were used in the same model. Therefore, models will be developed for the three lifelines separately in order to maximize the number of observations used in each model. The base model developed with the maximum number of observations previously will be used in the development of the infrastructure models.

In the development of the best fit model for each lifeline, different permutations of the explanatory variables available for each lifeline will be added to the base model: singly; doubly; and for water and electricity, all together. The different permutations are used to determine the parsimonious model that most accurately reflects the impact of the lifeline service attributes on the household relocation decision.

In the development of the best-fit model for each lifeline, nested models of the different permutations will be compared to the base model to assess the improvement in the models' goodness of fit. To be able to do this comparison, observations used in the base model will be restricted to observations that have complete data among that lifeline's variables. This will guarantee that the same observations are used among the nested models and therefore can be directly compared to each other.

This restriction of the base model observations in the development of the best-fit model for each lifeline will result in the reduction of the number of observations used in the base model due to missing data in that lifelines' variables. Consequently, changes in the base model covariates' parameters and significance levels, as well as the base-model's goodness of fit are expected. None the less, no modification on the covariate list constituting the best-fit base model will be made because it was based on a larger number of observations and, therefore, better reflects the household behavior in the surveyed community.

4.2.2.1 Piped Water

The water situation in Nepal is more complicated to capture compared to electricity. As described in subsection 2.2.2.3, not all households have access to piped water in the first place. Also, households normally depend on more than one source of water for their different needs, even if they have access to piped water. In addition, people reported that the water aid delivered to affected people after the earthquake was constantly available with sufficient quantities and adequate quality, unlike the water situation before the earthquake. A comprehensive understanding of the role of water service and the ceteris paribus impact of piped water requires controlling for all water sources as well as water aid. However, the available data was restricted to piped water only. As a result of this data limitation, model outcomes will be limited.

The survey included three explanatory variables reflecting the piped water service status that could be utilized for this study: duration of water supply the household received each week under normal conditions before the quake, if any, whether piped water was disrupted after the earthquake, and if it was, for how long. Correlation coefficients between these variables and the base model variables and are shown in Table 4.5.

The sub-sample used in the development of the relocation best-fit model that accounts for piped water service consists of the observations with complete data among the base model variables and piped water variables. The descriptive statistics of the sub-sample used for the development of the model are presented in Table 4.4. The base model's observations were also restricted to the same observations to allow for models nesting and the direct comparison of models' goodness of fit measures among the different models.

No hypothesis was developed for the effect of water disruption on the household's relocation decision after the 2015 Nepalese earthquake due to the inconsistency between the general theory in literature and the water situation in Nepal after the earthquake. The loss of utilities functions is expected to reduce the house's functional habitability. Therefore, piped water disruption is expected to be one of the factors that causes households relocation after disasters. Piped water disruption, however, was not a complete adversity to the water situation in Nepal after the 2015 earthquake. The availability of multiple sources of water, other than piped water, and the familiarity of these sources to households in Nepal might make the impact of piped water disruption on the house's usability less significant. At the same time, the improved water situation for households after the earthquake in Nepal, in terms of water quality, quantity and consistency in water availability provided by governmental and nongovernmental agencies was perceived by the people as an improvement in their living conditions in comparison with the conditions that existed before the earthquake (Uprety, 2014). The expected hypotheses of the impact of each of the variables used in the development of the piped water model are shown in Table 4.4.

Table 4.4 Piped Water Model Sub-Sample Descriptive Statistics (n=120)

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Relocation/Dislocation	Household vacated their neighborhood	34.17%	47.63%	-
Household Demographic Characteristics	Number of individuals*	5.85	2.72	-
	Number of females	2.81	1.54	-
	Females ratio to total number of individuals**	47.21%	12.92%	-
	Number of members below 18-years	1.15	1.63	-
	Number of members over 65 years	0.38	1.00	-
	HH with elderly members***	23.33%	42.47%	-
Ethnic/Linguistic Group	Newari	81.67%	38.86%	Positive
Socio-Economic Status	Income (Rs.)		-	Positive
	< 50,000 Rs.	28.33%	-	-
	50,000-100,000 Rs.	48.33%	-	-
	> 100,000 Rs	23.33%	-	-
	House ownership	94.17%	23.54%	Negative

Table 4.4 – Continued

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Socio-Economic Status	Education (highest degree obtained by any of the household members):		-	-
	10th Grade or Less	11.67%	-	-
	High School, VC, or Bachelor's Degree	76.67%	-	-
	Graduate Degree	11.67%	-	-
	HH own a car prior to EQ	1.67%	12.86%	-
Losses	Injury in the household	4.17%	20.07%	Negative
Structural Damage	Houses significantly or completely damaged	40.83%	49.36%	Positive
	Households in neighborhoods significantly or completely damaged	60.83%	49.02%	Positive
Piped water	Household with access to piped water	100.00%	0.00%	-
	Duration of water supply under normal conditions (hr/week) for households who had access to it	6-15 hours per week	-	No hypothesis
	Households experienced disruption to piped water after EQ	45.00%	49.96%	No hypothesis
	Duration of post-EQ piped water disruption(day) for households who experienced disruption	1-2 weeks	-	No hypothesis

* A positive impact implies that an increase in the variable results in an increase in the impacted or dependent variable (household dislocation), while a negative impact implies that as the variable increases the dependent variable decrease.

