ABSTRACT

Title of Dissertation: POST-HURRICANE RECOVERY IN THE
                           UNITED STATES: A MULTI-SCALE
                           APPROACH

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As we increasingly consider resilience as a central strategy for addressing climate change, recovery emerges as an important dimension that is often the focus of public policy. The progression of global climate change will cause an increase in the scale and magnitude of disasters, so it is more important than ever to understand how we can not only prevent impacts, but also recover from them. This research was carried out with the primary goal of examining recovery at multiple scales, while simultaneously considering the social and economic forces and community behaviors that influence recovery outcomes. This dissertation proposes new ways of

conceptualizing and quantifying recovery and analyzes the way that neighborhood characteristics and community engagement influence the recovery process at multiple dimension and temporal scales. The findings emphasize the importance of assessing recovery progress on multiple timescales and highlight the opportunities that emerge as a result of community engagement with local government throughout the recovery process.

The first analytical chapter considers the interaction between vulnerability and recovery by studying power outages and restoration following Hurricane Isaac in Louisiana. This approach uses power restoration as a metric by which to better understand short-term recovery of a specific infrastructure system, building a model for recovery that takes into account antecedent conditions, impact, hazard and prioritization. The next chapter considers 311 requests in Houston TX as a potential proxy measure for civic engagement and social capital. This chapter analyzes 311 contact volumes across the City of Houston and identifies the neighborhood characteristics that influence proclivity to call. Finally, the 311 data is used to better understand system-level recovery and community engagement in the recovery process in Houston TX following Hurricane Harvey in 2017. The chapter compares neighborhood-level use of 311 services prior to Hurricane Harvey to the way it was used for storm-related concerns in the weeks directly following the storm.

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A MULTI-SCALE APPROACH

by

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1. Introduction

In recent years, resilience has become a prominent concept in climate and disaster recovery research, adding a significant new dimension to previous methods for assessing and addressing climate and disaster risk. Twigg argues that the main difference between resilience and more traditional risk analysis approaches to adaptive capacity is that resilience "goes beyond specific behavior, strategies and measures… that are generally understood as capacities" (Twigg et al., 2013). It takes a broader, more pragmatic approach to addressing risk, where "agility and discipline" (Tierney, 2014) collide.

Traditionally, risk analysis work has put its primary focus on protecting and strengthening infrastructure systems so that they can withstand anticipated shocks. In contrast, resilience demands a more holistic approach and stresses that resilient infrastructure must be complemented by resilient communities and resilient systems of governance. In doing so, the resilience approach requires that focus be directed towards more than simply withstanding the anticipated hazard; learning and organizing in such a way that the system or community will be better prepared to face a broad spectrum of potential shocks in the future must also be considered (Godschalk, 2003). This is particularly important because the increasing interconnectedness of our communities and our reliance on countless interdependent infrastructural systems and subsystems creates unprecedented levels of complexity, for which it would be nearly impossible and wholly impractical to identify and

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address the risks and possible failures of each system component (Linkov et al., 2014).

The complexity and unpredictability of system and community vulnerabilities are even more prominent when climate change is brought to the forefront of the resilience conversation. Although climate change is a scientific certainty, there are still many unknowns, especially with regards to the anticipated time horizons, severity, scale and nature of impacts (Linkov et al., 2014). These unknowns make it nearly impossible and economically infeasible for a community to prepare for these changes solely by relying on more traditional risk analysis and hazard mitigation techniques. Although these traditional hardening and disaster preparedness approaches continue to have a valuable place in a strong disaster management strategy, they are no longer, and perhaps never were, sufficiently robust on their own (Godschalk, 2003). A resilience approach is what is needed to fill in these gaps.

This dissertation begins with a literature review that will be organized around three interconnected concepts: resilience, recovery and social capital (Figure 1.1). It begins with an overview of the definitions of resilience as presented in the literature, along with a discussion of the ways that resilience is approached and understood. After establishing this conceptual groundwork, I will focus on two key elements of resilience: recovery and social capital. As will be shown below, a common theme among definitions of resilience is that they all include some conception of recovery, so this section will outline how recovery is defined, measured and modeled.

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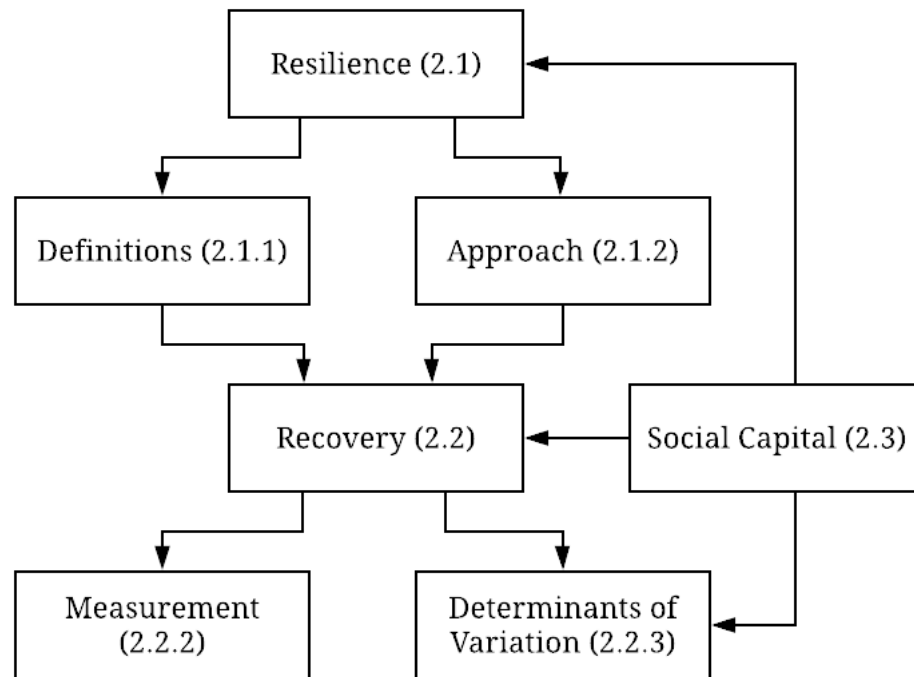
Figure 1.1: Schematic of Literature Review

As we think about recovery, we must consider outcome variations and what factors underlie these differences. Central among these is social capital, which will be the focus of the final section of the literature review. The literature suggests that social capital is not only a determinant of recovery, but also a key dimension of resilience. This section will define social capital and discuss approaches to measurement, with an emphasis on the way it relates to the earlier sections on resilience and recovery.

The literature review will conclude with a brief section discussing the questions that emerge from the literature on resilience, recovery and social capital, and how these gaps have informed the research questions and research design that are

central to this dissertation, before providing an overview of the three analytical

chapters that follow, each of which use quantitative metrics to better understand the

impacts of socio-economic inequalities and civic engagement on the recovery process

at multiple scales.

2. Literature Review

2.1 Resilience

2.1.1 Defining Resilience: Origins and Evolution

While the concept of resilience is relatively new to the disaster and climate change fields, most literature indicates that the concept had its origin in the field of psychology and psychiatry in the 1940s (Johnson & Wiechelt, 2004; Manyena, 2006). This conception of resilience is quite different from the way it is used today. It referred to the risk of psychological impacts when young children are exposed to traumatic life events, such as death and divorce – the coping strategies that the children developed because of these events caused negative outcomes as they matured (Peek, 2008).

In 1973, Holling introduced a different perspective on resilience into the ecology literature. He defined the concept as "a measure of the persistence of systems and their ability to absorb change and disturbance and still maintain the same relationship between populations or state variables" (Holling, 1973). He revisited and expanded upon this definition at several points in his career (Holling, 1986), eventually settling on the idea that resilience is "the buffer capacity or the ability of a system to absorb perturbations, or the magnitude of disturbance that can be absorbed before a system changes its structure by changing the variables and processes that control behavior" (Holling, 1995). The common thread that runs through these definitions is that in an ecological context, resilience is preoccupied with the overall functioning of a system, rather than the persistence or well-being of its component

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parts (Pisano, 2012). As the definition of resilience evolved, it was recognized that after a shock, a system does not necessarily need to return to its initial equilibrium state in order to be considered resilient. Populations within the system can change, and the system does not even need to produce a steady ecological state as long the system as a whole retains its identity (W.N. Adger, 2000).

The link between ecological and societal resilience was introduced in Adger's 2000 paper "Social and Ecological Resilience". He argues that the 'population or state variables' featured in Holling's 1973 work can be extended to apply to human societies rather than just the plant and animal populations to which the original definition referred. Nonetheless, there are significant differences between ecological and social systems, and therefore they must be separately defined. Adger defines social resilience as "the ability of human communities to withstand external shocks to their social infrastructure, such as an environmental variability or social, economic and political upheaval" (W.N. Adger, 2000). Although certainly not the final word on the definition of resilience, this moved the concept from the ecological into the social spheres, significantly broadening its potential applications.

While ecological and social resilience are related to the concept of resilience as it appears in the engineering literature and have overlapping applicability, they are also distinct. In engineering, a system's ability to function efficiently and to return to a steady state in the aftermath of a shock is of central importance to the concept of resilience (Folke, 2006). This definition appears with some frequency in disaster response literature. When applied, it typically involves a consideration of the

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likelihood that a catastrophic event will occur and a calculation of the likely level of loss. In the aftermath of an event, resilience will be measured by how quickly and efficiently the city or region returns to its pre-shock functioning (Pendall, Foster, & Cowell, 2010).

In 1998, Walker argued that any discussion of resilience must "…begin with the question: resilience to what" (B. Walker, 1998) (Pendall et al., 2010). However, as the definition evolved over time and was embraced in the context of global environmental change, there has been the growing acknowledgement that a truly resilient system cannot simply be prepared for known threats. As climate change encroaches, the environmental unknowns become an increasing threat, and as a result, the literature has embraced a version of resilience that produces flexible systems that can withstand both the expected and the unexpected (Godschalk, 2003). Resilience can no longer simply refer to the ability to plan for and recover from well-defined eve nts and hazards.

The IPCC has included the concept of resilience in its Assessment Reports since the third report was published in 2001, however it definitions of the concept have, along with the broader resilience literature, evolved over time in terms of both content and scope (Table 2.1). The AR3 definition of resilience is very basic, and quite similar to Holling's conception of ecological resilience (IPCC, 2001). By contrast, the influence of Adger's work on the definition in AR4 (2007) is undeniable; resilience's applicability in both social and ecological contexts is clearly stated (IPCC, 2007). The A5R definition of resilience is by far the broadest of the

three. It expands to include economic, alongside social and ecological, systems.

Further, it emphasizes the importance of the capacity to adapt, learn and transform.

This idea that a resilient system is one that can learn from past events and use that

knowledge to transform for the better is a fairly recent addition to the original

definition, but one that has quickly become central to the literature. A resilience

system is not simply one that can withstand shocks, but one that can be built back

better in the aftermath (IPCC, 2014).

Table 2.1: IPCC Definitions of Resilience

Report	Date of Publication	Definition
AR3	2001	"Amount of change a system can undergo without changing state"
AR4	2007	"The ability of a social or ecological system to absorb disturbances while retaining the same basic structure and ways of functioning, the capacity for self-organisation, and the capacity to adapt to stress and change." (IPCC, 2007)
AR5	2014	"The capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning and transformation." (IPCC, 2014)

The growth of resilience as a prominent concept and central goal in climate

policy is also reflected in the text of the UNFCCC climate agreements. The Kyoto

Accord did not mention resilience at all (UNFCCC, 1998), and it was only mentioned

briefly and in passing in the Copenhagen Accord (UNFCCC, 2010). By contrast, the

concept was of central importance in the 2015 Paris Agreement, where it is featured

as one of the core goals (UNFCCC, 2015). Similarly, we see a growing international

focus on resilience from the disaster risk reduction standpoint. The World Conference on Disaster Risk Reduction in 2005 named "Building a culture of safety and resilience" as one of their five priorities for action. In this framework, they defined resilience as "The capacity of a system, community or society potentially exposed to hazards to adapt by resisting or changing in order to reach and maintain an acceptable functioning and structure. This is determined by the degree to which the social system is capable of organizing itself to increase this capacity for learning from past disasters for better future protection and to improve risk reduction measures" (UNISDR, 2005). Despite the fact that disaster risk conceptions can be quite narrow, this definition is exceptionally broad and forward thinking for its time. It acknowledges that resilience can be achieved through hardening, increased flexibility, and reduced risk, and it emphasizes the importance of learning from past experiences to better prepare for the future.

Evidently, there have been many attempts over the years to define resilience, and the precise meaning has evolved considerably since it emerged as a key issue in the social environmental sphere (Twigg et al., 2013). Different definitions choose to include or omit certain elements of resilience, and there often disagreements over whether resilience is best seen as an outcome (the ability to recover after a shock), or a process (the ongoing act of learning and improving) (Cutter et al., 2008a). Despite these differences, there is broad agreement that resilience encompasses the following broad characteristics (W. Neil Adger, Arnell, & Tompkins, 2005):

- **The capacity to absorb**: Among the first qualities attributed to resilience was the ability of a system to absorb shocks. While the definition has evolved in the sense that this is no longer the only focus of resilience, it remains a key characteristic

- **The capacity to adapt**: One of the major strides in resilience literature has been the expansion of the definition to go beyond a system simply returning to its baseline level of functioning. A truly resilient system must learn from past experiences and adapt so as to better prepare for future hazards.

- **The capacity to recover**: This is a multi-scalar, multi-dimensional, multi-temporal process by which individuals, communities and regions return to normal functioning or, ideally, a new, improved normal (Tierney, 2014).

- **The capacity to organize as a society**: The development of social networks is a key element of resilience, allowing for collective action and flexible responses in the aftermath of a shock.

2.1.2 <u>Approaches to Studying Resilience</u>

Given that resilience is an important component of disaster preparedness and climate change policy, the literature has produced a number of models and frameworks designed to better understand resilience as a process and to more accurately measure resilience as an output. Engle et al.'s 2014 paper focuses primarily on measuring resilience as an output, with the goal of developing methods to assess and maximize resilience in development initiatives. It explores the relative strengths and weaknesses of quantitative, qualitative and mixed method approaches to

measuring resilience. Quantitative measures are attractive due to the ease with which such results can be compared, assessed and ranked. However, methodological and theoretical challenges to a purely quantitative approach make this analytical strategy problematic, because it tends to oversimply a very complex concept. A qualitative approach to measuring resilience can solve many of these problems. Case studies, on their own or as a comparative study, can provide important insight into local resilience strategies. They can also be a useful complement to quantitative research, either by validating indicators, or by identifying processes can be used to develop better quantitative models (Engle, de Bremond, Malone, & Moss, 2014).

Ultimately, Engle et al. propose a resilience framework that stresses the importance of a multi-scalar "hybrid" approach to quantifying resilience. First, it captures the importance of multiple timescales, incorporating short term coping in the direct aftermath of a shock as well as long-term adaptation to changing conditions. Second, it connects various spatial scales so as to be mindful of the fact that although research often happens on the national and international levels, resilience projects are more likely to be implemented at the local and regional scale. Finally, it acknowledges the complementary value of quantitative and qualitative research, and encourages combining the strengths of both (Engle et al., 2014).

Engle et al.'s resilience framework focused on the outputs of a resilient system, but other models concentrate more on the process by which resilience is achieved. Cutter's Disaster Resilience of Place (DROP) Model focuses on clarifying the connection between vulnerability and resilience in the context of community

responses to an adverse event. Recent literature recognizes that vulnerability and resilience exist on a continuum and are complementary concepts. This model proposes that prior to an event, antecedent conditions are established based on social systems, the built environment and natural conditions.

When a hazard event strikes, antecedent conditions are combined with coping responses, to determine the short-term impact of the hazard. If the impact exceeds the community's absorptive capacity, damage will be done, and recovery will be necessary. The effectiveness of the recovery process will depend on the community's level of adaptive resilience, and these outcomes will impact the system's antecedent conditions from that point forward. Cutter emphasizes the difficultly of moving from this conceptual model to actual measurement. Quantitative indicators are the most commonly used approach, but the difficulty of developing valid, robust measures cannot be understated (Schipper & Langston, 2015). Indeed, attempts to quantify resilience have been criticized as overly subjective, lacking in key variables and unable to be aggregated to different scales. More research in this field is required (Cutter et al., 2008a).
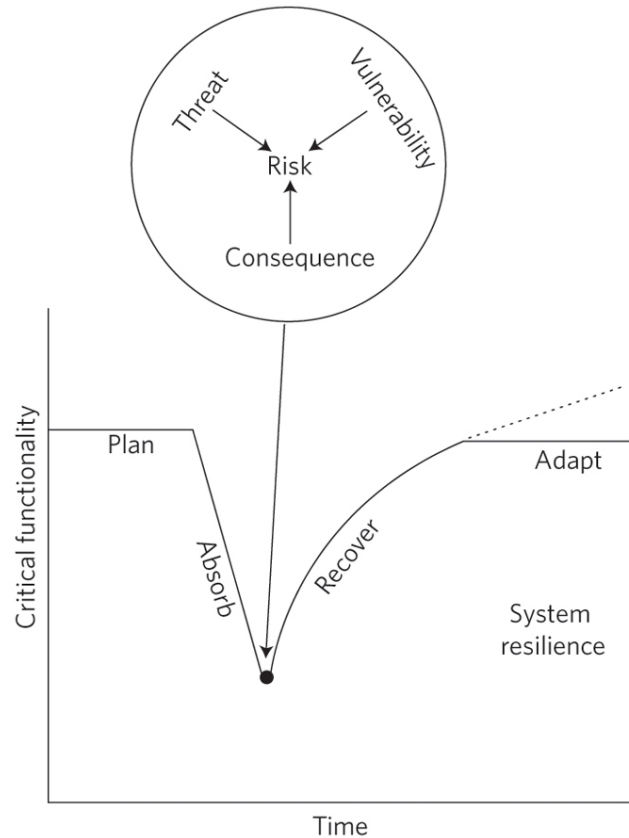
Figure 2.1: Resilience Management Framework (Linkov et al., 2014)

Linkov et al. (2014) proposed a resilience management framework (Figure 2.1) that is in many ways similar to Cutter's 2008 DROP model. However, this approach "…integrat[es] the temporal capacity of a system to absorb and recover from adverse events, and then adapt". While Cutter's model did acknowledge the temporal element of resilience, its impacts are explicitly built into Linkov's model, as the time scale impacts the nature of the absorption slope and the recovery curve. In this framework, risk is defined as "the total reduction in critical functionality", and resilience is viewed primarily as the mechanism through which the system recovers, not the degree to which the system absorbs the shock. This approach also makes

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explicit acknowledgment that after a shock, a sufficiently resilient system may recover to a better state than the pre-shock baseline, improving overall functioning and better preparing the system for future shocks (Linkov et al., 2014).

While resilience is an important consideration that should be addressed at multiple scales, local-level resilience is featured with particular focus in the literature (Godschalk, 2003; Leichenko, 2011; Twigg et al., 2013). Although climate change is a global phenomenon, its impacts are local (van Aalst, Cannon, & Burton, 2008). Cutter explains that "…from the hazards research perspective, natural processes and impacts are localized and event-specific" (Cutter et al., 2008a). Approaches to resilience are most effective when they are tailored to local experiences and needs, and therefore resilience research is best done with a bottom up approach: collecting local level data and aggregating upwards to larger spatial scales.

Cities are particularly vulnerable to changing climate, and therefore present an important opportunity for the development and implementation of climate adaptation and resilience policy. Indeed, a number of partnerships and initiatives such as the ND-GAIN Urban Adaptation Assessment, C40 Cities, and the Rockefeller Foundation's 100 Resilient Cities have emerged that are built to support and encourage local-level governments to take a more central role in climate policy and tailor resilience and adaptation policies to local needs. A focus on resilience at the local level gives cities the tools to proactively strengthen their own capacities and address their vulnerabilities rather than relying on higher level of government to

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address climate change and reactively dealing with shocks and challenges after they happen (Corfee-Morlot, Cochran, Hallegatte, & Teasdale, 2011).

2.2 Recovery

2.2.1 Recovery as a dimension of resilience

Among the various frameworks and definitions discussed in the previous section, it is clear throughout that recovery is an essential dimension of resilience, and often the focal point of the field as a whole. It is impossible to build a society so resilient that it can fully absorb every shock without damage, and as a result, the concept of recovery, and particularly resilient recovery is of central importance in the resilience literature. Tierny defines resilient recovery as "a series of processes taking place at multiple scales that can lead to successful adaption to a new normal or to continued dysfunction and poor recovery outcomes" (Tierney, 2014). This effectively summarizes several of the themes that are consistent in definitions of resilience more broadly. Like resilience, recovery is a process that must occur on many interdependent scales simultaneously. This definition also emphasizes the importance of not just building back but building back better. A resilient recovery process should encourage learning from past experiences and work towards establishing a new, more resilient baseline.

Cutter's DROP model emphasizes the fact that the recovery process is instrumental in establishing a new normal ("antecedent conditions") that will, along with the characteristics of the event itself and the community's short-term coping response, determine the outcome of the next disaster that the community faces. Her

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model proposes that the quality of the recovery process is determined by the level of adaptive resilience in the community, as expressed by improvisation and social learning. Cutter defines improvisation as "impromptu actions which may aid in the recovery process" (Cutter et al., 2008a), and social learning is defined as "the diversity of adaptations, and the promotion of strong local social cohesion and mechanisms for collective action" (W. Neil Adger et al., 2005). According to Cutter, social learning occurs "when beneficial impromptu actions are formalized into institutional policy for handling future events" (Cutter et al., 2008a). It is the mechanism by which a new, better baseline is established.

2.2.2 Measuring Recovery

Much like resilience, researchers are constantly looking for new ways to measure recovery so that the process can be subjected to ranking and evaluation in order to better understand the qualities and characteristics of recovery approaches that produce successful outcomes. When considering the measurement of recovery, it is important to identify what exactly is being measured. According to Aldrich, there are five dimensions of resilient post-disaster recovery:

- Personal and familial socio-psychological well-being
- Organizational and institutional restoration
- Economic and commercial resumption of services and productivity
- Restoring infrastructural system integrity
- Operational regularity of public safety and government.

These dimensions range in scale from the individual to the regional level, and encompass nearly all spheres of public and private life (Aldrich, 2012a).

Recovery also happens along multiple timescales, which Burton breaks down into four clear phases: "(1) an emergency period that is characterized by search and rescue, sheltering, and the clearing of major arteries; (2) restoration, during which repairable essentials of urban life such as utilities are restored; (3) reconstruction, during which infrastructure and housing is provided for; and (4) a commemorative or betterment reconstruction phase" (Burton, 2014). Each of these phases has different goals and different endpoints making it challenging to embed all of them into a single analysis. Further, the phases each occur on different timescales with each one likely taking considerably longer than the last (Finch, Emrich, & Cutter, 2010).