Table 4.5 Correlation Matrix - Variables Used in the Development of the Piped Water Model

	1	2	3	4	5	6	7	8	9	10
1 Household vacated their neighborhood	1.000									
2 Newari	0.151*	1.000								
3 Income (Rs.)	0.003	-0.080	1.000							
4 House ownership	-0.060	0.045	-0.013	1.000						
5 Injury in the household	-0.016	0.093	-0.057	-0.021	1.000					
6 Houses significantly or completely damaged	0.366***	-0.039	-0.155*	-0.023	0.139*	1.000				
7 Households in neighborhoods significantly or completely damaged	0.327***	0.067	-0.203**	-0.018	0.126	0.647***	1.000			
8 Duration of water supply under normal conditions (hr/week)	-0.135	-0.040	-0.269**	0.205*	-0.133	-0.203*	-0.002	1.000		
9 Households experienced disruption to piped water after EQ	-0.039	0.095	-0.220**	-0.008	0.232**	0.083	0.313***	0.059	1.000	
10 Duration of post-EQ piped water disruption(day)	0.005	0.098	-0.167*	-0.006	0.318***	0.121	0.286***	0.062	0.891***	1.000
11 Percent of HH experiencing water disruption in the ward	-0.096	0.162*	-0.169*	0.069	0.026	0.011	0.195*	0.263**	0.345***	0.378***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The three piped water variables were added to the base model singly, doubly, then all together for the development of the best fit parsimonious piped water model, as shown in Table 4.6. As indicated in the table, one-tail tests were used for reporting the significance level of the base model variables and two-tail tests were used for the piped water variables' in the different permutations. Two-tail tests were used for piped water variables because we had no hypotheses of the impact of these variables on relocation.

All models, model 1 to 7 in Table 4.6, are statistically significant at level of 0.0001. All models increased Pseudo R-square above that of the base model, but only models 1 and 5 reduced the Akaike Information Criterion. Water disruption variable is significant in models 5 and 7, while the variables of the normal pre-quake duration of water supply and the duration of disruption are not significant in any of the models. The impact of piped water disruption in the models do not comply with the general theory in the literature; water disruption is generally expected to increase the odds of relocation, while in models 5 and 7 piped water disruption has a significant impact in reducing these odds[8].

In the Nepalese context after the 2015 earthquake, the water situation for many people was much better after the earthquake; people were satisfied with water quantities and quality after the quake versus the economic burden, dissatisfaction and worry associated with the water insecurity that they suffered from before the earthquake (Uprety et al., 2017).

Based on the specifics of this context, one could hypothesize that the governmental and nongovernmental water aid that people received because of water disruption and water quality deterioration after the earthquake have turned this adversity into an advantage. In this hypothesis, we would expect that higher degrees of water disruption in a neighborhood/ward would attract more aid, which in turn could improve the attractiveness

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[8] Multicollinearity has been checked using Pearson Correlation Coefficients, shown in Table 4.5, and Variance Inflation Factors. No high multicollinearity issues were found.

of staying at home from water availability, water quantities and water quality perspective. Consequently, in this hypothesis we would expect that higher degrees of water disruption in a neighborhood/ward would increase the likelihood of staying. To test this hypothesis, the effect of the level of water disruption in a neighborhood/ward on relocation will be examined. The survey indicated the ward each household resided in. A variable was generated by calculating the percentage of households experiencing piped water disruption in each neighborhood. This variable was intended to possibly reflect how much water aid was attracted to the ward, and therefore, provide a measure of the living conditions enhancement in the ward.

In each ward[9], about 43% of the households that had access to piped water experienced disruption on average. Table 4.5 shows the correlation between this variable and the rest of the variables used in the development of the piped water model. The different permutations of the generated variable, i.e., the percent of households experiencing water disruption in the ward, with the original piped water variables are shown in Table 4.7.

All models of the different permutations are statistically significant at level of 0.0001. All models have slightly enhanced the goodness of fit measures from the base model, i.e., increased Pseudo R-square and reduced AIC. All water variables used in model 3 are significant based on two-tail test p-values. The model also has the lowest AIC. Therefore, model 3 in Table 4.7 will be considered the best fit parsimonious model of the effect of piped water disruption on household relocation.

The odds ratio of the percent water disruption in a neighborhood supports the established hypothesis. It is hypothesized here that larger extent of water disruption in a neighborhood would attract more water aid to the neighborhood which could lead to

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[9] The survey covered 16 wards.

increasing the attractiveness of the water situation in that neighborhood. The enhancement in the water situation in a neighborhood is then expected to decrease the household's likelihood of leaving. Twenty five percent increase in the extent of piped water disruption in the neighborhood, based on model 3 in Table 4.7, decreases the odds of leaving by about 50%[10]. The event of piped water disruption in the house reduces the odds by about 90%. The results of the model support the hypothesis established earlier.