Given the multi-scalar, multi-dimensional, and multi-temporal nature of recovery, it is difficult to measure in a consistent and complete way that lends itself well to comparative analysis. Both quantitative and qualitative approaches are common throughout the literature, with quantitative methods having the advantage of easy comparability and further analysis. However, they tend to struggle to capture recovery in its multiple dimensions and at its many scales, instead focusing on select sub-components of the larger recovery process. Alternatively, qualitative methods give researchers the ability to study community recovery as a whole rather than breaking it down into its component parts, but these approaches lack the easy comparability and assessment that comes along with more quantitative outputs.

Burton's 2014 analysis of recovery in coastal communities post-Hurricane Katrina is an excellent example of both the strengths and downfalls of quantitative methodology in recovery assessment. Geospatial imaging was used to survey reconstruction efforts along the coast between October 2005 and October 2010. The images were analyzed for signs of recovery, distinguishing between the markers of recovery for the separate phases of the process. This study specifically focuses on reconstruction of the built environment, which is only one component of a robust recovery process. However, the benefit of such an approach is that it can be used as a recovery metric in future quantitative analyses. In this case, Burton uses his recovery measure to validate resilience indicators (Burton, 2014).

Other papers take a more technical approach to estimating recovery curves. For example, Zobel (2014) proposes a technique for mathematically characterizing non-linear recovery in the aftermath of disasters that generates a ratio of the area above and below a general response curve, summarizing recovery into a single calculable value, β. He applied this technique to post-Hurricane Sandy recovery, estimating the recovery curve of power restoration for Con Edison Power Company in New York City. This allowed him to compare recovery behaviors and make conclusions about the relative efficiency of recovery in different boroughs (Zobel, 2014). This approach shares common strengths and weaknesses with Burton's geospatial measuring. While it has a clear and easily comparable output, it is again unable to look at the recovery process as a whole, instead focusing on very limited recovery dimensions.

Finch et al. (2010) use population return as a metric for recovery in post-Hurricane Katrina New Orleans, using USPS delivery data for the time periods immediately before and three years after the hurricane. The rate of mail return served as a rough estimate for population return (Finch et al., 2010). This is an interesting approach to measuring recovery because repopulation captures a number of the dimensions that are outlined by Aldrich as markers of resilient recovery, from personal well-being to operational regularity of public safety (Aldrich, 2012a). As a result, it succeeds as a fairly multi-dimensional measure. However, it is quite limited from a temporal perspective. The analysis only provides a single snapshot of the recovery process 3 years after the event occurred.

In yet another study of New Orleans post-Hurricane Katrina, Elliot et al. (2010) used a survey to collect data from a representative sample of approximately 100 adults in each neighborhood included in their study. The survey questions were retrospective in nature, asking participants to recollect their experiences in different phases of the disaster. The researchers used previous examples of surveys on disaster aid and recovery (Beggs, Haines, & Hurlbert, 1996) to develop their survey instrument. Because a close ended survey was employed, the researchers were able to perform a quantitative analysis on the role of social ties in the recovery process with their data (Elliott, Haney, & Sams-Abiodun, 2010a). This study is an excellent example of the strengths of a mixed methods approach when attempting to measure complex concepts in social science.

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Alternatively, many researchers choose to use exclusively qualitative methods for collecting data on the recovery process (Aldrich, 2012a; Chamlee-Wright & Storr, 2011; Consoer & Milman, 2016a; Jordan, 2014). These approaches typically use open-ended interviews to talk to community members and stakeholders about their experiences throughout the recovery process. This method, of course, leads to the development of broader and more expansive narratives, but it also produces results that are more difficult to evaluate and compare.

2.2.3 Explaining Variations in Recovery

In order to properly understand the causes of uneven recovery outcomes, Tierny argues that first we must understand the nature of risk (Tierney, 2014). Beck's risk society theory suggests that modern society is the product of long-term society-driven change, and that the risks (particularly the environmental risks) to which we are exposed today are not the product of natural inevitability but instead of prior decision making (Beck & Ritter, 1992). This approach has garnered criticism on the basis that it presents modern society as unique in its production of risk, as well as the fact that power imbalances and structural injustice are not made central to the theory (Tierney, 2014). However, despite these criticisms, his argument that the choices we make and policies we adopt as a society are instrumental in producing and enhancing risk has merit. Economic losses due to natural disasters have been increasing over time, not because the physical shocks themselves are becoming more destructive, but because as society grows and evolves, exposure increases as both human populations

and infrastructure investment grows and becomes more densely concentrated (Tierney, 2014).

The fact that the majority of risks that are faced by society are manufactured through decision-making and power structures is of great relevance to the concept of recovery, and more specifically to the question of what causes certain communities to bounce back more quickly than others after being subjected to a shock. Wisner et al. (2003) describe the physical shocks as the "triggers" for disasters but argue that social and historical forces cause risk to build up in such a way that a trigger is able to set it off. This gives rise to the inevitability that vulnerable and marginalized populations are the most at risk for disasters, not only because they tend to live in the neighborhoods and buildings that are more exposed to risk, but also because they lack to resources to cope with disaster in the short term (Wisner, Cannon, & Davis, 2003).

Vulnerability, resilience and recovery are complementary concepts, and just as there is variation in levels of exposure to natural disaster, there will also be variation in the hardship experienced during the recovery process, resulting for some in worse long-term recovery outcomes (Zakour & Swager, 2018). Disasters and their resulting damages are often brought on by both the historical and current choices made by society, and these differences in recovery outcomes are also not products of random chance. There are a number of clear, identifiable factors that determine the relative success of the recovery process for individuals and their communities (Phillips & Fordham, 2009).

Generally speaking, low-income individuals and communities struggle more than others during every phase of the recovery process (Fothergill & Peek, 2004a). This is in part due to a basic lack of resources and income, which compounds hardship and stress (Bolin & Stanford, 1998), and a lack of access to translocal social networks of family and friends who are able to provide material and moral support during times of stress and hardship (Elliott et al., 2010a). Lower incomes and higher levels of income inequality are also found to have a significant and detrimental impact on disaster outcomes and recovery at the macro level (Tselios & Tompkins, 2019).

Low-income residents are also found to be less capable of navigating the bureaucratic systems necessary in order to obtain government-issued aid, whereas higher-income residents are better equipped to deal with these sorts of administrative obstacles. As a result, they are less likely to apply for and receive disaster recovery funds (Fothergill & Peek, 2004a). Low-income residents are also more likely to experience severe damage to their homes in the aftermath of disasters. This can lead to homelessness and severe shortages of low-incoming housing in the aftermath of disaster (Greene, 1992). Indeed, when poorly managed the recovery process is often observed to perpetuate and further entrench the disempowerment of marginalized groups such as women and minorities while enriching private corporations and increasing income inequality (Sovacool, Tan-Mullins, & Abrahamse, 2018).

Other factors that are commonly thought to influence recovery outcomes include the quality of governance, aid allocation, extent of damage and population

density. Governance has been found to make macro-level differences in disaster outcomes: an analysis of disaster deaths in 73 countries between 1980 and 2002 found that democracies and other countries with well-functioning institutions experience fewer natural disaster deaths (Kahn, 2005). However, on a more micro level, this association does not always hold, as nearby neighborhoods under the same governance structures that have experienced similar levels of damage often do not enjoy similar rates of recovery. Research has failed to find a causal link between the amount of aid funding and the rate of recovery, and research on the relationship between damage and recovery is inconclusive (Aldrich, 2012a).

Many studies point to social capital as a significant, and perhaps the most significant driver of recovery outcomes (Aldrich, 2012a; Elliott et al., 2010a; Kawamoto & Kim, 2016). It is seen as critical to understanding vulnerability differentials and is central to coping with risk. Indeed, Aldrich calls social capital the "core engine of recovery" and argues that social capital is an even better predictor of recovery outcomes than socio-economic status (N. Adger, 2003).

2.3 Social Capital

2.3.1 Defining Social Capital

Social capital emerged as a clearly articulated concept in the 1980s. When it was first introduced by Pierre Bourdieu, who defined the term as "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition" (Bourdieu, 1985). This means that having a social network gives an individual access

to more potential and/or realized resources than they would have in isolation. These socially-accessible resources are social capital. Coleman expanded on this definition in his 1988 work, describing social capital as a "variety of entities with two elements in common: they all consist of some aspect of social structures, and they facilitate certain actions of actors – whether persons or corporate actors – within the structure" (Coleman, 1988). This extends the definition introduced by Bourdieu by clarifying that social capital need not simply be limited to the exchange or potential exchange of resources, but can take the form of facilitating any action, whether resource-oriented or more abstract. This definition also emphasizes that social capital need not take place in a person environment, but that corporate relationships can generate social capital as well.

In 2000, Putnam transformed social capital literature by theorizing that it has two sub-categories: bonding social capital and bridging social capital. He summarizes this distinction by saying "bonding social capital constitutes a kind of sociological superglue, whereas bridging social capital provides a sociological WD-40" (Putnam, 2000). Bonding social capital is gained from relations in more insular settings, typically among fairly homogenous groups of people. This helps to foster a strong group identity and a great deal of loyalty between group members. However, because of the insular nature of these communities, they tend not to have many social relations outside of the group. As a result, very little is brought into the network from the outside, which limits the group's potential pool of resources (Putnam, 2000). This

type of social capital is more commonly observed in poorer communities (Elliott et al., 2010a) and low-functioning states (N. Adger, 2003).

Bridging social capital tends to develop in more heterogeneous groups that have more outside connections, often to more powerful elements of society such as governance institutions, civil society, and the private sector. This naturally creates significant opportunities for the members of such groups, as they have access to a much wider range of outside resources. This is sometimes referred to as networking social capital in the literature (N. Adger, 2003). It is associated with wealthier communities (Elliott et al., 2010a), well-functioning states, and formal collective action (N. Adger, 2003). Evidently, these two different types of social capital bring very different forms of benefits and opportunity.

Although social capital might seem to arise naturally, Portes (1998) stresses that the social networks that foster social capital must not be seen as an inevitability, but rather "constructed through investment strategies oriented to the institutionalization of group relations, usable as a reliable source of other benefits" (Portes, 1998). Although the unequal distribution of social capital in our society is in part attributable to unearned privilege, the social networks that provide returns to their members have to be developed, fostered and nurtured. Further, it is important to recognize that although social capital is a mechanism through which individuals can derive gains, there must nonetheless be a transfer of benefits, and such a transfer demands both a recipient and a donor (Portes, 1998).

2.3.2 <u>Social Capital, Resilience and Recovery</u>

Social capital has significant explanatory power with regards to community-level resilience and recovery after a disaster or shock. The primary way that social capital impacts recovery trajectories is that it enables community organization in the aftermath of a disaster. This is particularly true in groups exhibiting strong bridging social capital because they often have networks that reach beyond the disaster-struck area, thereby giving them access to the much-needed resources and support necessary for a speedy recovery. This is demonstrated in Consoer's study of the role of social capital in Vermont after Tropical Storm Irene, where the organization of informal 'recovery groups' in storm-impacted communities was driven by social capital. As a result, these communities enjoyed "proliferating social capital and access to high value resources" (Consoer & Milman, 2016a). Although communities that failed to organize eventually caught up to the high-social capital communities' recovery progress, they required increased government efforts in order to close the recovery gap.

Bonding social capital also plays a role in the recovery process, but it primarily helps residents to cope with the short-term effects of a shock. Communities that are exclusively rich in bonding social capital tend to be tightly knit, homogenous and closed off. As a result, when a disaster hits, these communities will only have networks connecting them to others who are also affected by the disaster. Although these connections are certainly important with regards to dealing with the immediate

aftermath of a disaster, they are less useful in mobilizing the resources needed for a successful recovery effort (Aldrich, 2012a).

Some literature on social capital takes the position that it has great potential to improve social well-being including recovery outcomes (Jordan, 2014). For example, Adger (2003) links social capital with health outcomes, stronger governance, and economic growth, going so far as to call collective social capital and social networks a public good (N. Adger, 2003). A recent study on the recovery process following the 2010 flooding in Pakistan, found that the levels of social capital and social support enjoyed by the victims of the floods was directly correlated with their quality of life, ability to readjust and optimism about the future following the natural disaster. As a result, the authors stressed that disaster managers must make a concerted effort to preserve social networks during the recovery process (Akbar & Aldrich, 2018).

However, other authors are more reserved in their analysis of the effects of social capital, acknowledging that along with its clear benefits as a social transmitter of resources, it also has clear drawbacks. Indeed, Aldrich explicitly states that social capital ought not be thought of as a public good, because it does not benefit everyone. Rather than a solution in itself, it is simply a tool by which a solution can, in some cases, be facilitated. It is "a potential source of benefits rather than a benefit in itself" (Aldrich, 2012a).

In this vein, some argue that viewing social capital as the social networks that transmit opportunity and resources is an overly simplistic analysis (Barnshaw & Trainor, 2007). The number of social networks to which an individual has access is

perhaps less important than the 'quality' of their networks, which is largely determined by the way that cultural and economic power is distributed throughout society. A person who has a very large network that is made up of individuals who lack any significant form of power is likely to be worse off than a person whose network is smaller but filled with elites. In that respect, social capital is not actually capital in itself, but rather the way that social connections can facilitate an individual's access to capital.

Lin (2001) notes that people's social networks tend to be filled with others who share a similar economic and/or cultural status in society. This creates a system in which the most privileged people in society have access to a network full of similarly powerful people with whom to share resources and opportunities. While the cultural and economically powerful are able to use social capital to secure high-paying jobs and political influence, social networks in more marginalized communities are likely to only have the resources necessary to help each other with more basic day-to-day coping. This results in a consolidation of power within the upper-echelons of society, thereby exacerbating pre-existing social and economic divides (Lin, 2001a).

There are also concerns that strong social capital within a community can lead to significant social and control exerted over its members (Portes, 1998). Bonding social capital in particular can perpetuate narratives within the group, which may ultimately reinforce incorrect information and entrench damaging societal norms (Chamlee-Wright & Storr, 2011; Wolf, Adger, Lorenzoni, Abrahamson, & Raine,

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2010). In a similar way, social capital can manifest in negative ways within groups that are brought together through shared struggles and feelings of rejection and isolation from mainstream society. This can lead to anti-social and even violent behavior, which is made more extreme by the social bonds shared among these groups. The high prevalence of gangs in poor and disenfranchised neighborhoods is an example of this phenomenon (Bourgois, 1995).

Taken together, the literature warns that a blind trust in the positive benefits of social capital is unadvisable. Oftentimes, when policy makers rely too heavily on it as a vehicle for recovery,"[i]ts utility and practical application are hampered by a lack of attention to social relations and power inequalities, which risks reinforcing vulnerability" (Jordan, 2014). Like all other forms of capital, its effectiveness will be a function of the distribution of power, privilege and wealth in society. Although it is certainly a tool that can be incredibly useful if wielded with care, it is crucial for policy makers to anticipate its shortfalls and plan for equalization efforts in order to ensure that its benefits are enjoyed more equally across society.

Aldrich presents an incredibly convincing case for both the importance of social capital and its potentially exclusionary nature in disaster recovery in a study of differential recovery following the 2004 Indian Ocean Earthquake and Tsunami. Different communities experienced differential rates of recovery, and the fast recovering communities were all observed to have local councils. These councils had long been an important source of bonding social, but in the aftermath of the tsunami they transformed into important engines of bridging social capital. They acted an

intermediary between their communities and externally-run aid efforts by communicating community requests, advocating on behalf of the community, and storing and distributing aid. In doing so, they enabled community-level collective action. (Aldrich, 2012a).

The strong bridging social capital facilitated by community councils improved the recovery outcomes of the communities as a whole, but not everyone benefited equally from their efforts. Prior to the tsunami, the councils had primarily been a source of bonding social capital and despite the development of bridging networks after the tsunami, the exclusionary nature of the bonding social capital persisted. Because the councils took control of aid storage and distribution, they also had the power to exclude certain out-groups in the community from receiving aid for which they qualified, ultimately reinforcing and exacerbating vulnerability among members of these out-groups (Aldrich, 2012a). The same phenomenon was observed following a 2009 cyclone in coastal Bangladesh. Although social networks played an important role in recovery at all dimensional and temporal scales, it also allowed for funds to be funneled to well-connected local elites rather than those who had the greatest need (Masud-All-Kamal & Monirul Hassan, 2018).

In Elliott's (2010) study of neighborhood resilience and recovery after Hurricane Katrina, social capital manifested in different ways, but produced similar results. The study found that inequalities in social capital were magnified as residents prepared for the disaster in the days leading up to the hurricane and coped with the damages in its aftermath. Residents from wealthier neighborhoods were able to access

what is referred to as 'translocal ties,' which are effectively bridging social capital – connections outside of the city that were able to offer assistance during and immediately following the hurricane and support throughout the long-term recovery process. The paper hypothesizes that either lower income neighborhoods lack these translocal connections altogether, their translocal connections are less equipped to help, or they are unable to access these connections during times of crisis (Elliott et al., 2010a).

In some contexts, social capital has been a driver of exclusively negative outcomes. As discussed above, one of the many functions of social capital is the proliferation of narratives, which has a significant impact on people's outlooks, and by extension their outcomes (Chamlee-Wright & Storr, 2011). A study of the way social networks impact individual responses to heat waves found that bonding social capital among the elderly may actually increase their vulnerability to heat waves. Interviews with elderly residents of London and Norwich indicated that they did not see heat waves as a legitimate threat to their health and wellbeing and felt that they were adequately equipped to cope with soaring temperatures. The authors hypothesize that narratives of resilience and self-reliance are transmitted and reinforced through social networks. This leads to network members over-estimating their ability to withstand hazards and being very reluctant to ask for outside help, even when it is desperately needed (Wolf et al., 2010).

Taken together, the literature demonstrates that social capital can be a powerful engine of recovery in the aftermath of disaster. Well-organized communities

are capable of collective action that helps them harness outside resources and begin the recovery process as quickly as possible. With this in mind, it is important to foster the development of community groups prior to disaster in order to build resilience, and to prioritize keeping communities intact during the recovery process. However, it is unwise to put too much faith in this process. Without oversight and intervention, it is likely that social-capital driven recovery will exclude community out-groups and favor wealthier individuals that have better access to translocal connections, thereby exacerbating the circumstances of society's most vulnerable (Elliott, Haney, & Sams-Abiodun, 2010b; Jordan, 2015; Lin, 2001b). In addition, bonding networks can proliferate the spread of inaccurate and unsafe information and coping strategies, leading members to miscalculate risk and choose not to seek help when needed. Efforts must be made to create well-connected bridging networks throughout all facets of society to ensure a more equitable flow of information, resources, and aid.

2.3.3 <u>Measuring Social Capital</u>

In order to link the presence of social capital to concrete outcomes, it is important to have a conceptual framework for social capital that can be empirically evaluated. Measuring social capital is a difficult task, as it requires that the researcher operationalize a very abstract idea: the presence and quality of social networks and social bonds. As with resilience, taking a quantitative approach to measurement is attractive because it can be compared, indexed and applied to quantitative models but this necessitates the challenging task of selecting proxies and metrics that can be validated and are not overly correlated with other potential influencers of recovery

outcomes, such as income. These issues can be more easily addressed with qualitative approaches to data collection, but these methods have the downsides of lacking scalability, comparability and straightforward applications to quantitative analyses.

Questions have been included in a number of large-scale surveys that are used by researchers to capture social capital. The World Values Survey (1981-1995) was designed by Ronald Inglehart to better understand the impacts of culture on development. It asks respondents whether they belong to associations, and whether they are actively involved in them, which serves to partially capture social capital. It does not, however, ask about the types of groups to which the respondents are associated, which would be important in distinguishing between bonding and bridging networks (Narayan & Cassidy, 2001).

In 2000, the Harvard Kennedy School (Saguaro Seminar) launched a massive telephone survey initiative called the Social Capital Community Benchmark Survey, asking 30,000 Americans about their civic engagement with the goal of better understanding the way that Americans connect to each other. The questions on the survey touched upon neighborly trust, local political participation, membership in a number of various organizations, and leadership positions within the community. Evidently, this survey addresses the lack of specificity that was problematic in the World Values Survey. A follow-up survey was performed in 2006 that returned to 11 of the same communities (KSG, 2000).

In recent years, the US Census Bureau has launched the Current Population Survey Civic Engagement Supplement, a nation-wide survey that attempts to

"provide information on the extent to which our nation's communities are places where individuals are civically active". The survey is by far the most expansive and up to date data set on American social capital, and was performed by telephone in November 2008, 2010, 2011, and 2013. Like the Harvard survey discussed above, this survey asks participants questions about whether in the last year they had involved themselves in local politics, participated in local clubs and organizations (distinguishing between different kinds) and taken on leadership roles. Respondents are also asked how often they spent time with friends, talked to neighbors and helped their neighbors. As a set, these questions paint a fairly accurate picture of the presence of bridging and bonding social capital in American communities today (Ruggles, Genadek, Goeken, Grover, & Sobek, 2015).

An example of operationalizing this sort of survey instrument in order to draw quantitative conclusions about the nature of social capital can be found in Guillen et al.'s 2010 paper. Questions from the European Social Survey, which focused on the amount of formal and informal contact people had with others over a set period of time, were used as a proxy for social participation, and the formal/informal distinction was used to roughly distinguish between bridging and bonding social capital. This was ultimately an imperfect index, because it only measured one component of social capital in a fairly simplistic way, but the paper indicates that the measure could likely be improved if social trust was included as an indicator of social capital alongside participation (Guillen, Coromina, & Saris, 2011).

Other researchers have worked to develop more complex quantitative indices for measuring social capital. The Index of National Civic Health was developed in 2000 in response to concerns that the American population was becoming increasingly disengaged. It proposed indicators in the categories of political engagement, trust, associational membership, security and crime. Although this index, as the name suggests, is designed to measure more than just social capital, its associated report explicitly names social capital as a benefit of civic engagement. Unfortunately though, this index was only proposed and never fully operationalized due to a lack of access to data on associational membership (Bennett & Nunn, 2000).