Although the results support our established hypothesis, it cannot be taken as a final and definitive evidence of the validity of the hypothesis. No additional analysis could be performed to further test this hypothesis due to data availability limitations; we only have data related to piped water in a community that depends on multiple sources of water even when it piped water is accessible. Also, no data regarding aid water provided to households and neighborhoods by the different agencies was available.

On the other hand, disruption duration had the expected impact according to the general theory in the literature; longer disruption durations decrease the tolerance to water disruption and cause inconvenience when households are looking to restore their livelihood to what it was before the earthquake. In the developed model, longer disruption durations are expected to increase the odds of leaving by about 65% per each category: 1-3 days, 4-6 days, 1-2 weeks, 3-4 weeks, 5-12 weeks, 13-24 weeks, More than 24 weeks (6 months).

In the piped water model, house damage has a significant impact too. High levels of damage, significant or complete damage levels, increased the relocation odds by more than 7 times.

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[10] Odds ratio represent the change in the odds of leaving for each 1% increase in the percentage of households experiencing piped water disruption in a ward. The impact of 25% increase in the percentage of households that lost piped water after the earthquake will decrease relocation odds ratio by (1 - 0.973^25) = 0.496

Table 4.6 Development of Best Fit Model for Piped Water

Household vacated their neighborhood	Base	1	2	3	4	5	6	7
Houses significantly or completely damaged	8.306****	7.108****	7.805****	9.344****	7.972****	7.314****	8.798****	7.948****
	(5.070)	(4.416)	(4.813)	(5.953)	(5.149)	(4.629)	(5.632)	(5.233)
Newari	1.697	1.951	1.794	1.883	2.173	1.948	2.018	2.110
	(1.038)	(1.211)	(1.105)	(1.195)	(1.413)	(1.214)	(1.299)	(1.378)
Households in neighborhoods significantly or completely damaged	1.609	2.296	1.837	1.501	2.133	2.236	1.724	2.117
	(1.068)	(1.625)	(1.271)	(1.005)	(1.521)	(1.594)	(1.199)	(1.524)
Income (Rs.)								
50k-100k	2.105*	1.719	1.978	2.316*	1.899	1.597	2.182*	1.733
	(1.154)	(0.990)	(1.106)	(1.314)	(1.131)	(0.936)	(1.258)	(1.059)
>100k	2.391*	2.273	2.394*	2.715*	2.578*	2.120	2.745*	2.332
	(1.586)	(1.513)	(1.586)	(1.882)	(1.793)	(1.438)	(1.901)	(1.656)
Injury in the household	0.437	0.649	0.538	0.463	0.685	0.500	0.583	0.526
	(0.462)	(0.708)	(0.593)	(0.498)	(0.757)	(0.564)	(0.656)	(0.595)
House ownership	0.475	0.422	0.447	0.400	0.356	0.462	0.368	0.409
	(0.464)	(0.461)	(0.457)	(0.405)	(0.401)	(0.494)	(0.392)	(0.452)
Duration of water supply under normal conditions (hr/week)				1.189ⱡ	1.184ⱡ		1.204ⱡ	1.130ⱡ
				(0.300)	(0.296)		(0.301)	(0.292)
Households experienced disruption to piped water after EQ		0.444ⱡ			0.446ⱡ	0.122*ⱡ		0.130*ⱡ
		(0.235)			(0.235)	(0.134)		(0.145)
Duration of post-EQ piped water disruption(day)			0.911ⱡ			1.480ⱡ	0.903ⱡ	1.454ⱡ
			(0.125)			(0.432)	(0.125)	(0.432)
Observations	120	120	120	120	120	120	120	120
Pseudo R^2	0.209	0.224	0.212	0.212	0.227	0.236	0.215	0.238
AIC	137.975	137.563	139.510	139.503	139.105	137.671	140.959	139.448

Exponentiated coefficients; Standard errors in parentheses; One-tail tests except where indicated otherwise

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$, ⱡ Two-tail test

Table 4.7 Development of Best Fit Model for Piped Water – incl. Variable of Percent HH Experiencing Disruption in a Ward

Household vacated their neighborhood	Base	1	2	*3*	4
Houses significantly or completely	8.306****	7.329****	9.048****	*7.746*****	9.180****
damaged	(5.070)	(4.676)	(6.014)	*(5.103)*	(6.253)
Newari	1.697	2.158	2.735*	*2.215*	2.719*
	(1.038)	(1.364)	(1.875)	*(1.419)*	(1.884)
Households in neighborhoods	1.609	2.410	2.235	*2.390*	2.249
significantly or completely damaged	(1.068)	(1.721)	(1.596)	*(1.731)*	(1.627)
Income (Rs.)					
50k-100k	2.105*	1.647	1.972	*1.423*	1.687
	(1.154)	(0.969)	(1.201)	*(0.865)*	(1.064)
>100k	2.391*	2.154	2.701*	*1.890*	2.306
	(1.586)	(1.448)	(1.907)	*(1.313)*	(1.675)
Injury in the household	0.437	0.577	0.618	*0.396*	0.433
	(0.462)	(0.633)	(0.692)	*(0.456)*	(0.496)
House ownership	0.475	0.432	0.310	*0.481*	0.359
	(0.464)	(0.504)	(0.383)	*(0.556)*	(0.439)
Duration of water supply under normal			1.383⸸		1.326⸸
conditions (hr/week)			(0.368)		(0.362)
Households experienced disruption to		0.544⸸	0.580⸸	*0.096***⸸	0.111*⸸
piped water after EQ		(0.299)	(0.317)	*(0.108)*	(0.127)
Percent of HH experiencing water		0.981⸸	0.975*⸸	*0.973**⸸	0.969**⸸
disruption in the ward		(0.013)	(0.014)	*(0.014)*	(0.015)
Duration of post-EQ piped water				*1.710**⸸	1.659*⸸
disruption(day)				*(0.510)*	(0.501)
Observations	120	120	120	*120*	120
Pseudo R^2	0.209	0.238	0.248	*0.260*	0.267
AIC	137.975	137.402	137.914	*136.048*	136.984

Exponentiated coefficients; Standard errors in parentheses; One-tail tests except where indicated otherwise
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$, ⸸ Two-tail test

4.2.2.2 Electricity

The sub-sample used in the development of the relocation best-fit model that accounts for electricity service consists of the observations with complete data among the base model variables and electricity variables. The descriptive statistics of the sub-sample used for the development of the electricity model are presented in Table 4.8.

Three explanatory variables reflected the situation of electricity supplied by the government in the survey: the duration of electricity outage the household experienced under normal conditions before the earthquake, whether the household experienced electricity disruption after the earthquake, and if any, the duration of this disruption. Correlation coefficients between the base model variables and electricity variables are shown in Table 4.9.

Based on the literature, the Nepalese context characteristics and the nature of the data available, it is expected that electricity was of primary importance for households in Bhaktapur when making their relocation decision. It is anticipated that electricity disruption would increase the odds of leaving, as would longer durations of disruptions. On the other hand, people who used to experience longer durations of normal electricity outages before the earthquake are expected to have higher tolerance for electricity disruption, and therefore, be less likely to leave. The hypothesized impact of all the variables used in the development of the electricity model are shown in Table 4.8 as well.

Table 4.8 Electricity Model Sub-Sample Descriptive Statistics (n=131)

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Relocation/Dislocation	Household vacated their neighborhood	27.48%	44.81%	-
Household Demographic Characteristics	Number of individuals	5.77	2.89	-
	Number of females	2.74	1.60	-
	Females ratio to total number of individuals	46.62%	12.95%	-
	Number of members below 18-years	1.27	1.64	-
	Number of members over 65 years	0.27	0.57	-
	HH with elderly members	20.61%	40.61%	-
Ethnic/Linguistic Group	Newari	82.44%	38.19%	Positive
Socio-Economic Status	Income (Rs.)		-	Positive
	< 50,000 Rs.	36.64%	-	-
	50,000-100,000 Rs.	45.04%	-	-
	> 100,000 Rs	18.32%	-	-
	House ownership	97.71%	15.02%	Negative

Table 4.8 – Continued

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Socio-Economic Status	Education (highest degree obtained by any of the household members):		-	-
	10th Grade or Less	11.45%	-	-
	High School, VC, or Bachelor's Degree	79.39%	-	-
	Graduate Degree	9.16%	-	-
	HH own a car prior to EQ	0.76%	8.74%	-
Losses	Injury in the household	9.16%	28.96%	Negative
Structural Damage	Houses significantly or completely damaged	48.09%	50.16%	Positive
	Households in neighborhoods significantly or completely damaged	70.99%	45.55%	Positive
Government-Provided Electricity	Household with access to government-provided electricity	100.00%	0.00%	-
	Duration of electricity outage under normal conditions (hr/week) for households who had access to it	41-80 hours per week	-	Negative
	Households experienced electricity disruption after EQ	87.79%	32.87%	Positive
	Duration of post-EQ electricity disruption (day) for households who experienced disruption	1-2 weeks	-	Positive

* A positive impact implies that an increase in the variable results in an increase in the impacted or dependent variable (household dislocation), while a negative impact implies that as the variable increases the dependent variable decrease.

Table 4.9 Correlation Matrix - Variables Used in the Development of the Government-Provided Electricity Model

	1	2	3	4	5	6	7	8	9
1 Household vacated their neighborhood	1.000								
2 Newari	0.151*	1.000							
3 Income (Rs.)	0.003	-0.080	1.000						
4 House ownership	-0.060	0.045	-0.013	1.000					
5 Injury in the household	-0.016	0.093	-0.057	-0.021	1.000				
6 Houses significantly or completely damaged	0.366***	-0.039	-0.155*	-0.023	0.139*	1.000			
7 Households in neighborhoods significantly or completely damaged	0.327***	0.067	-0.203**	-0.018	0.126	0.647***	1.000		
8 Duration of electricity outage under normal conditions (hr/week)	-0.032	0.058	0.021	0.096	0.028	0.044	0.093	1.000	
9 Households experienced electricity disruption after EQ	0.031	0.146*	-0.145*	-0.017	0.058	0.071	0.153*	0.169*	1.000
10 Duration of post-EQ electricity disruption (day)	0.057	0.028	-0.047	0.027	0.034	0.233***	0.299***	0.222**	0.722***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Different combinations of electricity variables were added to the base model to determine the best-fit electricity model, as shown in Table 4.10. The first model in the table is the base model with observations restricted as per electricity variables' data availability. Electricity variables are then added to the model singly, doubly, and at last, all together. Variance accounted for above the base model is significant in all models at level of 0.01. Pseudo R-square increased in all models. AIC decreased in all models, except model 2, which also shows the smallest increase in Pseudo R-square.