Despite the big data approaches to measuring social capital that were described above, often times the literature relies on small primary data in order to get a more complete picture of the presence of social capital in a much more localized setting (Masud-All-Kamal & Monirul Hassan, 2018; Ruef & Kwon, 2016; Sadri et al., 2018). Some researchers use survey instruments in order to collect data that can be used for quantitative analysis such as a study on earthquake recovery in Japan, which used an online survey to investigate the way that social capital impacted the efficiency of waste management and recovery in the aftermath of an earthquake. The survey asked questions about trust, interactions with neighbors and friends, and social participation (Kawamoto & Kim, 2016). Similarly, a study on the way that social capital impacts the public acceptability of different adaptation policies used a mail survey to ask questions about social trust, institutional trust, networks and reciprocity. Perhaps this study's most unique contribution was its approach to reciprocity:

respondents were asked whether they believed that their neighbors, family and close friends would help out if the respondent's home was in danger of flooding. This captures the degree to which an individual feels that they can rely on their community, which is central to the concept of social capital (Jones & Clark, 2014).

Qualitative methods such as open-ended interviews and focus groups remain the most common way that researchers study social capital. Although this limits the extent to which quantitative analysis is possible, these exploratory approaches allow for a more robust understanding of the multidimensional nature of social capital and lend themselves well to the theory-building that is necessary in order to strengthen and validate more quantitative approaches. For example, as discussed above, Wolfe et al. used semi-structured interviews to explore the way that UK seniors and their social contacts coped with heat wave. Qualitative coding software was used to draw common themes and narratives from the interviews, and illustrative quotes were used to emphasize key points (Wolf et al., 2010). Jordan's study of the role of social capital in disaster resilience in Bangladesh also used semi-structured interviews accompanied by focus group discussions (Jordan, 2014). Again, no quantitative methods were employed, but instead interpretive analysis and illustrative quotes were used to develop a narrative.

2.4 *Gaps in the Literature, Emerging Questions and Research Design*

When taken together, several important and unanswered gaps emerge in the literature that was surveyed in this chapter. The literature is unclear on how recovery can best me measured so as to capture its multi-scalar nature, and there is a lack of

knowledge about the linkages between recovery processes at different scales and the nature of their interdependencies. Although the literature has established that in generally, socio-economic inequalities impact recovery outcomes, little research has been done specific on the impacts of these socio-economic inequalities at specific scales of recovery. Finally, the literature would benefit from more focus on how best to develop recovery policies that put a clear understanding of multi-scalar recovery at the forefront.

The literature is clear on the fact that recovery takes place concurrently on many dimensional, spatial and temporal scales. This makes it a very challenging subject to study quantitatively, because numerical representations of the recovery process typically fail to capture the complexity of the operation. As a result, the literature has a tendency to focus on specific dimensions of recovery to the exclusion of others. This makes it difficult to develop a broad and robust understanding of what influences recovery and how communities interact with and engage in the recovery process.

The research design that guided the development of this dissertation seeks to expand on the gaps in the literature that have been identified above. In particular, it will seek to answer the following questions: (1) What metrics can be used to measure recovery at multiple scales? (2) How do socio-economic status, civic engagement and social capital, when taken together and as separate concepts, impact recovery at multiple scales? (3) How do the different dimensional, temporal and spatial scales of recovery interact? (4) How can policy members improve recovery outcomes?

The research was designed with the primary goal of examining recovery at multiple scales, while simultaneously considering the social and economic forces and community behaviors that influence recovery outcomes. As a result, the three chapters that follow propose new ways of conceptualizing and quantifying recovery and analyze the way that neighborhood characteristics and community engagement influence the recovery process at multiple dimensional and temporal scales.

Chapter 3, the first analytical chapter, considers the interaction between vulnerability and recovery by studying power outages and restoration following Hurricane Isaac in Louisiana. This approach uses power restoration as a metric by which to better understand short-term recovery of a specific infrastructure system, building a model for recovery that takes into account antecedent conditions, impact, hazard and prioritization.

Chapter 4 considers 311 requests in Houston TX as a potential proxy measure for civic engagement and social capital. This data is spatially precise, detailed and publicly available, so it is of great potential utility for social science researchers if it is properly understood and utilized. This chapter works to develop a more nuanced characterization of this data by analyzing request volumes across the City of Houston and identifying the neighborhood characteristics that influence proclivity to contact.

Finally, in Chapter 5, the 311 data is used to better understand system-level recovery and community engagement in the recovery process in Houston TX following Hurricane Harvey in 2017. The chapter compares neighborhood level use of 311 services prior to Hurricane Harvey to the way it was used for storm-related

concerns in the weeks directly following the storm. The temporal scale of the analysis

is then extended by examining decreases in storm request volume over time, testing

whether Zip Code Tabulation Areas (ZCTAs) with higher contact volumes

immediately following the storm continued to make frequent storm-related requests

as recovery progressed throughout the city.

3. Post-Disaster Power Recovery

Power outages are a very common impact of hurricanes in the United States, so outage data is a valuable tool by which to better understand the way that hurricanes affect built infrastructure in United States, and the way that the short-term infrastructure recovery process is managed in the aftermath of a natural disaster. In this paper, I perform a quantitative analysis on peak outages and total power recovery time in a given spatial unit in order to investigate whether the infrastructure damage and long recovery times that results from a hurricane disproportionately impacts socio-economically vulnerable populations and if so, whether this discrepancy is the result of vulnerable populations living in more hazard-prone spaces.

The literature indicates that in general, socio-economically vulnerable communities tend to experience worse recovery outcomes than their more fortunate counterparts. These poor outcomes manifest in the form of slower recovery times, and in some cases, a failure to ever return to the pre-disaster baseline. Using power restoration data, one would expect to observe that socio-economically vulnerable communities experience slower power restoration. This would be particularly troubling from a policy standpoint because the hardships caused by power outages are greater in low-income neighborhoods, where households have less access to generators and do not have the financial means to cope with the power outage by eating in restaurants and staying in hotels until their electricity is restored.

When approaching the task of restoring widespread outages, utilities claim to take a standardized and utilitarian approach, first focusing on fixing the issues that

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will restore power to the most clients possible as quickly as possible (Xu et al., 2007).

Earlier efforts are also focused on restoring outages that impact the provision of vital

services. As a result, neighborhoods on the same grid as local emergency services or

major grocery stores are likely to enjoy faster restoration times than others in the

community (Chang, McDaniels, Mikawoz, & Peterson, 2007; Maliszewski &

Perrings, 2012). However, there is a level of subjectivity inherent to the decision

making process that could cause inequalities in outcomes beyond those that would be

expected based on number of outages, proximity to high-priority services, and the

extent of the damage.

Further, it is possible that even if the power restoration strategy is followed

with complete objectivity and impartiality, lower income communities might

experience systematically slower restoration times if they are less likely to host the

health, emergency and retail infrastructure that leads to power restoration being

prioritized. For example, low-income communities are much less likely to be home to

grocery stores (R. E. Walker, Keane, & Burke, 2010). As a result, it is important to

consider not only unequal recovery when controlling for impact and infrastructure,

but also to investigate the possibility that wider and more systematic inequalities and

injustices impact the recovery process.

The primary research questions that I seek to answer in this chapter are (1)

does socio-economic inequality between communities have an effect on the short-

term damages that come about as a result of a natural disaster? (2) If so, are these

effects largely explained by differences in storm strength between communities? (3)

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Does socio-economic inequality between communities have an effect on the speed at which short-term recovery processes are carried out? (4) If so, can these effects be largely explained by differences in storm strength and/or presence of high priority infrastructure?

This paper begins with an overview of the electrical system in the United States, with a particular focus on outages and the power restoration process. Next, it provides context about the impacts of Hurricane Isaac in Louisiana, and the post-disaster recovery process in the state. I then discuss the data and methods used in the quantitative analysis, along with the results. The paper concludes with a discussion of its findings and the potential policy implications of the research.

3.1.1 The Electric System, Power Outages and Restoration

Power system reliability is carefully measured and monitored across the United States. Investor-owned, cooperative and municipal utilities are all required to report any power outage lasting longer than 5 minutes to the US Energy Information Administration (EIA). On average across the United States customers experience 1.3 interruptions per year, and lose power from the utility for 240 minutes, or four hours per year. Although some customers have backup generators that power their households during the outage periods, most have no electricity during this time (Darling, David & Hoff, Sara, 2018). Major environmental events such as storms, floods and heat waves account for more than half of the total average time without power; when they are excluded the average customer experiences 112 minutes of power outages per year.

Power outages stemming from major environmental events tend to be present differently than standard interruptions, and as a result require a different restoration strategy. Outages that are not caused by a major event tend to be the result of a single component failure. As a result, most generation facilities continue to function as normal and transmission and distribution infrastructure is unaffected. In contrast, natural disaster related outages usually result in multiple faults and disruptions occurring concurrently in the generation, transmission and distribution branches due to widespread system damage. Meanwhile, other infrastructure systems such as transportation and telecommunication networks will likely be damaged as well, and the interdependence between infrastructure systems means that this will present a significant obstacle in restoring any and all of the damaged systems (Wang, Chen, Wang, & Baldick, 2016).

The Edison Electric Institute outlines the seven general steps of power restoration after a major event as follows (Edison Electric Institute, 2014):

1. The utility ensures that any downed or damaged lines are no longer active, in order to prevent fires, injuries or death.

2. Power generation plants are assessed for damage and repaired as necessary.

3. Transmission lines are assessed for damage and repaired.

4. Substations are brought online.

5. Power is restored to essential services.

6. Lines to large service areas are repaired.

7. Lines to small groups and individual homes are repaired.

Power outages are a common impact of natural hazard events, but they are also very disruptive and even dangerous. Having access to reliable power is critical for both short and long-term recovery efforts, as well as the normal functioning of nearly every sector of society; a UK Department of Health study concluded that electricity is "the most vital of all infrastructure services… without it most other services will not function". Even brief outages can cause negative health, social and economic outcomes (Campbell, 2012).

A study on the impacts of a major, extended power outage in New York City in early August 2003 found that during the blackout, mortality increased for accidental and non-accidental (such as disease related) deaths. Further, mortality remained slightly increased for the rest of the month even after the power was restored, indicating that the outages did not just speed up eminent deaths (G. B. Anderson & Bell, 2012). Carbon monoxide poisonings increase during power outages due to incorrect operation of backup generators, and without power it becomes difficult to maintain proper food safety standards, causing an increase in gastrointestinal diseases. Power outages put people in danger of overheating or freezing, depending on the climate, and they can lead to social isolation of vulnerable groups, which compounds all other present risks (Klinger, Landeg, & Murray, 2014).

Disruption to power supply also causes economic losses to firms, households and the government. They cause firms to produce less, and in some cases lose prior output, such as computer files due to an unexpected shutdown. Food spoilage is a significant loss for some businesses and nearly all households, and households also

will experience losses of their leisure time. Although the economic losses brought about by outages will vary greatly depending on the length of the outage and the season and time of day at which the outage occurs, a Dutch study found that the losses associated with a power disruptions far exceeded the cost of the electricity that failed to be delivered (de Nooij, Koopmans, & Bijvoet, 2007).

Due to the costs, risks and inconveniences associated with power outages, efforts are made to reduce their frequency and duration making power infrastructure harder and more resilient. Hardening in this context refers to activities that physically change the infrastructure in order to make it more durable in the face of specific threats. To prevent outages due to flooding, equipment is elevated and pumps are installed and to make the system more capable of enduring high winds, power lines will be rebuilt and reinforced (Wang et al., 2016).

After major storms, there is often also talk from electricity customers, local officials and utility commissions about whether utility companies in the United States should work to phase in undergrounding, which is the process of burying power lines, making them less vulnerable to outages. However, the undergrounding process is very expensive (Hall 2013). Studies have estimated that on average, underground cables are 10-20 times more expensive to install (Campbell, 2012). Further, although underground lines are generally less vulnerable to extreme weather, they are not immune. In areas where flooding and storm surges are more of a concern than high winds, undergrounding actually increases the risk of damage, and when underground lines are damaged, the repairs are lengthier and more expensive. As a result, studies

conclude that in many cases, undergrounding is simply not worth the cost (Edison Electric Institute, 2014).

Vegetation management is a hardening technique wherein utilities proactively clear tree and plant growth near power lines to reduce the likelihood of the vegetation disrupting the power supply, usually caused by trees and branches falling and damaging lines. This is the most expensive recurring maintenance practice for utilities, but research indicates that the benefits outweigh the costs. It is also recommended that an effort be made to plant vegetation that is specifically known not to cause problems near power lines, generally because it does not grow to be very tall. This requires that utilities coordinate with municipalities and private property owners in consultation with trained arborists (Edison Electric Institute, 2014).

Broadly speaking, it is found that US utilities take appropriate action on infrastructure hardening, but even their best efforts cannot completely eliminate outages caused by extreme weather incidents. As a result, resilience measures must be taken to ensure that following an interruption power restoration happens as efficiently and effectively as possible. The most important action that utilities can take in this regard is ensuring that they have a sufficiently large labor force and available equipment so as to quickly make the necessary repairs. This requires accurate predictions of upcoming weather events, and the securing of additional crews as needed. The additional labor force can be generated by hiring contractors, or by mutual assistance agreements (MAAs). MAAs are voluntary agreements made between electrical utilities from across the country wherein members commit that in

the event of a major electrical outage the unaffected utilities will deploy their linemen to assist in restoration efforts. There are seven Regional Mutual Assistance Groups throughout the United States that manage the majority of the country's mutual assistance agreements. These groups take on a valuable coordination role by identifying available workers and assisting in the logistics of moving them to where they are needed (Campbell, 2012).

3.1.2 Hurricane Isaac

Hurricane Isaac began as a tropical storm on August 21, 2012 in the Atlantic Ocean. On August 28, the tropical storm was upgraded to a Hurricane, and a few hours later it made its first US landfall on Louisiana's southeast coast in Plaqumines Parish (Berg, 2013). The following day on August 29, it made landfall for a second time west of Port Fouchon. The storm moved slowly through the state, causing rain and high winds to persist for up to 56 hours (Miles 2014).

The persistent high winds caused massive power outages throughout Louisiana that peaked on August 30 when 43% of utility customers were without power. In total, 900,000 customers experienced power outages. This is on par with the number of outages following Hurricane Katrina in 2006 and Hurricane Gustav in 2008. Some of the hardest hit parishes experienced up to 90% power loss and restoration efforts took over 10 days.

Despite the fact that Hurricane Isaac caused power outages on a comparable scale to some of the region's most destructive and devastating storms, its other impacts were relatively mild. Wind damage to buildings was minor and although

some flooding did occur, the federal levee system, which was put to the test for the first time since Hurricane Katrina, generally worked as intended, protecting the more populated area of the state from high waters, so water damage was isolated and minimal. As a result, there was no wide-spread evacuation of the region, so people generally remained in their homes for the duration of the storm and recovery period (S B Miles, Jagielo, & Gallagher, 2016).

The fact that the electric system was severely damaged but other infrastructure systems survived the storm relatively unscathed makes Hurricane Isaac a unique case study. When a hurricane causes more widespread and varied damage, power restoration becomes a much more complex and interdependent process. Power crews must wait for flood waters to subside in order to safely restore electricity, and they must work amid the breakdown of various other infrastructure systems. In most regions, those were not significant obstacles after Hurricane Isaac (Scott B. Miles & Jagielo, 2014).

The power restoration process was a massive undertaking, which involved over 12,000 utility workers and 4,000 support personnel from 25 states, 20 mutual aid companies and 138 contractor companies. The fact that residents remained in their home during the restoration process added an extra layer of scrutiny to the process, and the utilities were criticized for poor planning and coordination. For example, Entergy did properly coordinate feeding and housing for the outside crews, and ultimately gave them lodging that was a two-hour commute from their primary work

sites. As a result, four hours were wasted every day as crews were bused back and forth from work (S B Miles et al., 2016).

Federal regulations prohibit utilities from using bucket trucks when winds are above the wind ratings provided by the truck manufacturers. The fleet used the utilities in Isaac restoration efforts were rated at 30 mi/h. The hurricane lingered over the state for an extended period of time, so it took 2.5 days for the wind speeds to subside so that the repair efforts could get underway. The crews used this time to scout out damages and stage themselves so they could begin repairs as soon as permitted by federal regulations (S B Miles et al., 2016).

The fact that people stayed in their homes during the hurricane caused widespread traffic congestion following the storm. This congestion slowed down the restoration process, because it hindered the utilities' ability to move crews and supplies around the region. Stuck in the Louisiana August heat without power, people took to their cars to enjoy air conditioning, observe the extent of the damages in their communities and search for operational gas stations.

Indeed, the power outage created a major fuel shortage in the region. Almost all gas stations in the New Orleans region were without power, and most did not have generators, so their pumps were inoperable. Grocery stores faced similar problems, and it is estimated at least $10 million of stock was lost to spoilage. In response, the state government spent a considerable amount of money supplying and delivering fuel and generators to local businesses so that they could reopen and supply their communities (Scott B. Miles & Jagielo, 2014).

Utilities and emergency services in the region had learned from Hurricane Katrina and Gustav and were generally well prepared with generators in order to minimize disturbances caused by power outages. There were no boil orders in the region, because water treatment plants made it policy to have a generator, fuel and a staff member on site during major weather events to ensure the continuation of services. Tier 1 hospitals were also all equipped with generators and 2-3 days of fuel and they proactively began running their generators before the storm began. However, some Tier 2 hospitals did not have generators and were required to evacuate, along with many nursing homes across the region (Scott B. Miles & Jagielo, 2014).

Hurricane Isaac ultimately caused five direct deaths in the United States, three of which were in Louisiana. Despite the fact that the storm was quite limited in its geographical scope, it is estimated to have caused $2.35 billion in damages across the United States, $970 million of which was insured. A further $407 million was paid out through the National Flood Insurance Program. In response to the hurricane, the USDA issued over 263,000 Disaster Supplemental Nutritional Assistance Program (DSNAP) cards, valued at over $100 million and unemployment claims peaked at 10,000 which is on par with the levels of claims filed after Hurricane Gustav. The storm damaged or destroyed 4500 distribution poles, 2000 distribution transformers, 95 transmission lines and 144 substations belonging to Entergy, costing an estimated $500 million in repairs (Scott B. Miles & Jagielo, 2014).

3.2 Data

This paper utilizes power outage data that was scraped from utility websites in Louisiana in the aftermath of Hurricane Isaac. The data collection was performed by Dr. Seth Guikema from University of Michigan. During major outages, utilities are required to regularly update their website with the number of customers without power in a given region, and using scraping techniques, Dr. Guikema's team retrieved this data from Entergy, the electrical utility that provides power to the majority of the state of Louisiana in real time, providing a detailed view of power restoration following Hurricane Isaac. The data outlines the number of households without power in 15-minute intervals at the zip code level. I was provided with a cleaned version of the data which included, at the Zip Code level, the total number of households without power and the time in minutes that it took to return to three bench marks: 50% restored, 80% restored and 95% restored.

Although this data was measured at the Zip Code level, socio-economic data collected by the US government is spatially aggregated by Zip Code Tabulation Areas (ZCTAs). Similarly, the hazard data is spatially generated and modeled using the longitude and latitude of ZCTA centroids. The ZCTA is a geographical unit that was developed by the Census Bureau for the 2000 Census in response to continued user requests for statistical data by Zip Code. Zip Codes are not necessarily continuous polygons, as they are assigned by the US Postal Service and designed to optimize postal delivery routes rather than to facilitate the collection of data or spatial analysis. As a result, the Census Bureau converted Zip Codes into polygons that can be used

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for spatial analysis by defining all the Zip Codes on a block, and then using the most frequently appearing Zip Code as the entire block's ZCTA.

The Zip Code and the ZCTA for a given address are the same the vast majority of the time, but in some cases, multiple Zip Codes are combined into a single ZCTA. Initially, this presented some problems during the data cleaning process because some Zip Code level dependent variable observations did not have a corresponding ZCTA and therefore did not have socio-economic and hazard data. In order to harmonize these discrepancies, I created a dataset with each Zip Code and its corresponding ZCTA and then merged this with the data set that included Zip Codes and the outage data.

The data used to generate the independent variables came from a variety of sources, designed to consider the role of socio-economic inequalities on impact and recovery. The rest of the variables were included to control for other factors influencing the speed of recovery, and are sorted into four categories: hazard, exposure, priority, and spatial (Table 3.1). Variable selection was carried out in consultation with the relevant literature on modelling power outages and restoration (Guikema, Quiring, & Han, 2010; Han et al., 2009; Mcroberts, Quiring, & Guikema, 2016).

Table 3.1: Data Sources for Independent Variables

Variable name	Variable source	Variable type	Analysis
Unemployment rate	Bureau of Labor Statistics	Socioeconomic	1,2
Median household income	American Community Survey	Socioeconomic	1,2
Population 65+ years	American Community Survey	Socioeconomic	1,2
Educational attainment	American Community Survey	Socioeconomic	1,2
Percent below poverty rate	American Community Survey	Socioeconomic	1,2
Maximum wind gusts (m/s)	Stormwindmodel	Hazard	1,2
Gust duration	Stormwindmodel	Hazard	1,2
Precipitation	NASA Giovani	Hazard	1,2
Flood Gauge Ratio	USGS Storm Gauges	Hazard	1,2
Soil moisture	NASA Giovani	Exposure	1,2
Total Households	US Census/	Exposure	1
Maximum outages	Dr. Guikema	Priority	2
Emergency Infrastructure	USGS	Priority	2
Health Infrastructure	USGS	Priority	2
Grocery stores	Zip Codes Business Patterns	Priority	2
Queen's contiguity lag of maximum outage	Generated	Spatial	1
Queen's contiguity lag of time until 95% restored (continuous)	Generated	Spatial	2

3.3 *Methods*

3.3.1 Analysis 1: Determinants of Maximum Outages

The models in this analysis examine the effects of community socio-economic well-being on the extent of damages caused by of Hurricane Isaac to electricity infrastructure across Louisiana. Specifically, they seek to identify whether any of the socio-economic indicators outlined in Table 3.2 will have an effect on the number of

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power outages that occurred at the ZCTA level. We test this both while controlling

for the storm strength, and while omitting these controls in order to assess whether

differential impacts are because communities of a given socio-economic status are

clustered in areas that experienced more intense weather as a result of the hurricane.

The dependent variable used in this analysis is the Maximum Outage measure

that was included in Dr. Guikema's scraped data. This represents the total number of

customers that experienced a power outage during the measurement period. As

discussed, above, when converting Dr. Guikema's data from Zip Codes to ZCTAS,

there were cases when multiple Zip Codes were assigned to a single ZCTA. To fix

this discrepancy, I summed the maximum number of outages for each Zip Code in the

ZCTA, generating a ZCTA level total outage figure.

Maximum Outage is a count measure, and as is often the case with count

variables it is both right skewed and over dispersed, meaning that the conditional

variance is greater than the conditional mean. As a result, the negative binomial

regression is the most appropriate model for this analysis. The negative binomial

regression is a generalized version of the Poisson regression that includes a dispersion

term to account for the fact that the data does not meet the Poisson assumption of

equality between mean and variance (Lawless, 1987).