Assessing the covariates odds ratios in the different models in the light of the aforementioned hypotheses shows that the disruption event and the normal pre-earthquake outage duration variables are significant in all models, while the disruption duration variable is insignificant in all models. Model 6 is the parsimonious model that has both the significant electricity variables and largest decrease in model's AIC. Therefore, model 6 will be considered the best fit model of the role of electricity on the household relocation decision.

The best-fit household relocation model that takes into account electricity service characteristics, model 6 in Table 4.10, shows that electricity disruption has the highest impact on people's relocation decision after the earthquake, higher than the impact of house damage. People who experience disruption in electricity are expected to have higher leaving odds by more than 12 times, while significant or complete house damage is expected to increase the odds of leaving by about 2.2 times. The level of electricity service before the quake also has a significant impact. Higher durations of normal electricity outages before the earthquake are expected to reduce the relocation odds by about 60% per each one category increase: less than 10 hours per week, 11-40 hours per week, 41-80 hours per week, and more than 81 hours per week.

In the best-fit electricity model, income and ethnicity are significant too. Newars are expected to have about 2.7 times higher odds of leaving than other ethnic groups, and households with annual income larger than Rs. 100,000 are expected to have about 2.6 times higher odds of leaving than households with annual income less than Rs. 50,000.

Table 4.10 Development of Best Fit Model for Electricity

Household vacated their neighborhood	Base	1	2	3	4	5	*6*	7
Houses significantly or completely damaged	2.333**	2.370**	2.284*	2.248*	2.607**	2.141*	*2.200**	2.378*
	(1.183)	(1.216)	(1.168)	(1.179)	(1.362)	(1.136)	*(1.181)*	(1.292)
Newari	3.207**	3.304**	3.239**	2.789*	3.214**	2.794*	*2.692**	2.632*
	(2.122)	(2.215)	(2.146)	(1.870)	(2.170)	(1.873)	*(1.861)*	(1.837)
Households in neighborhoods significantly or completely damaged	4.740**	4.407**	4.612**	5.432**	4.804**	5.087**	*5.334***	5.989**
	(3.537)	(3.311)	(3.465)	(4.147)	(3.629)	(3.918)	*(4.159)*	(4.753)
Income (Rs.)								
50k-100k	1.596	1.631	1.547	1.739	1.871	1.622	*1.849*	2.116*
	(0.756)	(0.778)	(0.746)	(0.857)	(0.931)	(0.814)	*(0.930)*	(1.117)
>100k	1.677	1.837	1.646	2.167	2.093	2.101	*2.568**	2.880*
	(1.028)	(1.159)	(1.016)	(1.396)	(1.355)	(1.370)	*(1.743)*	(1.985)
Injury in the household	0.766	0.657	0.759	0.926	0.631	0.916	*0.812*	0.787
	(0.545)	(0.472)	(0.542)	(0.674)	(0.453)	(0.672)	*(0.601)*	(0.581)
House ownership	0.269	0.321	0.270	0.180	0.338	0.181	*0.199*	0.206
	(0.370)	(0.440)	(0.370)	(0.255)	(0.475)	(0.253)	*(0.283)*	(0.301)
Duration of electricity outage under normal conditions (hr/week)				0.501**		0.484**	*0.398****	0.401***
				(0.155)		(0.152)	*(0.136)*	(0.137)
Households experienced electricity disruption after EQ		5.661*			10.748**		*12.902***	23.633**
		(6.171)			(13.535)		*(16.479)*	(34.111)
Duration of post-EQ electricity disruption (day)			1.041		0.850	1.092		0.855
			(0.124)		(0.135)	(0.138)		(0.143)
Observations	131	131	131	131	131	131	*131*	131
Pseudo R^2	0.123	0.147	0.124	0.157	0.154	0.161	*0.199*	0.205
AIC	151.129	149.462	153.014	147.810	150.380	149.317	*143.443*	144.542

Exponentiated coefficients; p-values in parentheses; One-tail tests

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

4.2.2.3 Vehicle-Accessible Roads

Two explanatory variables describing the vehicle-accessible roads status were available: whether the vehicle-accessible road was disrupted for the household who had access to it, and if it was, for how long. The sub-sample of households with access to vehicle-accessible roads and complete data along the different variables used in the development of the roads model is summarized in Table 4.11.

The literature has discussed the role of roads disruption in decreasing the neighborhood livability; consequently, roads disruption is expected to increase the household's desire to leave their home (Wright & Johnston, 2010). Longer durations of roads disruption are also expected to have a positive impact in increasing relocation as well. Table 4.11 summarizes the impact hypotheses for the variables used in the model development. The correlation matrix of these variables is shown in Table 4.12.

The different permutations of the explanatory variables for the vehicle-accessible roads is shown in Table 4.13, are shown below. Although all models are significant at level of 0.005, roads explanatory variables are insignificant in all models at a level of significance of 0.1[11].

The insignificance of roads to households in making their relocation decision in the models developed do not mean that roads do not have a significant effect on households' relocation behavior in general. The results of these models show that in the Nepalese context after the 2015 earthquake, vehicle-accessible roads did not have a significant impact. This could be a result of the fact that over 99% of the households in the sample did not own a motorized vehicle. This indicate that vehicle-accessible roads

[11] One-tail test is used because a hypothesis about the effect of roads disruption on relocation decision is developed based on the literature and the context specifics.

might not have a significant impact on the relocation decision for households in Nepal who do not own motorized vehicles.

A best fit model has been developed incorporating each infrastructure service's variables separately, and the results of each model were discussed. In the next section, we will present the conclusion of this study and the implications of the results found. The limitations of the analysis results will be summarized and suggestions for future research will be presented.

Table 4.11 Vehicle-Accessible Roads Model Sub-Sample Descriptive Statistics (n=121)

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Relocation/Dislocation	Household vacated their neighborhood	33.06%	47.24%	-
Household Demographic Characteristics	Number of individuals*	5.78	2.91	-
	Number of females	2.78	1.63	-
	Females ratio to total number of individuals**	47.20%	13.71%	-
	Number of members below 18-years	1.32	1.94	-
	Number of members over 65 years	0.36	1.00	-
	HH with elderly members***	20.66%	40.66%	-
Ethnic/Linguistic Group	Newari	81.82%	38.73%	Positive
Socio-Economic Status	Income (Rs.)		-	Positive
	< 50,000 Rs.	25.62%	-	-
	50,000-100,000 Rs.	53.72%	-	-
	> 100,000 Rs	20.66%	-	-
	House ownership	94.21%	23.44%	Negative

Table 4.11 – Continued

Category	Variable	Mean/Percentage	Standard Deviation	Impact hypothesis*
Socio-Economic Status	Education (highest degree obtained by any of the household members):		-	-
	10th Grade or Less	11.57%	-	-
	High School, VC, or Bachelor's Degree	76.03%	-	-
	Graduate Degree	12.40%	-	-
	HH own a car prior to EQ	0.83%	9.09%	-
Losses	Injury in the household	8.26%	27.65%	Negative
Structural Damage	Houses significantly or completely damaged	42.98%	49.71%	Positive
	Households in neighborhoods significantly or completely damaged	61.16%	48.94%	Positive
Vehicle-Accessible Roads	Household with access to vehicle-accessible roads	100.00%	0.00%	-
	Household experienced vehicle-accessible roads disruption after EQ	63.64%	48.30%	Positive
	Duration of post-EQ vehicle-accessible roads disruption (day) for households who experienced disruption	3-4 weeks	-	Positive

* A positive impact implies that an increase in the variable results in an increase in the impacted or dependent variable (household dislocation), while a negative impact implies that as the variable increases the dependent variable decrease.

Table 4.12 Correlation Matrix - Variables Used in the Development of the Vehicle-Accessible Roads Model

	1	2	3	4	5	6	7	8
1 Household vacated their neighborhood	1.000							
2 Newari	0.151*	1.000						
3 Income (Rs.)	0.003	-0.080	1.000					
4 House ownership	-0.060	0.045	-0.013	1.000				
5 Injury in the household	-0.016	0.093	-0.057	-0.021	1.000			
6 Houses significantly or completely damaged	0.366***	-0.039	-0.155*	-0.023	0.139*	1.000		
7 Households in neighborhoods significantly or completely damaged	0.327***	0.067	-0.203**	-0.018	0.126	0.647***	1.000	
8 Household experienced vehicle-accessible roads disruption after EQ	0.227**	0.158	-0.271**	-0.015	0.069	0.223**	0.485***	1.000
9 Duration of post-EQ vehicle-accessible roads disruption (day)	0.311***	0.162*	-0.200*	-0.037	0.061	0.312***	0.545***	0.877***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.13 Development of Best Fit Model for Vehicle-Accessible Roads