The econometric specifications of the models are:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 W_{yi} + \varepsilon \qquad\qquad (1)$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \qquad\qquad (2)$$

Where Y is the maximum number of outages in ZCTA *i*. In both models 1 and 2, X_1 represents the socio-economic variable of interest in ZCTA *i*, of which there are three in total (Table 3.2). Each was tested individually. Both models also include X_2, which represents the number of total housing units and businesses within a given ZCTA. This is meant to serve as an approximation of the total number of electric customers within the unit of analysis. The actual number of customers is not publicly available, which is why this proxy was required.

Table 3.2: Detailed Overview of Socio-Economic Independent Variables

Variable	Year	ACS Description
Education	2012 (5-year estimate)	Total; Estimate; High school graduate (includes equivalency
Poverty	2012 (5-year estimate)	Percent below poverty level; Estimate; Population for whom poverty status is determined
Median income	2012 (5-year estimate)	Median income (dollars); Estimate; Households

Model 2 also includes X_3, which represents a series of hazard variables that were included because Hurricane Isaac hit ZCTAs with varying levels of force. These differences can be anticipated to have an effect on the number of resultant power outages. However, the literature indicates that low-income and otherwise disadvantaged communities are more likely to be located in high-risk areas. So even if differential outage rates among ZCTAs can be explained by differences in storm strength, this does not necessarily preclude the conclusion that socio-economic inequality effects disaster impacts.

As discussed above, Hurricane Isaac's primary meteorological threat was its high winds, but the storm also produced rain and flooding, so those measures were

included in the analysis as well. Maximum wind gusts and sustained wind duration where both generated using the stormwindmodel package for R (B. Anderson, Schumacher, Guikema, Quiring, & Ferreri, 2018). Flood gauge ratio was calculated using the available USGS flood gauges within the ZCTA. (Table 6).

Table 3.3: Detailed Overview of Hazard and Exposure Independent Variables

Variable	Unit	Description
Maximum wind gusts	Meters/second	Maximum value of surface-level (10 meters) gust winds, in meters per second, over the length of the storm at the given location
Sustained wind duration	Minutes	Length of time, in minutes, that surface-level winds were above a specified speed (30 mi/h)
Precipitation	Millimeters	Accumulated amount of precipitation in 5 days (1 day before disaster arrival through 3 days after)
Flood gauge ratio	No unit	Maximum value of observed flood ratios
Soil moisture	Kilogram per meter squared	Average amount of soil moisture for three days preceding the disaster arrival
Total customers	Customers	Estimate of total number of households in ZCTA plus the number of business establishments.

Finally, models 1 and 2 each include W_y, which is a spatial lag of the dependent variable Y. Spatial autocorrelation is a potential problem in any model that uses geographic spaces as units of analysis. Similarities tend to be geographically clustered, meaning that the variables of interest in one ZCTA may be influenced by other ZCTAs in its proximity. This violates assumptions of independence, so it is advisable to create a spatially lagged version of the dependent variable to include in the analysis, thereby controlling for spatial autocorrelation. A Moran's I test was performed to test for spatial autocorrelation in the dependent variable, and as shown

in Table 3.4 the results indicated that spatial autocorrelation is indeed present.

Therefore, a first order Queen's Contiguity Matrix was generated using GeoDa

(Anselin, Syabri, & Kho, Youngihn, 2006) and used to create a lag variable that takes

an average of each neighboring ZCTA's value of Y (Jeanty, 2010). Within the data

set, there is one neighborless, or island, observation. Rather than removing that

observation from the dataset, its closest ZCTA was assigned to be its weight.

Table 3.4: Moran's I Test for Maximum Outage

Statistics	Normal Approximation	Randomization
Moran's I	0.7374	0.7374
Mean	-0.0034	-0.0034
Standard Deviation	0.0391	0.0391
Z-Score	18.9387	19.1150
P-value	0.0000	0.0000

3.3.2 <u>Analysis 2: Determinants of Recovery Time</u>

The dependent variable used in the second analysis is the time at which the

ZCTA in question experienced a 50%, 80% and 95% threshold of power restoration.

This variable's purpose is to measure recovery and to compare the speed at which a

basic level of power restoration is achieved in different communities. This is an

important area of study because of the fact that many other recovery processes require

electricity, so power restoration is central to making recovery progress on a wider

scale.

While developing this variable, it was observed that in some cases a Zip Code

would reach a restoration benchmark, and then some customers would lose power

again, bringing the Zip Code back below the benchmark. As a result, some Zip Codes

reached a benchmark multiple times as they regained electricity, lost it again and then

had it restored to the benchmark for a second time or even third time. In such cases,

the analysis uses the number of minutes before the community reached the

benchmark for the final time. The goal of this analysis is to measure reliable and

permanent restoration, because that is what brings a sense of stability and wellbeing

to a community

The initial dataset included observations for 389 different Zip Codes. Of

these, 82 zip codes reported less than 20 maximum outages, these were removed from

the data set because with fewer than 20 households without power, a 95% restoration

benchmark is not a meaningful or useful metric. This left a total of 305 observations.

As with the dependent variable in Analysis 1 it was necessary to manipulate

the data so that the spatial unit of analysis was the ZCTA rather than the Zip Code.

When multiple Zip Codes were assigned to a single ZCTA, an average of the

restoration times for each Zip Code was taken, weighted by the maximum outage:

$$restoration_{zcta} = \frac{restoration_{z1} \times maxoutage_{z1} + restoration_{z2} \times maxoutage_{z2}}{maxoutage_{z1} + maxoutage_{z2}}$$

In most cases, the differences between combined Zip Codes were fairly small,

which was expected because they were neighbors and spatially proximate polygons

tend to be more similar. In any case, a weighted average provides the closest

approximation to the actual restoration time within the larger ZCTA. The process of

converting Zip Codes to ZCTAs, as well as dropping observations for which no

demographic data was available caused the total number of observations within the

data set to be further reduced to n=289.

Professor Guikema and his team scraped the utility website for a total of

13760 minutes beginning on August 27, 2012 at 12:00 pm. This is equal to 229 hours

or roughly 9.5 days. Some zip codes did not reach the benchmark of 50%, 80% or

95% restoration at that point, so for these observations, it can simply be said that

restoration time was greater than 13760 minutes. In total, nine of the 289 observations

did not reach 95% restoration during the data collection period. Of those, seven did

not even reach 50% restoration during this time frame, indicating that there was

substantial work yet to be done.

Table 3.5: Summary Statistics For Zip Codes that Reached 95% Restored

Variable	Mean	Std. Deviation	Min	Max	Median
Maximum Outage	2625.073	4138.772	25	21343	911
Time95	8828.785	2730.881	2815	13760	8460

The fact that the dependent variables are primarily continuous, with a limited

number of undefined results is challenging from an analytical perspective. Several

options were investigated. First, I considered simply using a truncated continuous

variable that dropped the observations with an undefined recovery.

Table 3.6: Summary Statistics for Zip Codes that did not reach 95% Restored

Variable	Mean	Std. Deviation	Min	Max	Median
Maximum Outages	2464.778	4432.46	219	14122	895

However, it is problematic from an analytical perspective to remove the most

extreme cases because the goal of this project is to identify the characteristics that

make recovery succeed in some communities and fail in others. To ignore the

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communities that were among the worst off in the power restoration process defeats the purpose of this research. A review of the summary statistics for the maximum outages in these very slow recovery ZCTAs indicates that these spatial units experienced a significant number of outages, and are very similar by this measure to ZCTAs that recovered more quickly (Table 3.6). Therefore, there is no real theoretical basis for removing them from the analysis.
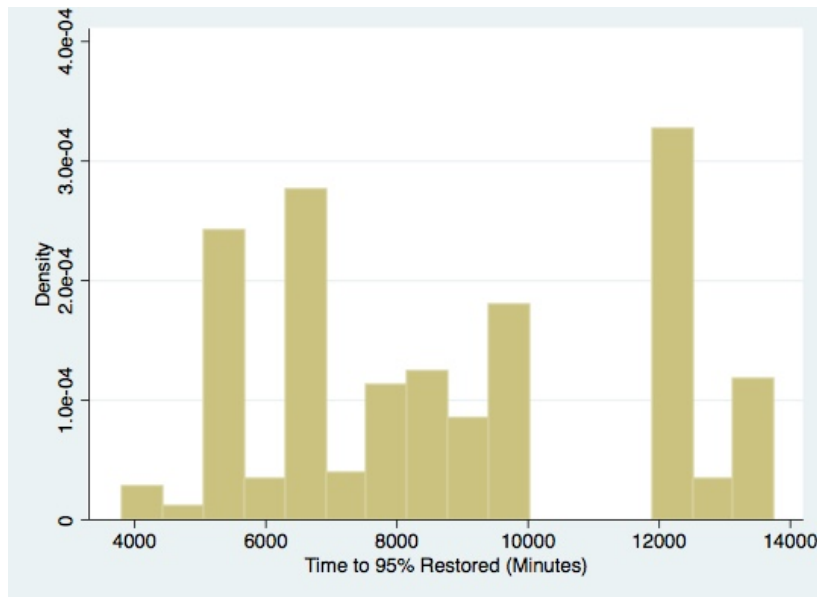
Figure 3.1: Histogram of Time to 95% Restored

Further, an examination of the distribution of the continuous restoration variables indicated that it would be challenging from a modeling perspective. A histogram of Time to 95% restored (Figure 3.1) indicates that the data does not follow any conventional distribution. Log, root and power transformations yielded no better results. The same was true for the 50% and 80% restoration times.

It is evident that a continuous variable is not the best option for analyzing this data set, particularly given the presence of numerically undefined observations. As a result, it was determined that the best path forward would be to create an ordinal categorical variable that separated the ZCTAs into five groups based on the relative speed of their restorations. Although there are downsides to using an ordinal categorical variable rather than a continuous one, most notably the loss of precision, in this case it was the best available option.

Table 3.7: Categorical Variable Construction for Restoration Time in Minutes

	Time to 95%		Time to 80%		Time to 50%	
Category	N	Time Range	N	Time Range	N	Time Range
1	50	3815-5605	84	3815-5634	121	2465-5647
2	73	6151-7912	78	6151-7889	90	6151-7820
3	78	8100-9770	73	8100-9770	50	8100-9770
4	58	12020-12235	49	12030-12235	26	12039-12045
5	36	12540-13760+	11	12540-13760+	8	13760-13760+

The dataset has natural breaks between large waves of restoration during which no ZCTAs reached the restoration benchmarks. The gaps in the 95% recovery dataset were used as a guide by which to divide the data into ordinal categories, with category 1 representing the fastest recovery times and category 5 representing the ZCTAs that were slowest to recover (Table 3.7). These same categorical boundaries were used to create categorical variables for time to 50% and 80% restoration. The same natural breaks that were used to guide the categorical boundaries for Time to 95% restoration were present for the other two thresholds as well.

Due to the fact that the dependent variable is in the form of categories that are ordered, the most appropriate model is an ordered Probit model. An OLS analysis

will not work because the dependent variable does not have a cardinal meaning: movement from category 1 to category 2 is not quantitatively equal to movement from category 2 to category 3.
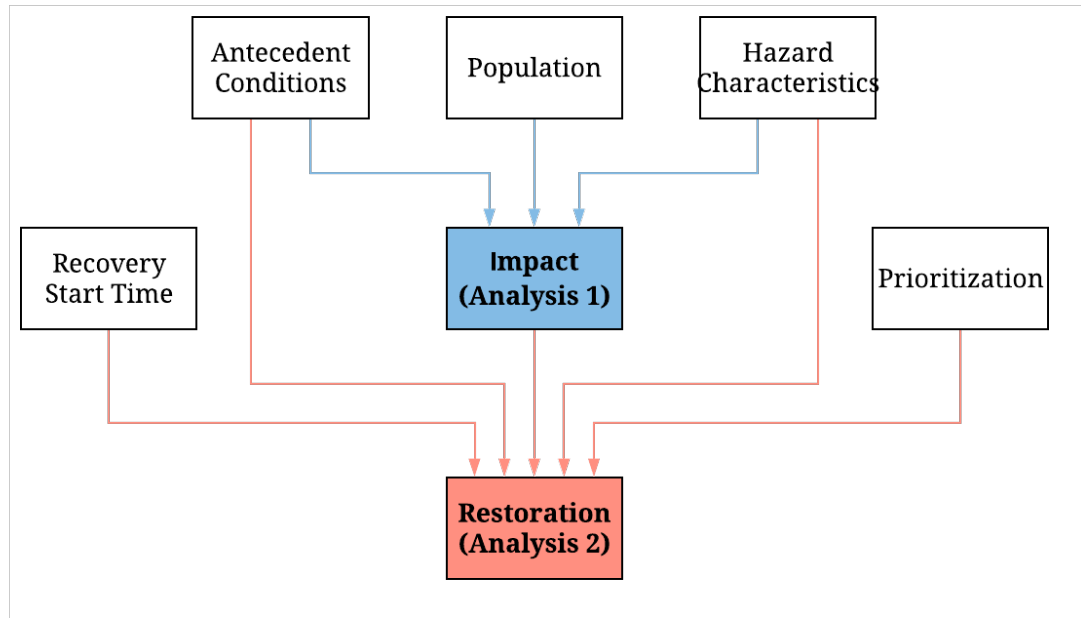
Figure 3.2: Determinants of Recovery

When conceptualizing the model that would be used for this portion of the analysis, I considered the literature on the determinants of recovery. Recovery outcomes are known to be a product of a variety of inputs, as is detailed in Figure 3.2. These include antecedent conditions, the extent of the damage to the system being recovered, obstacles to recovery such as flooding or debris, the point at which the recovery process is able to begin in a given spatial unit, and the extent to which a given unit is prioritized within the broader recovery operations (Cutter et al., 2008a; Cutter, Schumann, & Emrich, 2014; Tierney, 2014).

With this in mind, the model specifications are as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 W_{yi} + \varepsilon \tag{3}$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \tag{4}$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 W_{yi} + \varepsilon \tag{5}$$

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 W_{yi} + \varepsilon \tag{6}$$

Where Y is an ordinal categorical variable that describes the speed at which

ZCTA i reaches 95%, 80% and 50% power restoration following Hurricane Isaac.

The limits of each category are outlined in Table 3.7.

As in Analysis 1, X_1 represents the socio-economic variable of interest in

ZCTA i, of which there are three in total (Table 3.2). Each will be used separately and

represents the antecedent conditions that influence recovery. All three models also

include X_2, which represents Maximum Outages. This was the dependent variable in

Analysis 1 and quantifies the extent of the damages in a given ZCTA. It is possible

that Maximum Outages could influence recovery time in either direction, because

although there is more damage for the power crews to repair, it is also likely that

communities with many outages will be prioritized.

X_3 is introduced in Model 4 and represents the duration of sustained winds

over 30 miles per hour, which, due to federal regulations is the speed over which

elevated power restoration trucks were forbidden to operate. This means that it

represents the length of time before which power restoration crews were unable to

begin the recovery process. This measure was introduced in Analysis 1 Model 2,

along with several other hazard variables that are represented by X_4. These variables

measure wind speed, precipitation levels and flooding and were included in Model 5

because all of these variables present obstacles to the recovery process, such as inundation and fallen tree branches (Table 6).

Table 3.8: Priority Variables

Variable	Unit	Description
Emergency Services	Count	Ambulance services, American red cross facilities, emergency response facilities, fire stations, EMS stations, law enforcement stations, offices of emergency management.
Health Services	Count	Hospitals, medical centers.
Grocery Stores	Count	Grocery stores (excludes corner stores)

As discussed above, utilities have formal policies in place for determining high priority areas for power restoration. As a result, variables were introduced in order to identify whether a ZCTA experienced faster restoration due to the concentration of high-priority infrastructure in the spatial unit. These prioritization variables are represented by X_5 in Model 6. The literature indicates that emergency services like fire stations and hospitals and retail facilities like grocery stores may be prioritized so these were introduced into the analysis as independent count variables (Table 3.8).

Similar to Analysis 1, it was likely that the dependent variable in Analysis 2 would be spatially autocorrelated. A Moran's I test was performed on a truncated version of the continuous variable, and spatial autocorrelation was indeed observed (Table 3.9).

Table 3.9: Moran's I Test for Time to 95% Restored

Statistics	Normal Approximation	Randomization
Moran's I	0.6803	0.6803
Mean	-0.0034	-0.0034
Standard Deviation	0.0391	0.0392
Z-Score	17.4768	17.4398
P-value	0.0000	0.0000

However, it not possible to create an accurate spatial lag of an ordinal variable because it is not cardinal. As a result, the continuous Time to 95% restored variable was used create the spatial lag. Within this continuous variable some values at the upper limits are undefined. For the purposes of the spatial lag variable, the undefined variables were coded with the maximum defined value within the data set. While not an ideal strategy, it is preferable to removing the very slow recovery ZCTAs from the analysis altogether.

3.4 *Results*

3.4.1 Analysis 1: Determinants of Maximum Outages

Descriptive Statistics

The mean maximum outages at the ZCTA level was 2282.159, and the median was 620, indicating a strong right skew. This is confirmed in the histogram seen in Figure 3.3, where we again observe a strong right skew with the majority of ZCTAS having between 1 and 1250 outages. This distribution is common to both count data in general and power outage data in particular, and it is why a negative binomial regression model is the most appropriate analytical approach.
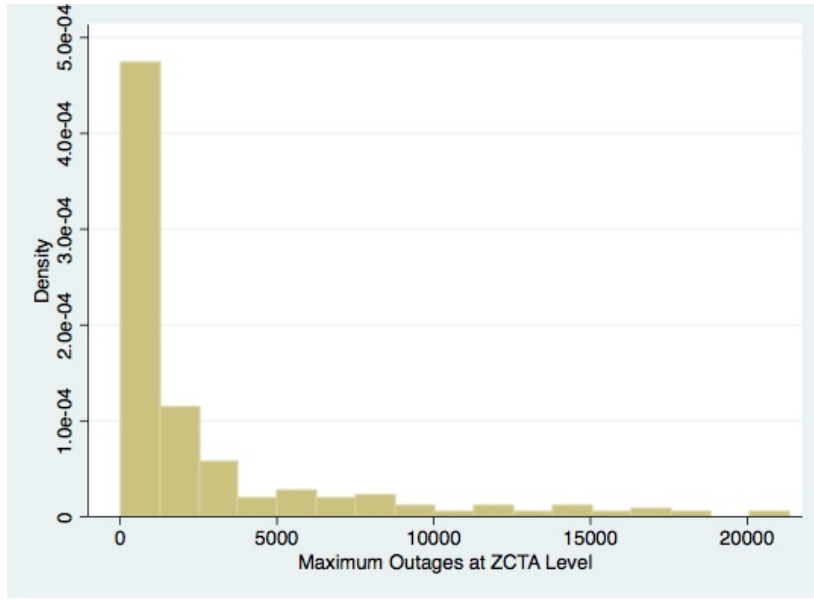
Figure 3.3: Maximum Outages At ZCTA Level

A series of maps were produced in order to visualize and better understand the way that Hurricane Isaac's damages and impacts were distributed across Louisiana. All maps include only the ZCTAs for which outage data is available. As can be seen in Figure 3.4, the flooding caused by the storm was centralized in a few ZCTAs in the southeastern region of the state. The 5-day precipitation trends followed a very similar pattern to the flooding, as seen in Figure 3.5.