Household vacated their neighborhood	Base	1	2	3
Houses significantly or completely damaged	3.611***	3.913***	3.834***	3.856***
	(1.875)	(2.060)	(2.017)	(2.041)
Newari	1.896	1.622	1.667	1.650
	(1.136)	(1.005)	(1.024)	(1.030)
Households in neighborhoods significantly or completely damaged	2.566*	1.875	1.792	1.775
	(1.477)	(1.206)	(1.158)	(1.160)
Income (Rs.)				
50k-100k	1.394	1.523	1.504	1.513
	(0.728)	(0.807)	(0.795)	(0.805)
>100k	2.455*	2.637*	2.470*	2.497*
	(1.540)	(1.658)	(1.546)	(1.590)
Injury in the household	0.375	0.382	0.369	0.370
	(0.301)	(0.309)	(0.304)	(0.305)
House ownership	0.329	0.310	0.337	0.333
	(0.294)	(0.283)	(0.311)	(0.311)
Household experienced vehicle-accessible roads disruption after EQ		1.787		1.095
		(1.020)		(1.091)
Duration of post-EQ vehicle-accessible roads disruption (day)			1.156	1.138
			(0.143)	(0.244)
Observations	121	121	121	121
Pseudo R^2	0.149	0.156	0.158	0.158
AIC	146.721	147.682	147.325	149.317

Exponentiated coefficients; p-values in parentheses; One-tail tests

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

5. CONCLUSION

The following subsection will discuss the conclusions drawn from the analysis conducted in the previous section and suggest implications of the results of the analysis where applicable.

5.1 Conclusion

The impact of infrastructure services on relocation has been assessed in this case study of household dislocation following the 2015 Nepalese earthquake. Variables capturing different attributes of infrastructure services have been used to model the household relocation decision. Other variables have been also used in these models, variables capturing demographic, social and economic drivers of relocation in order to better capture the ceteris paribus impacts of disruption of infrastructure services. In all models, the built environment in terms of damage to homes, damage to the neighborhood's built environment and damage and disruption of infrastructure services have proven to have a significant impact on household decision to relocate following the earthquake.

House damage had a significant role in driving a household decision to relocation in all models. High levels of house damage increased the household's relocation odds by over 2 to 7 times the likely dislocation of households living in houses with no or slight damage levels following the earthquake. As anticipated, neighborhood livability had a significant influence on household's desire to relocate. Neighborhood livability was captured in the level of neighborhood damage in this study. Households residing in neighborhoods with high levels of damage had 2 to 5 times higher odds of relocation.

The consequences of infrastructure damage and disruption was not unequivocally clear across all infrastructure types. Indeed, the analysis suggested that while disruption to electricity had clear and consistent effects, the consequences of disruption to water was unexpected and largely influenced by the pre-earthquake and post-earthquake water situations, and the consequences of transpiration were non-existent. The following provides a more nuanced discussion of these findings.

Piped water played a significant role in the relocation decision-making process; however, the impact of piped water disruption did not conform with the general expectation in the literature. A closer look at the water service situation before and after the earthquake in Nepal reveals several distinctive attributes that could have caused this unanticipated impact. The pre-earthquake conditions of water in Nepal coupled with the characteristics of the post-earthquake water aid gave rise to a counterintuitive hypothesis about the impact of piped water disruption on relocation.

People in Nepal relied most often on several sources of water for their different needs. Not all households had access to piped water, and even for households who had access to it, the short durations of water supply and the unreliable quality of piped water drove many people to rely on other sources for their water needs besides piped water. After the earthquake, the disruption to piped water and the deterioration of water quality attracted water aid. Indeed, this aid provided households with something they rarely experienced prior to the earthquake – the continuous availability of sufficient quantities of safe water. Consequently, while we hypothesized initially that disruption to piped water would increase the probability of dislocation, we found that disruption actually decreased the likelihood of dislocation. Based on our examination to the water situation that the Nepalese household experienced before and after the earthquake, we modified our hypothesis of the impact of piped water disruption on relocation. In the models developed to test this hypothesis, piped water disruption reduced the odds of household relocation as hypothesized. Larger extents of water disruption in a neighborhood reduced the odds of leaving too as it probably attracted more water aid.

The water situation in the Nepalese context suggests the role of redundancy and resourcefulness in infrastructure services in enhancing the resilience of the community. It points out to the possible effects of pre-disaster redundancies and post-disaster resourcefulness in providing lifeline services in reducing the probability of household relocation. Yet, these results are only preliminary and require further investigation due to the unavailability of data capturing the disruption in the other sources of water in Nepal and the aid water supplied to affected communities.

Disruption in government-provided electricity had the highest impact on relocation among all the examined variables. Households that experienced electricity disruption had 12 times higher odds of choosing to relocate. The high impact of electricity disruption on relocation supports the general expectations found in the literature. It is probably attributed to the role of the pre-earthquake conditions and the post-earthquake actions. In general, societies have high dependency on electricity for meeting their different needs. And as is the case in many societies, people in Bhaktapur relied almost completely on electricity provided by the government. Households did not have backup sources for generating electricity before the earthquake and no alternative sources for electricity were provided after the earthquake. These factors made the households in Bhaktapur highly sensitive to electricity disruption.

The high impact of electricity disruption provides support to the expected impact of infrastructure resilience on community resilience, at least with respect to dislocation issues. A robust infrastructure system will retain higher levels of function and undergo lower extents of function loss after a disaster. Robustness decreases the probability of experiencing disruption and decreases the number of households who might experience any disruption, thus, reducing the likelihood of household relocation and enhancing community resilience after disasters. However, as with the case of water, the level of electricity service before the earthquake had a significant impact on relocation too. People who experienced longer durations of electricity outages under normal conditions before the earthquake were probably more accustomed to the disruption in the electricity service after the earthquake, which in turn had significantly lowered their odds of leaving their homes.

The consequences of disruption to transportation infrastructure – in the sense of access to roads, showed no consequence for household dislocation. Specifically, it was expected that disruption in access to roadways would lead to higher probability of dislocation in part because these disruptions might lead to reduced access by household and other community entities to goods, resources and services necessary for daily activities and household functions. However, disruption to vehicle-accessible roads did not have any significant impact on households' relocation decision in this study. This could be due to the fact that less than 1% of the households, in our sample of 222 observations, had a car or vehicle before the earthquake. This result suggests that the role of roads disruption in neighborhood livability might be diminished for households who do not own motorized vehicles, and therefore, roads disruption is not expected to have a significant impact on their relocation.

5.2 Limitations

As with all research there are limitations and potential areas of improvement. The following highlights some of the limitations, not only in terms of the specific research conducted herein, but also in terms of its generalizability to other research settings.

One of the limitations of this research stems from the nature of the dependent variable itself – that is, whether or not the household dislocated. As discussed in the literature, there are many meanings associated with the notion of dislocation, displacement, evacuation that all capture the idea that the household leaves their home for some duration due to an actual or anticipated disaster. In this study, household informants were asked whether the household left their pre-earthquake neighborhood or not following the earthquake. For purpose of this research, leaving one's neighborhood was interpreted as leaving one's homestead. While it is expected that a household would leave the whole neighborhood when they relocate, there is a possibility that some households have left their home but remained in the same neighborhood. Therefore, the numbers of households who relocated as defined by their response to the neighborhood question potentially underestimated actual dislocation from the pre-earthquake residence/home.

As discussed extensively above, model development and specification, which had consequences for the nature of the results, were constrained by the availability and comprehensiveness of the sample size and intra-sample available data. The research team who provided the data used in this study was only able to collect data from 222 households during the field surveys. This placed a rather low ceiling on the possible complexity of the models that might be developed initially. However, in addition to the small sample size, missing data further restricted the method of analysis and led to limitations in the outcomes. The survey questions provided 22 predictors that could have an impact on relocation: 9 demographic and socioeconomic variables, and 13 variables related to the built environment. Missing data in the different observations among the different variables reduced the number of observations that could be used in the analysis even further.

For each infrastructure service, only the sub-sample of households who had access to that service were asked the questions related to it. As a result, larger numbers of missing data existed in infrastructure variables. Therefore, for the uttermost utilization of available data, a base model was developed first using all the variables that are not related to infrastructure, i.e., house damage, neighborhood damage and demographic and socioeconomic variables, as these variables had a larger set of observations. Then, infrastructure variables were added to the best fit base model for the development of infrastructure models.

Missing data in infrastructure services' variables were not consistent. Utilizing all these variables in the same model would have reduced the number of observations beyond the number required for conducting the analysis. Hence, relocation models were developed separately for each infrastructure service: piped water, government-provided electricity and vehicle-accessible roads.

The sub-samples used in the development of the relocation models that incorporated infrastructure services were smaller than the sub-sample used for the development of the base model. For that reason, parameter estimates and significance levels changed for almost all the base model variables. Most base model variables were not significant when incorporated with infrastructure variables. Nevertheless, the variables in the base model were not changed while developing the other models as it was developed utilizing a larger sample; and consequently, it reflects the represented population better.

Piped water model outcomes were limited due to the unavailability of data related to the disruption of the other water sources people in Nepal used to rely on before the earthquake and the unavailability of data related to the aid water supplied to affected people after the earthquake. Capturing the effect of piped water service on relocation properly requires controlling for the disruption in all water sources and the provision of alternative sources of water. Thus, the confidence in the results of the piped water model is limited.

5.3 Future Research

Our comprehension of the drivers and dynamics of relocation is very limited. People who are expected to evacuate do not, and people who should not leave often times do (Dash & Gladwin, 2007). Researching and developing strategies towards durable solutions addressing household and community displacement are shared responsibilities among researchers, practitioners, governmental agencies, and NGOs. The complex multi-faceted dimensions of displacement can only be tackled through multidisciplinary approach in disaster research (Esnard & Sapat, 2018).

Relocation models that incorporate the different social, economic, psychological and built environment predictors that can influence the relocation behavior in the community are required. Further research should be directed to increasing our understanding of the role of infrastructure services while eliminating the dependency among the predictors and controlling for any correlation. Theoretical and empirical models are necessary to produce robust research as well.

Studies should account for the governmental responses and nongovernmental aid activities in relocation models. Including these variables in relocation models would enhance our conception of the impacts and consequences of plans and policies and allow for the exploration of “what if” scenarios with a greater degree of confidence.

More research is required to address relocation in the international context. Comprehending the different drivers of human behavior among communities and places is essential for the development of thorough and robust relocation models. Also, models addressing household relocation in the post-disaster phase remain limited and require further investigation.

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