When examining the distribution of peak wind gust speeds across the state (Figure 3.6), a similar pattern emerges. The most extreme winds were located in the southeastern region of the states, and the wind speeds decreased as the storm moved north and west. This falls in line with what would be expected given the official NOAA reporting on the storm.
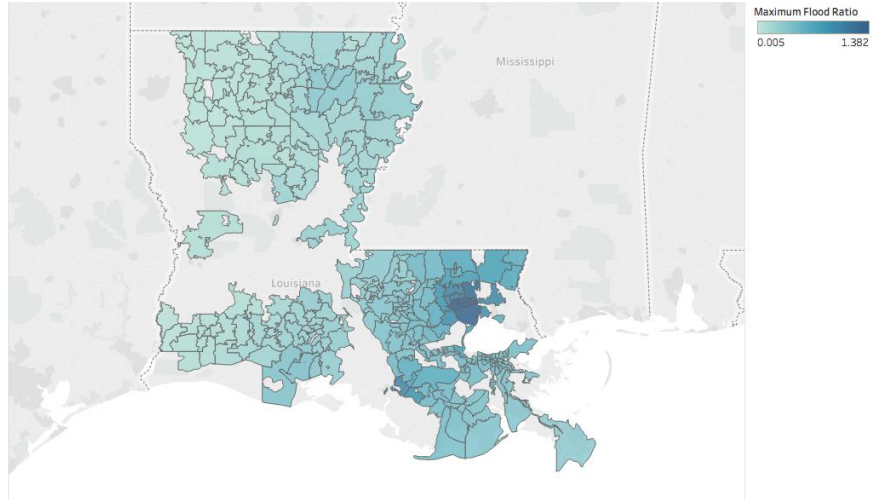
Figure 3.4: Distribution of Maximum Flood Ratio
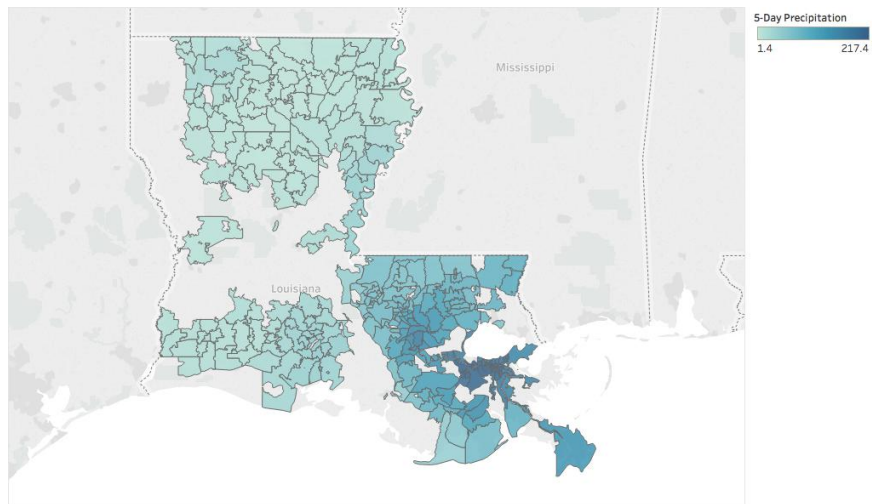
Figure 3.5: Distribution of 5-Day Precipitation
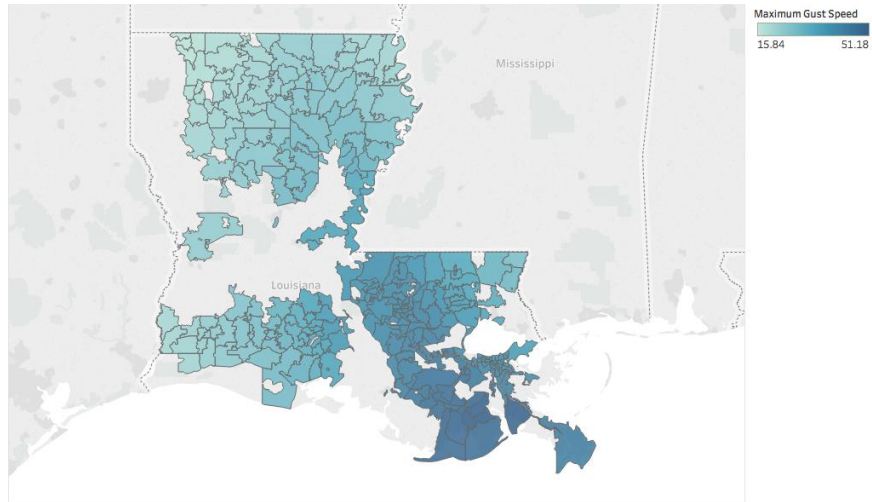
Figure 3.6: Distribution of Maximum Wind Gust Speed
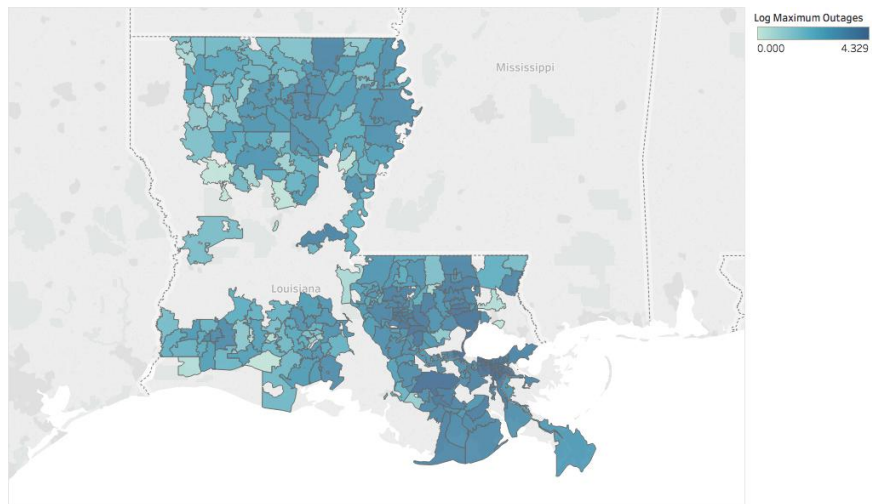
Figure 3.7: Distribution of Maximum Outages(Log)

However, when a map is created tracking the maximum outages at the ZCTA level, the results do not take on a clear pattern. Figure 3.7 shows a heat map of the log of Maximum Outages. There does appear to be some concentration of high-outages ZCTAs in the southeast where the most extensive flooding, heaviest precipitation and highest winds were also observed. However, the pattern is certainly not as consistent.

Maps were also created that attempted to normalize the maximum outages to the number of customers, but this exhibited even less of a coherent spatial pattern than the map displayed below.
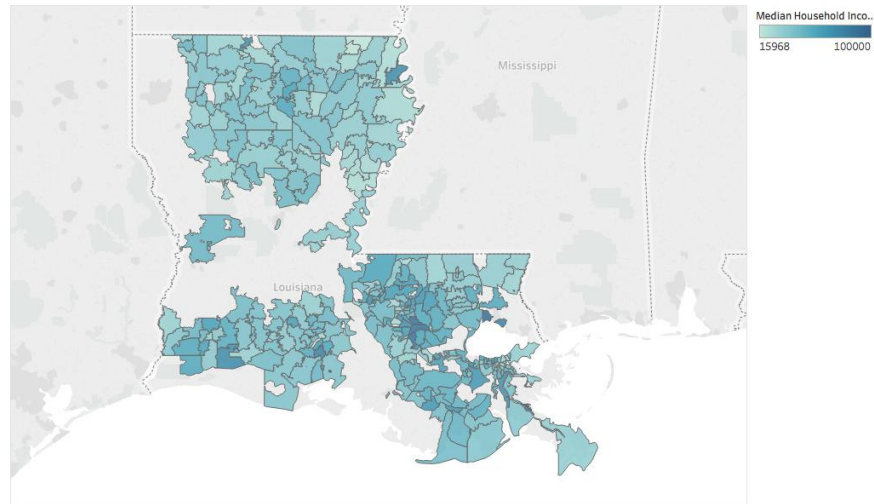
Figure 3.8: Distribution of Median Household Income

Maps were also created in order to visualize the distribution of the socio-economic variables across the state. As seen in Figure 3.8 below, household income tends to be somewhat higher in the southeast region of the state where we also observed more extreme weather as a result of Hurricane Isaac.

Regression Analysis

Table 3.10 reports the results for the negative binomial regression model that examines the effects of socio-economic indicators on the ZCTA-level maximum outages without controlling for Hurricane Isaac's meteorological conditions. We find that none of the three socio-economic indicators under examination had a statistically significant relationship with maximum outages. In all three models, we can observe

that there is a significant, positive relationship between the estimated number of total
customers in the region and the number of outages.

Table 3.10: Determinants of Maximum Outages (Model 1)

Max Outage			
% Below Poverty	0.0000619		
	(0.0000578)		
Median Income		2.53E-06	
		(5.32E-06)	
% With Bachelor's Degree			-0.02253
			(0.0001651)
Estimated Customers	0.0001295***	0.0001461***	0.0001651***
	(0.0000303)	(0.0000186)	(0.0000209)
W_y Maxoutage	0.0001957***	0.000203***	0.000211***
	(0.0000283)	(0.0000282)	(0.000029)
Constant	5.8087***	5.7571***	5.9960***
	(0.1087)	(0.2520)	(0.1450)
Log Alpha	0.4817***	0.4338102***	0.4476***
	(0.06683)	(0.06681)	(0.06620)
Observations	339	328	334
Pseudo R2	0.0433	0.0438	0.0441

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 3.11, shows the results for the negative binomial regressions that
examine the effects of socio-economic indicators on the ZCTA level maximum
outages while controlling for the meteorological impacts of the storm. In the model
that uses the percentage of the population below the poverty level as the socio-
economic indicator, we observe that a one percentage point increase in proportion of
the population below the poverty level corresponds to a 0.001283 unit increase in the
maximum number of power outages. A similar pattern is observed in Model 2,
wherein a one-unit decrease in median income corresponds to a small but significant
increase in the maximum number of outages at the ZCTA level. No statistically

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significant relationship is observed between the percentage of adults with a bachelor's degree and the maximum number of outages.

We also observe that both maximum wind gust velocity and maximum flood ratio are significantly and positively correlated with the number of power outages in all three of the models. When the gust velocity increases by one unit, the number of power outages increases by approximately 0.05, depending on the model. Similarly, when the maximum flood ratio increases by 1 unit, the maximum number of outages increases by between 1.31 and 1.45. Neither 5-day precipitation nor gust duration are statistically significant in any of the models.

Table 3.11: Determinants of Maximum Outages (Model 2)

% Below Poverty	0.0001283*		
	(0.0000519)		
Median Income		-9.88E-06*	
		(4.76E-06)	
% With Bachelor's Degree			-0.01377
			(0.01265)
Max Gust Velocity	0.0586879**	0.0575678**	0.05166*
	(0.01839)	(0.01834)	(0.1819)
Gust Duration	-0.0002164	-0.0001826	-0.0001929
	(0.002817)	(0.002798)	(0.0002832)
5-Day Precipitation	0.00255	0.0023005	0.002278
	(0.002031)	(0.002004)	(0.002012)
Maximum Flood Ratio	1.307236**	1.377633**	1.4458***
	(0.4173)	(0.4244)	(0.4282)
Estimated Customers	0.0000995***	0.0001527***	0.0001595***
	(0.000271)	(0.0000174)	(0.0000181)
W_y	0.0000816**	0.000086**	0.0000948***
	(0.0000816)	(0.0000301)	(0.0000315)
Constant	3.689055***	4.133963***	3.9923***
	(0.3467)	(0.3611)	(0.312)
Log Alpha	0.234869***	0.2250765**	0.2305***
	(0.6830)	(0.06868)	(0.06852)
Observations	329	326	327
Pseudo R2	0.0593	0.0593	0.0588

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Similar to the models outlined in Table 3.10, the estimated number of customers has a positively and statistically significantly relationship with the maximum outages, and the spatial lag of the dependent variable remains significant.

Table 3.12: Correlation Between Median Income and Hazard Variables

	Gust Velocity	Gust Duration	Flood Ratio	Precipitation
Median Income	0.3148	0.2821	0.1713	0.2123

It is interesting to note that the socio-economic independent variables of interest only become significant when the model controls for the meteorological variation of Hurricane Isaac. This would indicate that in this case the socio-economic variation in power outages is not because low-income communities tend to be located in more meteorological vulnerable spaces. Indeed, that median household income is positively correlated with all of the hazard variables, which suggests that higher-income ZCTAs actually experienced the storm's most severe impacts.

3.4.2 <u>Analysis 2: Determinants of Recovery Time</u>

Descriptive Statistics

As discussed in the previous section, the fact that the dependent variable, restoration time was not normally distributed and has an undefined upper boundary meant that it was required to be transformed into an ordinal categorical variable for the purposes of analysis. However, it is still useful to examine the descriptive statistics of the continuous variable. Table 3.13 provides as overview of the summary statistics for Time to 50%, 80% and 95% restored in minutes, using both a complete

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set of the data which includes the upper undefined values, and a truncated data set in which the undefined values are removed.

The fastest any ZCTA arrived at 50% restoration is 2465 minutes, or roughly 41 hours, and the first ZCTAs to reach 80% and 95% restoration arrived at those benchmarks after 3815 minutes or approximately 68.5 hours. This slow start to recovery is likely because Hurricane Isaac lingered over Louisiana for an extended period of time and federal regulations prohibited the use of elevated machinery until wind speeds fell below 30 miles per hour. As a result, there was a considerable delay between when the outages occurred and when the linemen were able to begin the recovery process.

Table 3.13: Descriptive Statistics for Restoration Times

	N	Mean	Std. Deviation	Min	Max	Median
Time to 50%	295	--	--	2465	>13760	6540
Time to 80%	295	--	--	3815	>13760	7705
Time to 95%	295	--	--	3815	>13760	8460
Time to 50% Truncated	288	6972.50	2193.21	2465	13760	6450
Time to 80% Truncated	288	7884.00	2475.18	3815	13760	7040
Time to 95% Truncated	286	8828.79	2730.88	3815	13760	8460

The number of observations in each of the three truncated datasets is very similar. The truncated datasets exclude values that are greater than 13760 because they are undefined. The 9 ZCTAs that did not reach 95% restoration in 13760 minutes or less, only two reached 50% and 80% within that time frame. Closer examination reveals that both of these ZCTAs reached 50% restoration at 12045

minutes. One reached 80% at 12540 minutes and the other at 13520. This indicates that most of the ZCTAs that were very slow to reach 95% restoration also reached 50% and 80% restoration very slowly.
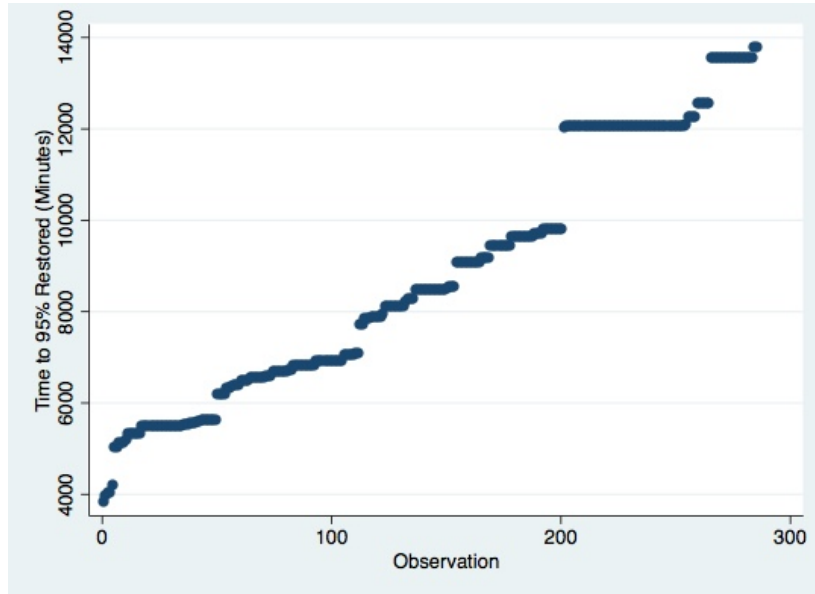
Figure 3.9: Scatter Plot of Time to 95% Restoration

As discussed above, the Time to 95% continuous measure was not normally distributed. The problem with the data became clear after creating a scatter plot of the individual observations (Figure 3.9). The restoration time has a step-like distribution, indicating that restoration progress happened in waves. For example, it is clear that many ZCTAs reached the 95% restoration benchmark at approximately 12000 minutes following a stretch of 2000 minutes wherein no ZCTAs reached 95% restored. This pattern is consistent with what is known about the power restoration process; it is likely that when many customers were restored at once it was because a repair was made to the upstream infrastructure upon which many neighborhoods rely.

Once this fix was made, a huge amount of households all got power at once, pushing

many Zip Codes to the 95% completion benchmark at the same time. Further lending

credence to this theory is the fact that over 25% of ZCTAs reached the 80% and 95%

restoration benchmarks at the same time.

However, it is important not to ignore the possibility that this issue may be the

result of unreliable reporting rather than the actual pattern of restoration. Perhaps

ZCTAs were reaching the 80% and 95% benchmarks at a steadier pace, and Entergy

simply failed to update their outage numbers in real time, instead releasing bulk

updates at less frequent intervals.
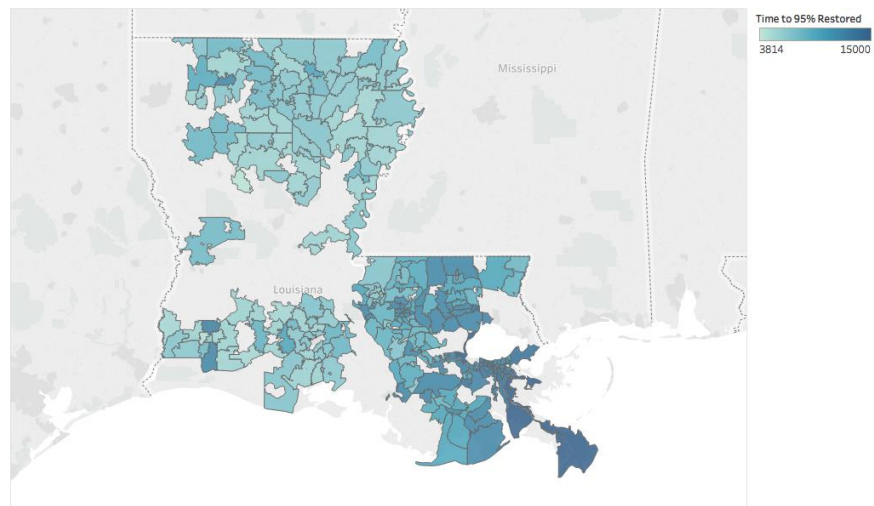
Figure 3.10: Distribution of Time to 95% Restored in Minutes

Figure 3.10 shows the time in minutes to 95% restored across the Louisiana at

the ZCTA level. ZCTAs with an undefined restoration time greater than 13760 were

coded as 15000 for illustrative purposes. A visual analysis indicates that these time

distributions closely match the distribution of flooding, precipitation and wind speeds

(Figure 3.4; Figure 3.5; Figure 3.6) across the state. Indeed, the outage restoration

time appears to follow distribution of the weather patterns caused by the Hurricane much more closely than maximum outage did (Figure 3.3).

Regression Analysis

Although the regression models were run using three socio-economic variables, percent below the poverty level, median income and percent of the adult population with a bachelor degree, the focus will be on the results for percent below the poverty level and median income, because third variable did not yield any results of interest.

Table 3.14: Percent Below Poverty Level as a Determinant of Recovery (Model 3)

	95%		80%		50%	
% Below Poverty	-.00141	.00427	.00165	.00753	-.00185	-.00024
	(.00632)	(.00662)	(.00639)	(.00695)	(.00654)	(.00711)
Maximum Outages	.00018***	5.9e-05**	.00013***	1.9e-05	9.5e-05***	-2.7e-05
	(1.9e-05)	(2.1e-05)	(1.6e-05)	(2.0e-05)	(1.5e-05)	(2.0e-05)
W_y		.00053***		.00069***		.00077***
		(4.2e-05)		(5.0e-05)		(6.0e-05)
/cut 1	-.73857***	3.224***	-.30195*	4.4268***	-.04759	4.7333***
	(.15667)	(.34758)	(.15166)	(.37916)	(.15279)	(.40304)
/cut 2	.13823	4.491***	.48849**	5.7458***	.8298***	6.1385***
	(.15101)	(.37688)	(.1529)	(.42358)	(.15857)	(.45085)
/cut 3	.97494***	5.9223***	1.3549***	7.4153***	1.5595***	7.634***
	(.1586)	(.44101)	(.16761)	(.51241)	(.17588)	(.54426)
/cut 4	1.9208***	7.338***	2.5531***	9.5257***	2.4253***	10.066***
	(.18452)	(.49541)	(.22183)	(.61342)	(.22437)	(.78327)
Observations	285	285	285	285	285	285
Pseudo R2	0.116	0.327	0.083	0.379	0.051	0.363

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 3.14 and Table 3.15 display the results of the ordered probit models that test the impacts of the percentage of households below the poverty level and the

median income of the ZCTA on recovery time, only controlling for the maximum

number of outages.

Table 3.15: Median Income as a Determinant of Recovery (Model 3)

	95%		80%		50%	
Median Income	7.8e-06	3.4e-06	5.7e-06	-4.7e-07	2.7e-06	-4.9e-06
	(4.3e-06)	(4.5e-06)	(4.3e-06)	(4.8e-06)	(4.5e-06)	(4.9e-06)
Maximum Outages	.00018***	5.7e-05**	.00013***	1.9e-05	9.2e-05***	-2.5e-05
	(1.9e-05)	(2.1e-05)	(1.6e-05)	(2.0e-05)	(1.5e-05)	(1.9e-05)
W_y		.00053***		.00068***		.00077***
		(4.2e-05)		(4.9e-05)		(5.9e-05)
/cut 1	-.39349	3.2693***	-.09374	4.2547***	.09781	4.5565***
	(.20866)	(.35776)	(.21017)	(.38374)	(.21638)	(.416)
/cut 2	.49033*	4.536***	.70375***	5.5831***	.96603***	5.9552***
	(.20977)	(.38814)	(.21314)	(.42784)	(.22046)	(.45897)
/cut 3	1.3461***	5.9882***	1.5619***	7.236***	1.6883***	7.4709***
	(.21845)	(.4501)	(.22243)	(.5038)	(.23251)	(.5453)
/cut 4	2.2639***	7.3801***	2.6997***	9.3343***	2.4968***	9.8599***
	(.23534)	(.49863)	(.26166)	(.6062)	(.26892)	(.78331)
Observations	290	290	290	290	290	290
Pseudo R2	0.116	0.327	0.081	0.380	0.048	0.367

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The tables both show that neither independent variable of interest has any

statistically significant impact on the time to 95%, 80% or 50% recovery regardless of

whether or not the spatial lag is included in the model. All of the models indicate that

the maximum number of outages has a significant and positive effect on the

restoration time. Also of note, the pseudo R2 measures are much higher for the

unlagged model at the 95% threshold than for the other two, suggesting that

Maximum Outage explains more of the variation in 95% recovery times than it does

at the 80% and 50% levels.

Following this, variables were added to the models to control for the length of time following the outages before power restoration was allowed to begin. Table 3.16 and Table 3.17 display the results of these models, using percent below poverty level and median income as the socio-economic variables of interest respectively.

Table 3.16: Percent Below Poverty Level as a Determinant of Recovery (Model 4)

	95%		80%		50%	
% Below Poverty	.00807	.00573	.01234	.00987	.00565	.00233
	(.0065)	(.00671)	(.00663)	(.00707)	(.00679)	(.00722)
Maximum Outages	.00013***	5.7e-05**	7.7e-05***	1.4e-05	4.0e-05*	-3.6e-05
	(2.0e-05)	(2.1e-05)	(1.7e-05)	(2.0e-05)	(1.7e-05)	(2.0e-05)
Sustained Wind Duration	.00091***	.00018	.00103***	.00024	.00094***	.00031*
	(.00011)	(.00013)	(.00011)	(.00013)	(.00011)	(.00012)
W_y		.0005***		.00064***		.00071***
		(4.9e-05)		(5.6e-05)		(6.3e-05)
/cut 1	.68705**	3.2298***	1.4178***	4.4842***	1.5972***	4.8944***
	(.22818)	(.34799)	(.24082)	(.37975)	(.2548)	(.40645)
/cut 2	1.7634***	4.5127***	2.4541***	5.8446***	2.6524***	6.3384***
	(.24438)	(.37804)	(.26717)	(.42858)	(.27803)	(.45774)
/cut 3	2.8109***	5.9601***	3.5073***	7.5112***	3.4778***	7.8157***
	(.2721)	(.44384)	(.29439)	(.51514)	(.29879)	(.54603)
/cut 4	3.8583***	7.3628***	4.7925***	9.566***	4.4194***	10.108***
	(.29764)	(.49659)	(.33555)	(.61122)	(.33898)	(.76545)
Observations	285	285	285	285	285	285
Pseudo R2	0.205	0.329	0.196	0.383	0.150	0.371

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Very few of the independent variables are statistically significant when the spatial lag is included in the model. This a phenomenon that is commonly reported in the literature, attributable both to the extremely strong significance of the lag variable, and the fact that many of the other independent variables also spatially biased,

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meaning that the spatial lag controls for some of the effects of the other variables

(Minkoff, 2016).

Table 3.17: Median Income as a Determinant of Recovery (Model 4)

	95%		80%		50%	
Median Income	-2.1e-06	2.0e-06	-5.7e-06	-2.6e-06	-8.2e-06	-8.6e-06
	(4.5e-06)	(4.7e-06)	(4.6e-06)	(4.9e-06)	(4.8e-06)	(5.2e-06)
Maximum Outages	.00012***	5.6e-05**	7.6e-05***	1.6e-05	3.8e-05*	-3.4e-05
	(2.0e-05)	(2.1e-05)	(1.7e-05)	(2.0e-05)	(1.7e-05)	(1.9e-05)
Sustained Wind Duration	.00091***	.00015	.00103***	.00021	.00098***	.00034**
	(.00011)	(.00013)	(.00011)	(.00013)	(.00012)	(.00013)
W_y		.0005***		.00064***		.00071***
		(4.9e-05)		(5.5e-05)		(6.3e-05)
/cut 1	.43374	3.1957***	.93929***	4.1794***	1.1956***	4.5366***
	(.23278)	(.36326)	(.24377)	(.38403)	(.26274)	(.41111)
/cut 2	1.5066***	4.4747***	1.9739***	5.542***	2.2467***	5.9801***
	(.24742)	(.39201)	(.26452)	(.42828)	(.27943)	(.45557)
/cut 3	2.5667***	5.9389***	3.0122***	7.1926***	3.0719***	7.4821***
	(.27053)	(.45307)	(.28327)	(.50272)	(.2971)	(.53949)
/cut 4	3.5877***	7.3205***	4.2406***	9.2416***	3.9539***	9.717***
	(.29135)	(.50153)	(.32072)	(.60457)	(.33322)	(.76089)
Observations	290	290	290	290	290	290
Pseudo R2	0.201	0.328	0.191	0.383	0.150	0.377

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

The maximum number of outages continues to be a strong predictor of

recovery time to 95% and 80% restoration, but it becomes less significant at the 50%

recovery threshold. Like in Table 3.14 and Table 3.15, neither socio-economic

variable is a significantly correlated with recovery time. However, sustained wind

duration has a consistently positive and significant relationship with recovery time,

indicating that the longer the period of time before recovery crews can begin their

recovery efforts, the longer it takes for recovery efforts to be successfully carried out.

Next, variables were added to the models to control for weather conditions during the storm. In earlier models, maximum outages consistently had a strong positive statistically significant impact on the restoration time. This relationship is weaker and less consistent in the models that control for hazard (Table 3.18 and Table 3.19). It has a positive and significant effect on the time until 95% restored and no significant effect on time until 80% restored in the models using both percent below poverty level and median income. It had a significant negative effect on the spatially lagged model for 50% restored when percent below poverty is used as a variable, and no significance when median income is used as the variable of interest.

The weather-related control variables that were introduced have more of a statistically significant effect in the unlagged models. Within this subsection, maximum wind gust velocity and five-day precipitation have a consistently significant and positive impact on power restoration time across the recovery thresholds. Maximum flood ratio has a significant positive relationship with 95% and 80% recovery, but no such relationship exists for 50% recovery. Sustained wind duration remains significant in the unweighted models, but the coefficient, which was positive in Model 4, has become negative.

Table 3.18: Percent Below Poverty Level as a Determinant of Recovery (Model 5)

	95%		80%		50%	
% Below Poverty	.00639	.00591	.0147*	.01274	.00798	.00481
	(.00676)	(.00686)	(.0069)	(.00722)	(.00707)	(.00742)
Maximum Outages	5.9e-05**	4.5e-05*	2.6e-05	1.8e-05	-1.5e-05	-4.4e-05*
	(2.2e-05)	(2.2e-05)	(2.0e-05)	(2.1e-05)	(1.9e-05)	(2.1e-05)
Sustained Wind Duration	-.00059*	-.0004	-.00065*	-.00035	-.00075**	-.00036
	(.00026)	(.00026)	(.00027)	(.00027)	(.00029)	(.0003)
Maximum Flood Ratio	1.422***	.71297	1.0008*	.50755	.57986	.28038
	(.41169)	(.43246)	(.41257)	(.43337)	(.41899)	(.43694)
5-Day Precipitation	.015***	.00635**	.0131***	.00098	.01402***	.00493*
	(.00194)	(.00238)	(.00191)	(.00239)	(.00195)	(.00227)
Maximum Wind	.04684*	.02899	.07763***	.04903*	.07535***	.04032
	(.01898)	(.01952)	(.01927)	(.02013)	(.01992)	(.02115)
W_y		.00039***		.0006***		.00062***
		(6.1e-05)		(6.7e-05)		(6.9e-05)
/cut 1	.84987*	2.8885***	2.2506***	5.0986***	2.3223***	5.0255***
	(.4129)	(.5302)	(.43046)	(.55799)	(.44887)	(.56565)
/cut 2	2.11***	4.2218***	3.5141***	6.519***	3.6205***	6.525***
	(.43543)	(.55748)	(.46471)	(.60142)	(.47406)	(.6016)
/cut 3	3.4378***	5.7249***	4.7833***	8.1817***	4.6124***	8.013***
	(.46488)	(.60603)	(.48824)	(.66138)	(.4891)	(.66268)
/cut 4	4.6612***	7.1218***	6.1827***	10.17***	5.6225***	10.103***
	(.47461)	(.63121)	(.51547)	(.73798)	(.52155)	(.85088)
Observations	285	285	285	285	285	285
Pseudo R2	0.294	0.341	0.284	0.391	0.247	0.382

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 3.19: Median Income as a Determinant of Recovery Time (Model 5)

	95%		80%		50%	
Median Income	-3.6e-06	3.2e-07	-9.6e-06*	-4.9e-06	-1.3e-05*	-1.1e-05*
	(4.6e-06)	(4.8e-06)	(4.8e-06)	(5.1e-06)	(5.0e-06)	(5.3e-06)
Maximum Outages	5.9e-05**	4.5e-05*	2.5e-05	1.9e-05	-1.5e-05	-4.0e-05
	(2.2e-05)	(2.2e-05)	(2.0e-05)	(2.1e-05)	(1.9e-05)	(2.1e-05)
Sustained Wind Duration	-.00056*	-.00037	-.00061*	-.00031	-.00071*	-.00033
	(.00026)	(.00026)	(.00027)	(.00027)	(.00029)	(.0003)
Maximum Flood Ratio	1.392***	.68732	.98543*	.51648	.54275	.26914
	(.41015)	(.43007)	(.41105)	(.43167)	(.41834)	(.43663)
5-Day Precipitation	.01505***	.00617**	.01334***	.0009	.01409***	.00479*
	(.00193)	(.00236)	(.0019)	(.00237)	(.00194)	(.00226)
Maximum Wind	.0442*	.02462	.07339***	.04238*	.07662***	.04185*
	(.01882)	(.01938)	(.01909)	(.02003)	(.01979)	(.02105)
W_y		.0004***		.0006***		.00063***
		(6.0e-05)		(6.6e-05)		(6.8e-05)
/cut 1	.52616	2.7448***	1.4897***	4.5579***	1.7197***	4.5611***
	(.36976)	(.50749)	(.3773)	(.52078)	(.39444)	(.52289)
/cut 2	1.7805***	4.0705***	2.7463***	5.9733***	3.0152***	6.0613***
	(.39168)	(.5334)	(.40871)	(.56061)	(.41642)	(.55586)
/cut 3	3.1124***	5.5835***	3.9984***	7.619***	4.0116***	7.5752***
	(.41972)	(.58076)	(.42628)	(.61381)	(.43087)	(.61817)
/cut 4	4.3079***	6.9618***	5.3436***	9.602***	4.9647***	9.6184***
	(.42858)	(.60694)	(.45264)	(.70013)	(.46138)	(.81253)
Observations	290	290	290	290	290	290
Pseudo R2	0.290	0.339	0.277	0.389	0.246	0.388

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

The percent below poverty level independent variable of interest has a significant positive relationship with 80% recovery time when the spatial lag is omitted from the model, suggesting that as the percentage of households below the federal poverty level increases, the recovery time does as well. However, this relationship does not hold true at either the 50% or 95% recovery thresholds.

Table 3.20: Percent Below Poverty Level as a Determinant of Recovery (Model 6)

	95%		80%		50%	
% Below Poverty Level	.00554	.00396	.01523*	.01141	.0095	.00453
	(.00682)	(.00693)	(.00697)	(.00731)	(.00714)	(.00751)
Maximum Outages	5.1e-05*	2.7e-05	3.2e-05	8.3e-06	-3.3e-06	-4.6e-05
	(2.3e-05)	(2.4e-05)	(2.2e-05)	(2.3e-05)	(2.2e-05)	(2.3e-05)
Sustained Wind Duration	-.00061*	-.00045	-.00063*	-.00037	-.00073*	-.00036
	(.00026)	(.00026)	(.00027)	(.00027)	(.00029)	(.0003)
Maximum Flood Ratio	1.4167***	.66723	.98278*	.47745	.58786	.28238
	(.41261)	(.43383)	(.41414)	(.43521)	(.4213)	(.43867)
5-Day Precipitation	.0155***	.00695**	.01287***	.00129	.01339***	.00497*
	(.00201)	(.0024)	(.00196)	(.0024)	(.002)	(.00229)
Maximum Wind	.04758*	.03048	.07662***	.04928*	.07483***	.04051
	(.01904)	(.01957)	(.01931)	(.02013)	(.01999)	(.02117)
Emergency Services	-3.7675	-3.7828	.05861	-.28435	.07254	.08898
	(119.73)	(105.56)	(1.1361)	(1.2377)	(1.0918)	(1.1521)
Health Services	-3.8265	-3.8534	-.0232	-.33719	.04103	.126
	(119.73)	(105.56)	(1.1387)	(1.2398)	(1.0951)	(1.1554)
Grocery Stores	3.8003	3.8473	-.0578	.32488	-.1054	-.08874
	(119.73)	(105.56)	(1.1368)	(1.2386)	(1.0927)	(1.1531)
W_y		.00041***		.00061***		.00063***
		(6.2e-05)		(6.9e-05)		(7.1e-05)
/cut 1	.92888*	3.2046***	2.2036***	5.2758***	2.2106***	5.0693***
	(.42184)	(.55293)	(.43803)	(.57951)	(.45499)	(.58207)
/cut 2	2.1971***	4.5641***	3.4677***	6.7045***	3.517***	6.5676***
	(.44601)	(.58365)	(.47209)	(.62339)	(.47935)	(.61664)
/cut 3	3.5279***	6.0862***	4.7429***	8.3691***	4.5149***	8.0571***
	(.47534)	(.63379)	(.49462)	(.68178)	(.49388)	(.67755)
/cut 4	4.7493***	7.4819***	6.152***	10.366***	5.5344***	10.158***
	(.4838)	(.65727)	(.52068)	(.7575)	(.52568)	(.86791)
Observations	285	285	285	285	285	285
Pseudo R2	0.296	0.347	0.285	0.393	0.250	0.383

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Similarly, in Table 3.19, there is a significant negative relationship between
median income and the time to reach the 80% threshold without spatial legs and the

50% recovery thresholds in both models. However, the same relationship is not observed for 95% recovery.

Table 3.21: Median Income as a Determinant of Recovery (Model 6)

	95%		80%		50%	
Median Income	-2.8e-06	2.2e-06	-9.5e-06*	-3.5e-06	-1.3e-05**	-1.1e-05*
	(4.7e-06)	(4.8e-06)	(4.8e-06)	(5.2e-06)	(5.0e-06)	(5.4e-06)
Maximum Outages	5.0e-05*	2.5e-05	2.9e-05	7.2e-06	-3.5e-06	-4.3e-05
	(2.3e-05)	(2.4e-05)	(2.2e-05)	(2.3e-05)	(2.1e-05)	(2.3e-05)
Sustained Wind Duration	-.00058*	-.00042	-.0006*	-.00034	-.00069*	-.00034
	(.00026)	(.00026)	(.00027)	(.00027)	(.00029)	(.0003)
Maximum Flood Ratio	1.3859***	.63551	.96925*	.48072	.55489	.27291
	(.41099)	(.4315)	(.41253)	(.43365)	(.42058)	(.43841)
5-Day Precipitation	.01558***	.00676**	.01321***	.00123	.01349***	.00481*
	(.00199)	(.00238)	(.00195)	(.00239)	(.00198)	(.00228)
Maximum Wind	.0451*	.02632	.07244***	.04283*	.07574***	.0424*
	(.01889)	(.01945)	(.01914)	(.02006)	(.01988)	(.02109)
Emergency Services	-3.9862	-3.7876	.10223	-.26022	.11415	.15635
	(203.91)	(105.61)	(1.1286)	(1.2366)	(1.092)	(1.1555)
Health Services	-4.0446	-3.8654	.03464	-.30995	.09978	.20703
	(203.91)	(105.61)	(1.1314)	(1.239)	(1.0955)	(1.1591)
Grocery Stores	4.0209	3.857	-.09867	.3073	-.1496	-.15872
	(203.91)	(105.61)	(1.1294)	(1.2376)	(1.0929)	(1.1566)
W_y		.00042***		.00062***		.00063***
		(6.2e-05)		(6.8e-05)		(6.9e-05)
/cut 1	.6644	3.2093***	1.4514***	4.8694***	1.5356***	4.6153***
	(.39226)	(.54838)	(.39928)	(.56253)	(.41386)	(.55518)
/cut 2	1.9282***	4.5632***	2.7081***	6.2957***	2.8386***	6.1143***
	(.41627)	(.57797)	(.42992)	(.60245)	(.43362)	(.58578)
/cut 3	3.2631***	6.0984***	3.9639***	7.9437***	3.8413***	7.6297***
	(.44381)	(.62698)	(.44541)	(.65315)	(.44655)	(.64667)
/cut 4	4.4556***	7.4754***	5.3156***	9.9353***	4.8029***	9.6869***
	(.45062)	(.65067)	(.46917)	(.73635)	(.47516)	(.84083)
Observations	290	290	290	290	290	290
Pseudo R2	0.292	0.345	0.278	0.392	0.249	0.388

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

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Finally, Table 3.20 and Table 3.21 show the results for Model 5, which adds variables to control for the presence of high-priority infrastructure such as hospitals, police stations and grocery stores. However, this infrastructure has no observed significant effect on the speed at which a ZCTA reaches any of the recovery thresholds under study, except in the 95% threshold weighted models wherein we observe a significant positive relationship between the presence of emergency service infrastructure and recovery time.

Otherwise, the effects that were observed in the unlagged model results displayed in Table 3.18 and Table 3.19 generally remain in effect in Model 6. Percent of households below the poverty level has a positive relationship with recovery time at the 80% threshold, while median income has a significant negative effect on the time it takes for a ZCTA to reach both 50% and 80% restoration. Table 3.21 indicates that the negative effect of median income on time to reach 50% recovery remains significant even in the weighted model.

Consistently significant and positive relationships between the recovery time and wind gust speed, precipitation, and maximum flood ratio are observed. Conversely, sustained wind duration is found to have significant a negative relationship with recovery time at all the recovery thresholds. Maximum number of outages has a positive relationship with recovery time at only the 95% threshold.

3.5 Discussion and Policy Implications

3.5.1 Maximum Outages, Hazards and Recovery

Analysis 1 finds that impact, measured as the maximum number of outages occurring within a given ZCTA is closely related to both hazard and vulnerability. The severity of the hazard in a given ZCTA, as measured by peak wind gust speeds and flooding, has a significant and positive impact on the number of customers without power, meaning that as wind speeds and flooding increase, the number of outages will increase as well.

Similarly, socio-economic vulnerability, as measured by the percentage of households below the federal poverty level and the ZCTA median income, is found to also have an impact on the maximum number of households without power. As median income increases and the percentage of households below the federal poverty level decreases, the number of customers without power decreases. This is in line with the existing literature on environmental justice and disaster vulnerability, which suggests that the socio-economically disadvantaged tend to be faced with a disproportionate amount of harm (Bolin & Stanford, 1998; Elliott et al., 2010a; Fothergill & Peek, 2004a).

However, the literature also suggests that a major reason why socio-economically disadvantaged populations experience more harm during disasters is because of increased exposure (Tierney, 2014). Poor communities are often located in more high-risk locations like flood plains because people with more financial resources will tend to avoid settling in these areas (Fielding, 2018). This was not the

case with Hurricane Isaac. Wealthier communities were found to have experienced the most extreme weather from the storm. As a result, the relationship between number of outages and socio-economic inequalities only emerged in the models after hazard control variables were introduced.

Given that the income-based differences in outage volume cannot be attributed to weather patterns, further research is needed in order to identify the source of this gap. One likely possibility is that routine maintenance, infrastructure hardening such as tree trimming and resilience efforts are not prioritized in low-income communities, which results in severe outages when extreme weather events occur. In any case, it is clear that the antecedent conditions that were discussed in Cutter's DROP model had an effect on this hurricane's impacts (Cutter et al., 2008b).

In order to observe the relationship between impact and recovery, the maximum number of outages was included as an independent variable in Analysis 2, in which the dependent variable was the time it took for a ZCTA to reach 50%, 80% and 95% power restoration. The impacts of maximum outages were mixed.

Throughout this analysis, it was found that the maximum number of outages at the ZCTA level had a significant and positive relationship with the time it takes for a ZCTA to reach 95% restoration, meaning that impact and recovery are closely related. However, the maximum number of outages has less of an impact on the time that it takes for a ZCTA to reach 80% and 50% restoration. A significant positive relationship is observed at all thresholds when the model does not control for hazards

or priority variables, but as soon as these variables are introduced, the significance is lost.

A possible explanation for these findings is that in the early stages of recovery, prioritization of some communities over others in the deployment of recovery crews is more present, whereas later in the process the head starts that some communities get due to being the early focus of recovery efforts becomes less relevant, because the process becomes largely determined by the volume left to restore. Based on what is known about power restoration prioritization, utilities will typically focus their early efforts on the repairs that will restore power to the largest number of people as quickly as possible. Therefore, once ZCTAs reach 90-95% restoration, all of the easy fixes have already been finished, and the more difficult jobs that will restore power to a small number of households are left. This is a much slower process, in which the volume of outages will become the determining factor.

3.5.2 Socio-economic inequalities and Recovery

Analysis 2 investigated the impact of socio-economic inequalities on power restoration time, focusing on two socio-economic variables of interest: percent of households below the federal poverty level and the median household income. The analysis examines the impact of these socio-economic variables on recovery time at three recovery thresholds: 95%, 80% and 50% restored.

Model 3 does not control for any hazard or priority variables, and no significant relationship between the socio-economic independent variables and recovery is found at any of the three thresholds under study. However, in Model 5,

which introduces hazard variables, and Model 6, which includes prioritization variables, a significant positive relationship between the percentage of households below the poverty level and 80% recovery time is observed. This would suggest that as the proportion of households below the poverty level increases, the time it takes for a ZCTA to reach 80% recovered also increases when we control for hazard characteristics. Similarly, a significant negative relationship between median household income and recovery is observed at both the 50% and 80% thresholds. This suggests that as ZCTA median household income increases, the time that it takes for the ZCTA to reach 50% and 80% power recovery will decrease.

No significant relationship exists between the socio-economic variables and recovery time at the 95% threshold in any of the models. Perhaps this is caused by the same phenomenon that was proposed above with regards to the significance of the maximum outage variable at the 95% threshold. It would appear as though wealthier neighborhoods are early targets for power restoration efforts, which brings them to the 50% and 80% recovery thresholds more quickly. However, at some point after 80% restoration is achieved, restoration progress shifts and becomes primarily determined by volume of remaining outages rather than socio-economic concerns. This is perhaps because the most difficult and small-impact restoration work is saved until the end of the process, and the slower pace of recovery allows neighborhoods that lagged behind but had fewer total outages to catch up with the others.

3.5.3 Hazard Characteristics and Recovery

The sustained wind duration variable that was introduced in Model 4 had a positive effect on recovery time. As discussed above, this variable specifically measures the length of time before sustained wind speeds dropped below 30 miles per hour. This is the federally mandated wind speed above which power restoration crews were not allowed to work in elevated trucks to fix the power lines. As a result, sustained wind speeds measured the time at which recovery was allowed to start in a given ZCTA, and one would expect that the longer a power crew must wait before being allowed to begin the recovery process, the longer before power will be restored.

The hazard variables introduced in Model 5 had effects on recovery time that were very similar to the way that they impacted Maximum Outages in Analysis 1. Maximum wind gust velocity was consistently positively correlated with power restoration time at all restoration thresholds in the unlagged models, and in some of the weighted models. This would indicate that the higher the wind velocity within a ZCTA, the longer it will take for that ZCTA to reach a given recovery threshold.

Similarly, 5-day precipitation levels and maximum flood ratio were generally found to be positively correlated with recovery time in the unlagged models, and the significant positive relationship between precipitation and recovery time persisted even in the weighted models. This means that in ZCTAs with more extensive flooding and higher rainfall, recovery times tended to be slower, which is logically consistent with the theoretical framework established for this model.

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A more unexpected finding is the fact that after the hazard variables were added, sustained wind duration remained significant but switched from a positive to a negative coefficient. This means that after the model controlled for other hazard characteristics, ZCTAs where sustained winds persisted for longer periods of time had their power restored more quickly. Perhaps most of the effects that were observed from the longer high wind speeds were actually related to the damage done by the hazard and not then recovery start time, and that in reality the delay gave the power crews time to plan their approach and get set up on the ground. In the end this preparation time might have resulted in a more efficient recovery process. However, more research is needed to fully explain this finding.

3.5.4 Prioritization Characteristics and Recovery

Model 6 introduced count measures for emergency and health services and grocery stores, as the literature suggests that these types of infrastructure are targets for early recovery efforts. However, these were not found to have a significant impact on recovery time. The one exception is that the presence of emergency services was significantly positively correlated with the recovery time in the weighted models at the 95% threshold, suggesting that as the amount of emergency service infrastructure increased, recovery time increased as well. This is contrary to what theory would suggest.

Otherwise, it would seem as though the prioritization of recovery is more complex and nuanced than a simple count of infrastructure. Attempts were also made to normalize the infrastructure variables so that they reflected infrastructure counts

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per 1000 inhabitants and infrastructure counts per square mile, but it did not change the significance of the results.

3.5.5 Policy Recommendations

One of the most important findings in this paper is that judging recovery outcomes by looking at a single threshold, such as 95% recovered is insufficient. Recovery is a process, not an end point, and researchers and policy makers must consider the path that communities take in order to reach full recovery. Even if two communities reach a recovery end point at the same time, one cannot assume that the paths they took to arrive at this point in the recovery process were remotely similar.

The industry standard threshold for power restoration is 95% restored, but if this analysis had been limited to that threshold, most of the nuance in the discussion above would have been lost. Based on the analysis above, it appears that in the earlier stages of power restoration, higher income ZCTAs recovered more quickly, and it was only in the later stages, between 80-95% restored, that the lower income ZCTAs began to catch up and restoration progress became a product of outage volume rather than socio-economic status.

One of the weaknesses of this study is that it did not control for infrastructure characteristics such as the percentage of power lines in a given ZCTA that are undergrounded. This could have a significant impact on both the rate of outages and recovery time, but this data is simply not available. Greater transparency on the part of utilities with regard to this information would vastly improve the quality of the research that is possible on this important subject.

Further study is needed in order to identify whether these findings are unique to power restoration following Hurricane Isaac, a problem that is specific to the state of Louisiana and Entergy, or a more widespread phenomenon. However, it is difficult to apply these models to other hurricanes because electric utilities are very guarded with their detailed outage data. Despite the fact that this data is temporarily available to the public on their websites, utilities make it very difficult for the data to be compiled for statistical analysis. Not only are researchers required to scrape the data themselves, the utilities are known to change the format in which the data are presented mid-restoration. This poses a real challenge for the scraping algorithms, which are programmed to be able to navigate a set layout.

Given that power utilities are government-regulated natural monopolies, this information should be made more easily available to researchers, particularly because it appears as though vulnerable communities are currently the losers in power restoration efforts. This data is crucial in order to further define these recovery disparities, both the extent to which they exist, and what motivates the decision-making that prioritizes some communities over others, so that processes can be improved and made more equitable in the future.

4. Measuring Social Capital and Civic Engagement

In the literature, social capital is clearly linked to community resilience and recovery but in order to further study the relationship between social capital and concrete recovery outcomes, it is necessary to have a conceptual framework of social capital that can be empirically evaluated (Aldrich, 2012b; Elliott et al., 2010a). Measuring social capital is an incredibly difficult task because it requires that the researcher operationalize a very abstract idea: the presence and quality of social networks and social bonds. As with the study of resilience more broadly, taking a quantitative approach to measurement is attractive because it can be compared, indexed and applied to quantitative models. However, this necessitates the challenging task of selecting proxies and metrics that can be validated and are not overly correlated with other potential influencers of recovery outcomes, such as income. As discussed in Chapter 2.3, commonly used proxies for social capital include participation in community groups, volunteerism and civic engagement. While some measures for civic engagement are collected by the US Census Bureau, they are aggregated to the county level. As a result, they are not suitable for community-level analyses.

This chapter explores the potential for using 311 contact data as a proxy for community civic engagement. 311 requests are a low-cost way for community members to directly engage with local government to either request information or alert representatives of a problem in need of their attention. The mechanisms that would fuel the decision to reach out to local government through a dedicated phone

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line differ in some ways from the mechanisms that allow individuals to foster

bridging connections within and outside their communities, so this measure is not

directly analogous to the traditional definition of social capital. However, the

willingness of a community to engage in information transfer with local government

is a characteristic that is directly relevant to potential recovery outcomes.

This analysis explores the neighborhood characteristics influencing 311 use in

Houston TX between 2016 and 2017 prior to Hurricane Harvey using publicly

available logs of Houston 311 requests. In it, I will position 311 data as a valuable

tool for understanding civic engagement and the way that neighborhoods interact with

the government. The chapter begins with a brief introduction to 311 services and a

review of the relevant literature, with a focus on how 311 data has been used in social

sciences research. I will then introduce the data being used in this chapter and provide

a description of the methods and results. The chapter will conclude with a discussion

of the findings and potential policy implications and applications for this research.

4.1 *311 Services: Background and Literature*

In 1996, Baltimore became the first city in the United States to use 311 as a

city hotline through which citizens could contact the police service for non-

emergency problems such as graffiti and illegal dumping. The experiment was a

success, and the following year 311 was reserved nationwide by the US Federal

Communications Commissions to act as a toll-free line that citizens could call to

make non-emergency inquiries and complaints to the police (Wheeler, 2017). In the

1970s, 911 was reserved as an emergency call line, but it had become over-burdened

by calls, many of which were of a non-emergency nature. As a result, government officials felt that providing a second toll-free number that citizens could use in non-emergencies would increase the efficiency of 911 by reducing the number of non-urgent calls placed on the service (Wiseman, 2014). Further, it was designed to be tool for community policing, because it would help departments identify areas that were in need of services (Wheeler, 2017).

In 1999, Chicago launched its own 311 service, which expanded on the Baltimore model by making it so that the toll-free number allowed citizens to not only make non-emergency complaints to the police, but also to contact the city about a wide variety of municipal services. The service could be used for everything from requesting a bulk trash pick-up to inquiring about city services. This soon became the standard model for 311 lines, and many other major cities began launching similar programs, including Los Angeles in 2002 and New York City in 2003. Since then, cities have expanded their services to allow for online and even app service requests, although voice calls remain the most popular mode of contact. Now, more than 200 cities across the United States have their own 311 services, and hundreds more, smaller municipalities are paying to use private sector companies and apps to help them manage service requests (citylab 311 calls).

Applications to Social Science Research

As 311 services have become more pervasive across major US cities in the past 15 years, they have generated interest within social sciences research for their potential as a valuable source of data. On a very basic level, 311 systems provide

citizens with a low-cost, low-effort way to engage with their local government about a wide range of very specific issues related to low-level non-emergency crime and municipal services in real time; Fleming refers to them as a "front door for citizen access to government" (Fleming, 2008). They also provide a mechanism for city elected officials to better understand what their constituents care about, and provides a tool for performance measurement. 311 requests are an especially exciting tool for social science research because 311 logs are often publicly available through city websites. Given that cities receive hundreds, if not thousands of requests every day, this produces a very large dataset with extreme spatial and temporal disaggregation.

The literature tends to use 311 data in one of two ways. Some researchers use these service requests as a proxy measurement for physical neighborhood disorder. When used as a measure of disorder, researchers focus on the fact that the hotline provides citizens with an opportunity to alert the police to problems in the community like graffiti and illegal dumping. O'Brien et al. used data from Boston's 311 hotline to test the broken window theory[1] by looking at 311 requests that reference "private neglect and public denigration" and used investigator-initiated neighborhood audits to test whether the hotline data was a valid and reliable measure of physical disorder (O'Brien, Sampson, & Winship, 2015). Boggess et al. similarly used 311 data in Reno, NV, to investigate the reciprocal relationship between physical neighborhood

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[1] A criminology theory introduced James Q. Wilson and George L. Kelling (1982) that introduced the idea that visible signs of crime and disorder in urban environments will encourage further and more extreme crime and disorder.

disorder and violent crime (Boggess & Maskaly, 2014), and Wheeler used 311 data in Washington DC to test the relationship between requests for service and crime at the street intersection level (Wheeler, 2017).

A second group of researchers use 311 requests as a proxy measurement for civic engagement. Civic engagement is an important consideration in many fields of research, but it can be a frustrating area of investigation because it is difficult to measure accurately, especially at disaggregated spatial scales (Kerr, 2018). Other civic engagement measurement strategies include voter turnout and rate of census return, as well as less widely available data such as rates of volunteerism and participation in civil society groups (Haney, 2018; Portney & Berry, 2010; Ruef & Kwon, 2016).

Lerman et al. used New York City 311 data to investigate the impact of stop-and-frisk policies on neighborhood likeliness to engage with government via 311 service requests (Lerman & Weaver, 2014). Similarly, Levine et al. used 311 data to study the way that neighborhood racial makeups impact political participation (Levine & Gershenson, 2014) and Minkoff performed a tract-level analysis of 311 requests in New York City to broadly identify the neighborhood characters that led to higher rates of civic engagement (Minkoff, 2016).

White is more skeptical about the use of 311 requests as a proxy for civic engagement. This paper compares rates of 311 requests within New York City census tracts and precincts to three other measures of civic engagement: voter turnout, census return rate and political donations. Like making contact with a 311 line, voter

turnout and census return rate are relatively low cost forms of political participation, whereas political donations are a higher cost way of participating, so the paper expected to find a strong correlation between 311 requests and the two former comparative measures, and a weaker relationship between 311 requests and the latter. However, the paper found that neighborhoods that used 311 in higher volumes were less likely to complete their censuses and vote but were more likely to donate politically. The author hypothesizes that perhaps what is being observed is a small number of 311 'super-users' who are contacting 311 so frequently that they are driving trends. However, the author omits a number of control variables such as home ownership and spatial lags that were considered essential in other analyses, which may have also played a role in driving these unusual results (White & Trump, 2018).

Taken together, these papers provide important insights into the opportunities and challenges of using 311 data as a research tool. When approaching research using 311 data, one must be mindful of the fact that any 311 call is the "coincidence of two events" (O'Brien et al., 2015): the issue that prompts the call, and the decision to report it. These calls cannot be taken as an unbiased measure of disturbances because in order for the call to be logged, it requires that someone decide to report it to municipal services, and the proclivity to report varies across neighborhoods. Similarly, the calls cannot be taken as unbiased measures of civic engagement, because disturbances that prompt 311 calls are not evenly distributed across neighborhoods. However, the papers suggest solutions for both of these problems.

Minkoff's tract-level analysis of proclivity to contact in New York City provides insight into the social and economic characteristics that influence the degree to which different neighborhoods contact 311 services, all other things held equal. In his analysis, he looks at three different categories of 311 service requests: government goods, graffiti complaints and noncommercial noise complaints, where government goods refer to municipal services that are available to everyone, such as garbage pickup and streetlights. Government goods are expected to vary less across neighborhoods than the latter two categories, which are caused by human behavior and are likely experience more inter-neighborhood variation (Minkoff, 2016). Levine and Gershenson's paper focused exclusively on snowplow requests after snowstorms in Boston. Throughout the paper the authors emphasize the importance of focusing on the right category of request. Their strategy of only analyzing snowplow requests helps to address the 'condition problem', which refers to the fact that the volume of requests in a given spatial boundary is influenced by the amount of disorder within that space. If there are more problems to call about, one can assume that more requests will be logged (Levine & Gershenson, 2014).

Minkoff finds that an increase in percentage of owner-occupied households and the percentage of households with children under the age of 18 both cause an increase in calls about government goods, but a decrease in calls about graffiti and noise complaints. This would suggest that neighborhoods with these conditions have a higher propensity to call but lower levels of disorderly conditions, which is intuitively logical, given that homeownership and young children would both cause

households to have a higher degree of investment in their surroundings. Minkoff also finds that calls about government goods increase in neighborhoods that have higher median incomes.

4.2 Data

The analyses in this paper use 311 log data from the city of Houston Texas to build the dependent variable. Houston's 311 services are available 24 hours per day in both English and Spanish. Though the majority of the requests are made via voice call, they are also accepted and recorded through a wide variety of other mediums including SMS text message, mobile app, email and online. The data is publicly available to be downloaded from the City of Houston's website.[2] This data is very detailed; **Table 1** provides a small sample of the data categories that are included in the logs.

Table 4.1: 311 Log Data Categories

Label	Description
casenumber	Unique identifying number assigned to each request
srlocation	Street address or intersection of complaint or inquiry
department	Municipal department relevant to the request
division	Division of department relevant to the request
type	Description of the reason for the request
srcreatedate	Date and time that the request was placed
latitude	Y coordinate of the complaint or inquiry
longitude	X coordinate of the complaint or inquiry.
channel	Channel by which contact was initiated

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[2] http://www.houstontx.gov/311/

The spatial unit of analysis for this paper is Census Zip Code Tabulation Area (ZCTA). The ZCTA is a geographical unit that was developed by the Census Bureau for the 2000 Census in response to continued requests by data users for statistical data by ZIP Code. ZIP Codes are assigned by the United States Postal Services based on postal delivery routes, but they are not all continuous polygons, so the Census Bureau converted them into polygons that can be used for spatial analysis by defining all the ZIP Codes on a block, and then using the mode as the entire block's ZCTA.

Although the majority of the 311 logs included a Zip Code in the srlocation column, this was not always the case, because some requests were linked to intersections rather than home addresses. However, nearly all of the logs included spatial information about the site of the complaint in the form of latitude and longitudinal coordinates, the coordinates were mapped and joined to the Census Bureau's 2010 ZCTA shapefile. Each request was then tagged with the ZCTA within which it was located. In the two-year span under study between 2016 and 2017, over 644,000 311 requests were logged in 146 ZCTAs. During the data cleaning process, approximately 10,000 requests were removed because they did not contain any form of geographical data, making it impossible to link them to a ZCTA.

As shown in **Table 1**, there are several columns in the 311 logs that give specific information about the nature of the inquiry or complaint: department, division, and type. For example, if someone calls to complain that their garbage was not picked up as scheduled, the entry in the 311 log will indicate that the department is 'Solid Waste Management', the division is 'Collections' and the type is 'Missed

Garbage Pickup'. During the two-year span under study, requests were directed to 17

unique departments and 31 divisions, and they were categorized as 159 different

types. This level of specificity is important, because it allows for a significant level of

control when determining which categories of 311 requests are relevant for the

analysis.

In addition to the dependent variables, variables were included in the analysis

in order to control for demographic, neighborhood and spatial conditions that would

impact the volume of 311 requests that were placed. These variables came from a

variety of data sources as outlined in Table 4.2.

Table 4.2: Independent Variable Overview and Sources

Category	Description	Source
Socio-economic	Median income	American Community Survey (ACS)
	% Below Poverty Line	ACS
	% Limited English	ACS
	% 65 years and over	ACS
	Total households	ACS
Investment	% Owner occupied	ACS
	% With children under 18	ACS
Spatial	Distance from city center	TIGER/Line
	Population density	TIGER/Line, ACS
	Queen's contiguity lag of dependent variable	TIGER/Line, Houston 311

Selection of the variables was guided by the literature on 311 requests that

was discussed above. These included socio-economic variables such median income,

population size, racial demographics, education level, and age. The literature also

suggested that certain characteristics like having children or being a homeowner

rather than a renter impacted the level of investment that people have in their neighborhood, thereby influencing the frequency of their requests, so these characteristics were also included in the analysis. Population density and ZCTA area could impact the likelihood that problems are noticed and reported in, so those were considered for inclusion as well.

4.3 *Methods*

4.3.1 Analysis 1: Neighborhood Characteristics Determining 311 Request Volume

The dependent variable used in this analysis is a count of the total number of 311 requests within a given category per ZCTA in a specified time frame. As is often the case with count variables, it is skewed and over dispersed, meaning that the conditional variance is greater than the conditional mean. As a result, the negative binomial regression is the most appropriate model for this analysis. The negative binomial regression is a generalized version of the Poisson regression that includes a dispersion term to account for the fact that the data does not meet the Poisson assumption of equality between mean and variance. It has been used in the literature for estimations involving 311 requests (Levine & Gershenson, 2014; Wheeler, 2017).

Requests were grouped together to form a ZCTA-level count that was used as the dependent variable. In this analysis I am assessing the volume of requests made to 311 services under normal conditions, and as a result, the dependent variable was designed to be analogous to the government services measure that Minkoff developed to analyze 311 requests in New York (Minkoff, 2016). This will be used to analyze the way that the 311 services are used by different Houston ZCTAs under normal

circumstances, seeking to identify the neighborhood characteristics that influence

contact volume.

Table 4.3: Government Services Requests: January 1, 2016 - August 20, 2017

Department	Division	Type	Freq.
Public Works Engineering	Public Utilities	Fire Hydrant	4,680
		Water Leak	45,223
		Water Main Valve	7,632
		Water Quality	4,657
		Water Service	23,029
Solid Waste Management	Collections	Container Problem	47,692
		Missed Garbage Pickup	45,708
		Missed Heavy Trash Pickup	14,265
	Recycling	Missed Recycling Pickup	20,556
		Recycling Cart Repair or Replace	12,602

The variable includes types of requests that are related to government services

that can be expected to cause problems evenly across neighborhoods (see Table 4.3).

Requests related to problems that are caused by direct actions, like nuisance

complaints or graffiti were excluded, as were requests requesting services like yard

waste pickup, as these would be more prevalent in suburban neighborhoods where

most residents have yards. Requests about road conditions were also excluded, as

those are more likely to have been made by non-residents, and also would be more

prevalent in neighborhoods with more through-traffic. This approach to aggregating

the requests helps to manage the 'condition problem' that was described above; it can

be assumed that the conditions prompting the complaints arise at a roughly equal rate

across neighborhoods, then differences in call volume must be explained by other

neighborhood characteristics.

In addition, a second 311 call count variable was created that included nuisance complaints or requests about problems that are hypothesized to arise more frequently in lower-income neighborhoods (Table 4.4).

Table 4.4: Nuisance Call Categories

Department	Division	Type	Freq.
Neighborhood Services	Investigations	Nuisance on Property	23,762
		Junk Motor Vehicle	3528
Public Works Engineering	PDS Planning Development Services	Multifamily Habitability Violation	3909
Various	Various	Graffiti	1,017

The ZCTAs were then divided into income-based quartiles in order to compare the proportion of government services, nuisance, and other complaints made in the lowest income quartile ZCTAs and the highest income quartile (Table 4.5). As predicted, the proportion of nuisance complaints is significantly higher in the lowest income ZCTAs, and the proportion of uncategorized requests is higher in the highest income ZCTA. Due to the large sample size, the proportional difference between the volume of government services requests in the first and fourth quartile ZCTAs is significantly different, they are nonetheless quite similar, at 28.24% vs. 29.59% respectively. This adds credibility to the claim that the government services variable is an appropriate tool with which to analyze citizen engagement at the ZCTA level across Houston.

Table 4.5: Call Volume by Category

	Income Quartile 1		Income Quartile 4	
	Total	Percentage	Total	Percentage
Government Services	42,249	28.24	17,807	29.59
Nuisance	18,706	12.5	3,149	5.23
Other	88,670	59.26	39,230	65.18

Given that the data takes the form of a count and has a right-skew, I

considered both negative binomial regression models and ordinary least squared

regression models in order to perform the analysis. The econometric specifications of

the negative binomial and regression models respectively are as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \qquad (1)$$
$$sqrt(Y_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \qquad (2)$$

Where Y_i is the count of government services requests in ZCTA i within the

previously defined time period. For the OLS regression model, a square root

transformation of the count variable was used in order to better fit the data to the

model.

Table 4.6: Socio-economic covariates

Variable	Year	Description
Poverty	2016 (5-year estimate)	Percent below poverty level; Estimate; Population for whom poverty status is determined
Median income	2016 (5-year estimate)	Median income (dollars); Estimate; Households
Limited English	2016 (5-year estimate)	Percent limited English-speaking households; Estimate; All Households
Aged 65+	2016 (5-year estimate)	Percent of population over 65; Estimate

X_1 represents population characteristics within ZCTA i and includes both total

number of households and population density. X_2 represents the socio-economic

variables of interest in ZCTA i, which are outlined in Table 4.6. The models were run

separately using median ZCTA income and percent below the poverty level. The

other socio-economic covariates were included every time the model was run. Several

other socio-economic variables were considered for inclusion into the model, but due

to a lack of significance and/or strong correlation with existing covariates, they were

omitted from the final models.

X_3 represents covariates that were designed to represent the level of

investment that residents within ZCTA i will have in the long-term maintenance and

upkeep of their communities, and the spatial characteristics of their neighborhoods.

These variables are outlined in and were informed by the literature on 311 requests

that was described above. The possibility of including the percent of households that

were owner occupied into the model was also considered, but it was very strongly

correlated with the percent of households that are single units, so it was omitted from

the model. Similarly, household median tenure was considered, but it was so strongly

correlated the percent of single units, that it was omitted from the final model. A

measure for distance from city center was included because more central

neighborhoods are more likely to experience higher levels of thorough-traffic.

Table 4.7: Investment in neighborhood covariates

Variable	Year	Description
Households with children	2016 (5-year estimate)	Percent; estimate; households with own children of the householder under 18 years
Single units	2016 (5-year estimate)	Percent; estimate; households with one unit in structure
Distance from city center	n/a	Distance between a given ZCTA's centroid and Houston's centroid, calculated in QGIS

Finally, both models include a spatial lag of the dependent variable Y. Spatial autocorrelation is a potential problem in any model that uses geographic spaces as units of analysis, and the literature indicates that spatial autocorrelation is often a factor when conducting an analysis using 311 requests. Similarities tend to be geographically clustered, meaning that the variables of interest in one ZCTA may be influenced by other ZCTAs in its proximity. This violates assumptions of independence. Moran's I tests were performed on the service call count in order to test for spatial autocorrelation. This test confirmed that the dependent variable was positively and significantly spatially autocorrelated, so a spatial lag of the dependent variable was created using a first order queen's contiguity matrix, following the same methodology as was described in Chapter 3.

Table 4.8: Moran's I Test for Government Services Requests

	Normal Approximation	Randomization
Moran's I	0.4118	0.4118
Mean	-0.0106	-0.0106
Std. deviation	0.0610	0.0612
Z-score	6.9230	6.8973
P-value	0.0000	0.0000

However, at times spatial lags can have such a strong relationship with the dependent variable that they mask the significant impacts of the other covariates, particularly if the covariates are also spatially auto correlated. As a result, the models are all also run without the spatial lags in order to compare results (Minkoff, 2016).

4.4 Results

4.4.1 Analysis 1: Neighborhood Characteristics Determining Call Volume

Descriptive Statistics

Of the 95 Houston ZCTAs included in the analysis, the minimum number of government services requests placed during the established time period is 3, and the maximum is 7831. The mean number of government services requests at the ZCTA level within the period of study was 2703, and the median was 2550. The data has a skewness statistic of 0.4169, confirming that the data is right skewed, and the variance of 4417670 means that it is over dispersed, thereby fulfilling the characteristics of a dataset that is best modeled using a negative binomial regression model. A histogram of the data distribution further confirms that the data takes the appropriate shape for this model (Figure 4.1). However, the skew is clearly less dramatic than in some count data sets, which is why a square root transformation of the dependent variable was able to make this dataset fit into a standard OLS regression model.
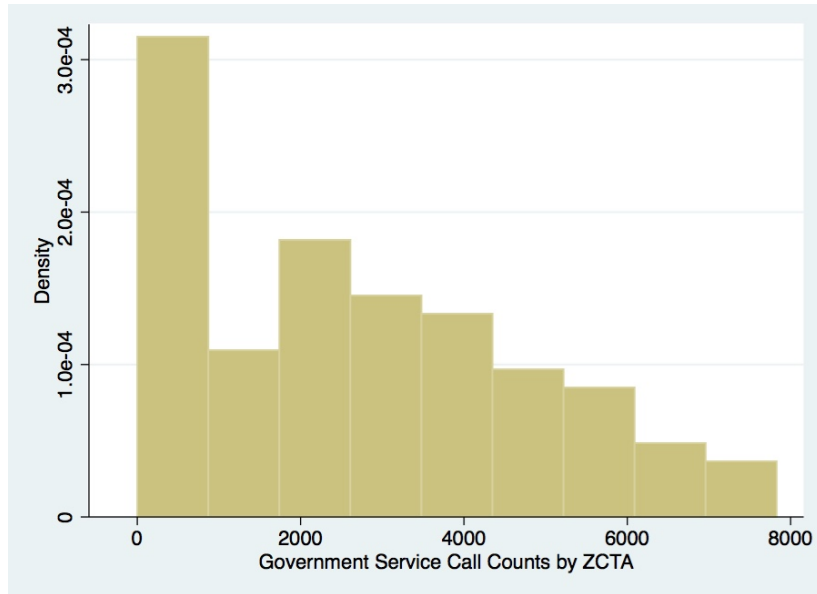
Figure 4.1: Government Services Requests by ZCTA

A series of maps were produced in order to visualize and better understand the way that 311 call volume and socio-economic status were distributed throughout the city. All maps only include the ZCTAs for which 311 call data was available. As can be seen in Figure 4.2 and Figure 4.3, government service call counts are distributed in similar ways throughout the city of Houston, with call volume being concentrated in the center and south-east of the city. When compared to the distribution of median income within the City of Houston (Figure 4.4), there appears to be a higher volume of government service 311 requests being placed in the regions of the city with lower median incomes.

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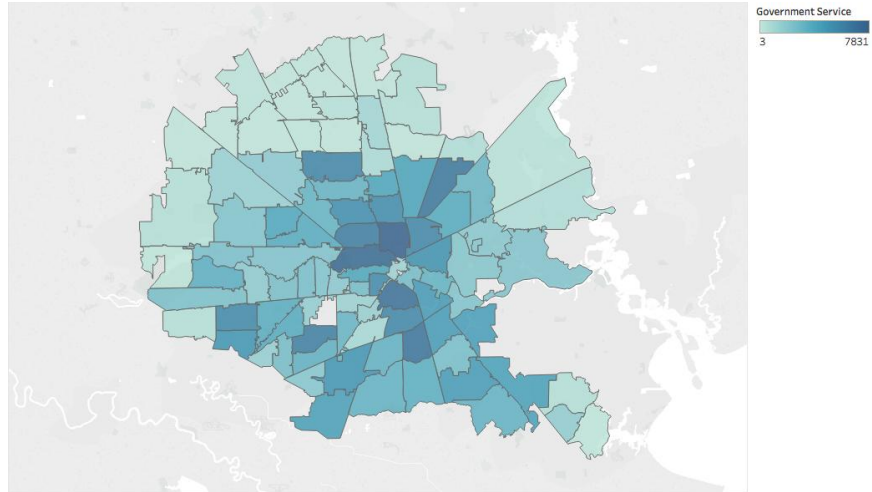
Figure 4.2: Distribution of Government Services Requests
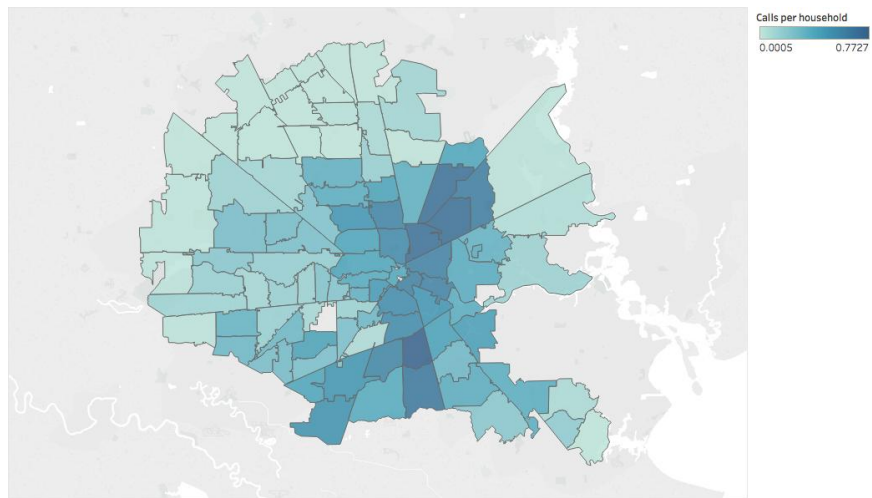
Figure 4.3: Distribution of Government Services Requests per Household

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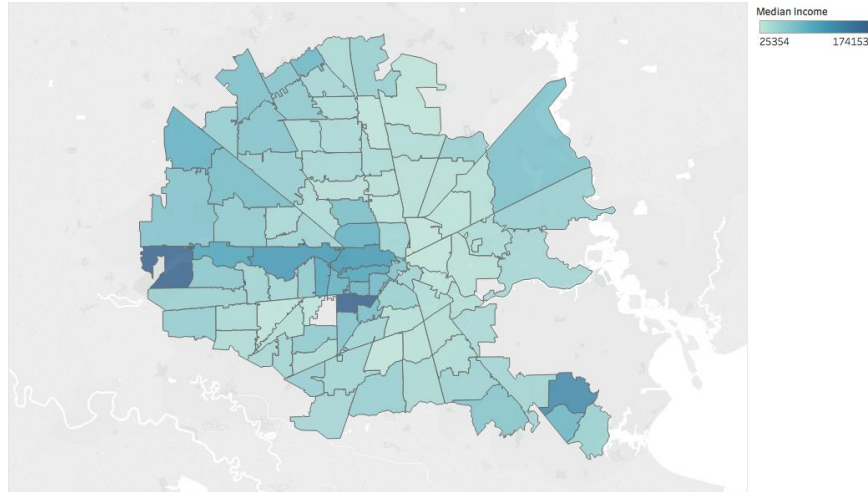
Figure 4.4: Distribution of Median Income

In the methods section above, it was noted that the distribution of call type varied across ZCTAs depending on their income. Income also had a statistically significant impact on the channel by which ZCTAs are most likely to make contact with the 311 services. Table 4.9 shows that lower income ZCTAs are much more likely to contact 311 services by voice calls (89.22% vs. 78.11%). However, the data does not distinguish between mobile and land line callers. In contrast, higher income ZCTAs were much more likely to make contact via the 311 website, whether on their smart phone (7.73% vs. 14.76%) or on a computer (2.55% vs. 6.32%).

	Income Quartile 1		Income Quartile 4	
	Total	Percentage	Total	Percentage
Face2Face	28	0.02	23	0.04
Fax	0	0	1	0
Mail	15	0.01	6	0.01
SMS	98	0.07	150	0.26
Voice	125,731	89.22	44,796	78.11
WAP	10,897	7.73	8,463	14.76
WEB	3,597	2.55	3,624	6.32
e-mail	562	0.4	289	0.5

Regression Analysis

Table 4.10 displays the results of the negative binomial regression models that seek to identify the neighborhood characteristics that influence the volume of government service related 311 requests at the ZCTA level within the city of Houston in 2016 and 2017 prior to Hurricane Harvey. As described above, these models control for socioeconomic variables, the level of investment in the neighborhood and population characteristics. They are all run both with and without spatial lags, because the literature indicates that the inclusion of a spatial lag can mute the impacts of other variables. The model was also run as an OLS regression using a square root lagged dependent variable, yielding very similar results.

The table shows that median income has a significant negative impact on the volume of government services requests made at the ZCTA level, both with and without weights. Similarly, the percent of households below the federal poverty level has a significant positive relationship with the number of 311 requests, with and without weights. The other socio-economic variables, percent of the population with

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limited English and percent of the population over the age of 65, had no significance

in any of the models.

Table 4.10: Determinants of Government Services 311 Call Volume (Model 1)

Total Households	0.00005391*	0.00003372	0.00006449*	0.00004088
	(-0.00002476)	(-0.00002646)	(-0.00002511)	(-0.00002754)
Population Density	273.65	329.38	238.1	266.99
	(-168.25)	(-187.01)	(-169.8)	(-195.4)
Median Income	-0.00001340**	-0.00001877***		
	(-0.00000479)	(-0.000004856)		
Percent Limited English	-0.02018	-0.03172	-0.0202	-0.02916
	(-0.01567)	(-0.01653)	(-0.01621)	(-0.01773)
Percent Over 65	2.5209	-0.1175	2.6598	-0.3419
	(-3.9336)	(-4.0815)	(-4.0257)	(-4.3398)
Percent With Children	0.01215	0.01163	0.007089	0.007287
	(-0.02054)	(-0.02249)	(-0.02158)	(-0.02425)
Percent Single Units	0.01583*	0.02164**	0.01512*	0.01933*
	(-0.006989)	(-0.00772)	(-0.007102)	(-0.008152)
Distance from City Center	-0.00004389*	-0.00008036***	-0.00003101	-0.00006604**
	(-0.0000201)	(0.00001974)	(-0.00002079)	(-0.00002204)
W_y	0.0004441***		0.0004905***	
	(-0.0001018)		(-0.00009997)	
Percent Below Poverty			0.03671*	0.04609**
			(-0.01527)	(-0.01713)
Constant	5.4060***	7.8369***	3.7173***	5.9477***
	(-0.9207)	(-0.792)	(-0.9484)	(-0.9113)
Log Alpha	-0.09432	0.04907	-0.08521	0.08999
	(-0.1302)	(-0.1282)	(-0.1301)	(-0.1277)
Observations	95	95	95	95
Pseudo R2	0.03162	0.02141	0.03099	0.01843

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Total number of households had a significant relationship with the call

volume in the weighted models only, and population density had no significance.

When the spatial lag is omitted, all models indicate that the percent of households

with children has a significant, negative impact on volume of 311 government service requests. The percent of households in single unit dwellings has a significant positive relationship with request volume across all models.

4.5 Discussion

4.5.1 Government Services Requests

This analysis finds that household income has a significant impact on the volume of government service requests being placed at the ZCTA level. Median income has a significant negative relationship with the volume of requests, meaning that as the median income decreases the number of requests placed within a ZCTA increased. Similarly, there is a significant positive relationship between the percent of a ZCTA below the poverty line and the number of government services 311 requests, which means that as the number of households living in poverty increases, the number of 311 requests also increases. These findings were surprising. The literature generally suggests that high-income neighborhoods are more likely to use 311 services, but this was not the case in Houston.

One possible explanation for this phenomenon is that the 311 system can be seen as the worst available option for contacting the city and advocating on behalf of a neighborhood. Wealthier neighborhoods may have more bridging social capital and as a result are better connected to local government, providing them with more efficient channels by which to lodge complaints. In contrast, perhaps low-income neighborhoods are less likely to have other means by which to contact the city, and as a result resort to 311 requests. However, it is also possible despite best efforts to only

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include requests in the government service category about problems that would be evenly distributed across the city, there remains some spatial and socio-economic bias, and the problems about which callers are complaining arise more frequently in lower income neighborhoods. Rather than an increased proclivity to call, there may be a governance deficit that requires these low income ZCTAs to log complaints with greater frequency.

The other socio-economic variables that were included in the analysis, percent of population with limited English and percent of population over the age of 65, did not have a significant relationship with the total number of government services requests, and several other socio-economic variables were also tested, found to lack significance, and omitted from the final models. It was expected that larger proportions of the population with limited English might hinder the use of 311, however this was not found to be the case. This is likely because even in low English speaking ZCTAs, this subgroup accounted for a relatively small proportion of the total population. Additionally, 311 services are also offered Spanish, which is the second most commonly spoken language in the Houston area, so most of the limited English households were still able to communicate with 311 services.

As expected, a positive and significant relationship was observed between the percentage of single housing units and the volume of 311 government services requests in the ZCTA. This is in large part because people residing in single units will deal more directly with failures in day-to-day government services like garbage pickup. In addition, the literature suggests that people who own their homes rather

than rent are more invested in the well-being of their neighborhoods and therefore are more likely to complain about neighborhood problems. The percent of the housing stock that is single units is very strong correlated with the percentage of owner-occupied units in a ZCTA, so it this variable is also picking up the effects of being in a ZCTA where more people own rather than rent. It was expected that people with children would be similarly invested in their neighborhood, and that this may spark increased call volume, but the model results did not find any such effects.

City centers tend to have the largest flow of people, and because 311 complaints about a given ZCTA are not necessarily made by people within that ZCTA, it is likely that areas that are visited by more non-residents will have more 311 complaints. This is confirmed by the fact that there is a significant negative relationship between distance from city center and the volume of 311 government services requests in three of the four models. This suggests that as the distance between a ZCTA's centroid and the city center increases, the number of 311 requests will decrease.

4.5.2 Research Implications

This analysis began with the hope of finding that 311 call volume would be an effective quantitative proxy for social capital, based on the fact that other measures of civic engagement are regularly used in this context. However, the results indicate that in the city of Houston, ZCTAs that contact 311 more frequently do not necessarily have the neighborhood characteristics that are typically associated with social capital such as socio-economic advantage. However, although it cannot be confidently

claimed that 311 requests are an accurate proxy for the generally accepted definition

of bridging social capital, it is nonetheless an interesting measure for citizen

engagement with local government.

311 services provide residents with a way of seeking information from the

local government and lodging complaints even if they do not have social connections

to people in power. This could credibly be a tool that helps communities to recover

following disasters, which will be explored in the following chapter by analyzing 311

contact patterns across Houston following Hurricane Harvey.

5. Post-Hurricane Recovery and Civic Engagement

This paper investigates the way that communities engage with their local government following major shocks by analyzing 311 requests for municipal services in Houston Texas during and after Hurricane Harvey struck the city in August 2017. Given the conclusions reached in the previous chapter about the way that 311 requests function during normal circumstances, several hypotheses can be drawn about the way that they might function during disasters and recovery.

311 requests serve two functions that are useful in the recovery process. First, they act as a mechanism for transmitting information from the local government to citizens. During times when internet and cellular data may not be functioning, 311 lines are a vital way of connecting people to the services and information that they need during and after a natural disaster. Second, 311 requests are a way for citizens to convey information and requests to the local government. By providing an easy and low-cost way for residents to alert the government about storm damage, citizens are able to act as the government's eyes and ears after a storm, and quickly alert the government to problems that require its attention. This has the potential to substantially speed up the recovery process because it increases the effectiveness and efficiency of problem identification.

As a result, there is expected to be a benefit associated with the act of contacting the government following a disaster, and that benefit should materialize in the form of a faster and more efficient recovery process. The review of the literature, as well as findings from the previous chapters, indicates that different neighborhoods

and different groups of people will tend to contact 311 services at different rates. If this holds true in disaster contexts, we may hypothesize that differences in 311 contact frequency may play a part in explaining why different communities experience different recovery outcomes.

This hypothesis builds on the literature that identifies social capital as a determinant of disaster recovery outcomes. The primary way that social capital is thought to contribute to recovery is by enabling communities to organize and advocate for themselves in the aftermath of a disaster. For example, in Consoer's study of the role of social capital in Vermont after Tropical Storm Irene the organization of informal 'recovery groups' was driven by social capital in some, though not all communities impacted by the storm. These communities enjoyed "proliferating social capital and access to high value resources" (Consoer & Milman, 2016b). Simply put, social capital helped communities to more easily connect with and communicate their needs to authorities, thereby improving their ability to advocate and engage.

Although social capital is shown to be a powerful force in the recovery process, it consistently favors those who are wealthy and well-connected, thereby leaving behind those who lack powerful social networks and potentially making them even worse off (Aldrich, 2012b). Research also indicates those who are less wealthy, educated and well-connected are less likely to receive government assistance during the recovery process because they likely to be less aware of the available programs and less capable of navigating the bureaucratic systems necessary in order to obtain

government-issued aid (Fothergill & Peek, 2004b). If properly operationalized, managed and promoted, 311 services could be a way to reduce these inequalities. It gives citizens a low-cost and low-effort way of communicating their needs to local authorities. It is also a way to inform people about the assistance programs for which they are qualified and help them navigate the red tape required to secure the aid.

This chapter will begin by providing an overview of Hurricane Harvey and Houston's recovery process, and then will go on to review the literature on the use of 311 requests during natural disasters. The analysis that follows builds upon the work done in the previous chapter by continuing to use 311 call data from Houston, TX, but shifting to consider the city's 311 use in the aftermath of Hurricane Harvey in 2017, linking these findings to the literature on social capital and recovery. I will then focus on the way that community characteristics impact recovery and government interaction over time, focusing on changing weekly volume of storm-related requests.

This analysis examines recovery at multiple time scales, first looking at 311 call volume in the first six weeks following Hurricane Harvey, and then widening the focus to the full breadth of storm-related 311 requests that were made over a 20-week period. Meanwhile, the dimensional focus includes the recovery of many different systems, because the 311 requests under study relate to different types of infrastructure and city services. Overall, the analysis seeks to determine the community characteristics of 311 use related to a natural disaster, while answering the questions: do communities that experienced more storm-related damages log more storm-related 311 requests? And do communities that placed a larger volume of

requests in the two weeks immediately following Hurricane Harvey tend to see their call volume reduce more quickly? Or more generally: does calling 311 services actually have an impact on the speed at which a community recovers?

5.1 *Hurricane Harvey*

Hurricane Harvey initially formed as a tropical storm over the Atlantic Ocean on August 17, 2017. It built up to hurricane strength over the Gulf of Mexico on August 24, and it reached Category 4 strength just before making landfall on the Texas coast near Corpus Christ on August 25. Hurricane Harvey moved inland very slowly and was almost stationary over South Eastern Texas for four days before moving back into the Gulf of Mexico and making second landfall in Louisiana on August 30th (Blake & Zelinsky, 2018). In anticipation of the Hurricane making landfall, Texas Governor Greg Abbott declared a State of Disaster for 30 counties in the state, and the US President approved a major disaster declaration for the State of Texas on August 25th, at the Governor's request.

Harvey would have been considered a strong and damaging hurricane just on the basis of its size and high winds. 52 tornadoes were reported during the storm, 36 of which occurred in and near the Houston metro area. Maximum sustained winds of 132 mph occurred just prior to the storm's first Texas landfall. Highest observed sustained winds were 110 mph near Aransas Pass just outside of Corpus Christi where the storm first made landfall and highest observed gusts were 146 mph nearby in Rockport, TX (Blake & Zelinsky, 2018). However, water is what made Hurricane Harvey an unprecedented disaster. Hurricane Harvey caused extreme flooding in

Houston and its surrounding areas (Van-Olderborgh et al., 2017). An estimated total of 33 trillion gallons of rain fell on Texas and Louisiana during the hurricane. Since reliable rainfall records became available in the 1880s, Hurricane Harvey is unmatched in United States history in terms of both scope and peak rainfall. (Blake & Zelinsky, 2018).

Storm surges were also significant. In eastern Houston, a tide gauge indicated that the peak water level was 10.5 feet mean higher high water (MHHW), but this figure was inflated by extreme rainfall runoff, so while it certainly paints of picture of the extreme flooding, it cannot be considered as an accurate storm surge measurement. United States Geological Survey sensor data indicated that the highest surges were 8-10 feet above ground level in the Port Aransasa and Matagorda areas (Blake & Zelinsky, 2018).

Hurricane Harvey's recorded-breaking flooding caused catastrophic damage throughout Texas and Louisiana, with the most severe impacts concentrated in South-Eastern Texas, including Harris County, which houses the Houston Metro area. When flooding was at its peak, it is estimated that 25-30% of Harris County was underwater. Over 300,000 structures and 500,000 cars were reported flooded, and 336,000 customers lost power because of the hurricane. Much of the flooding during the hurricane was caused by torrential rains rather than storm surges and flooding rivers, so the majority of residential flooding occurred outside of the 500-year flood plain. These areas have much lower participation in the National Flood Insurance

Program due to the lower perceived risk. As a result, only 17% of affected residents had flood insurance (Shultz JM & Galea S, 2017).

NOAA estimates that Hurricane Harvey caused $125 billion in damages, with a 90% confidence interval of $90 billion to $160 billion. This means that the hurricane will likely be the second most expensive hurricane in United States history after Hurricane Katrina, which caused $161.3 billion in 2017 dollars. FEMA has indicated that an estimated 13 million people were directly affected by the storm, which was responsible for at least 68 direct deaths in the United States, all of which occurred in Texas. This makes Hurricane Harvey the deadliest Hurricane in the United States in terms of direct deaths[3] since Hurricane Sandy in 2012, and the deadliest hurricane in Texas since the 1919 Florida Keys Hurricane. All but three of the hurricane's attributed direct deaths were the result of freshwater flooding. A further 35 deaths have been attributed indirectly to the hurricane, although attribution of indirect deaths is quite speculative and typically underestimated. 40,000 total people were evacuated and among them, 22,000 were rescued from floodwaters and 32,000 were temporarily housed in emergency shelters. Nearly 894,000 people applied for FEMA aid following Hurricane Harvey (Lozano, Juan, 2017), which is almost double the 450,000 applicants that FEMA predicted would apply (Blake & Zelinsky, 2018).

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[3] Direct deaths refer to deaths that were caused as a direct result of the storm, such as death by drowning, high winds or lightning strike. This count does not include deaths that are caused by by-products of the storm, such as downed power lines, a lack of access to medical care, or car accidents from sub-optimal road conditions.

5.1.1 <u>Response and Recovery</u>

In the weeks that followed Hurricane Harvey, the general consensus was that the hurricane response was relatively well managed, and that political officials managed to avoid the major mistakes that the public has come to associated with other recent storms like Hurricane Katrina (Wallace, 2017). The Kaiser Family Foundation conducted two surveys of people living in the 24 Texas Counties most heavily impacted by the Hurricane, one in October and November 2017, about three months following the Hurricane and a follow-up survey in June and July 2018, almost one year after the storm hit the region. The surveys investigate how residents are coping, how they perceive the recovery process, and to what extent the hurricane has and/or continues to disrupt their lives. Taken together, these surveys give important insight about the successes and failures of the recovery process to this point, as well as the areas that require more attention as the region moves into the phase of long-term recovery (Hamel et al., 2018).

One year after the hurricane, 58% of residents reported that they had been affected by Hurricane Harvey, which the survey defines as having "incurred damage to their home or vehicle, or that they or someone in their household lost a job, had hours cut back at work or experienced some other loss of income as a result of Harvey". Among the affected residents, 70% reported that their lives were "largely" or "almost" back to normal in the June-July 2018 survey. This is an increase from 56% who reported a return to normalcy in the October-November 2017 survey. However, nearly a year after the storm 21% of affected residents reported that they

were "still somewhat disrupted" and 9% report being "still very disrupted". Black and low-income residents reported ongoing disruption in higher numbers. Further, 8% of respondents to this survey indicated that they had evacuated their home during the storm and that their displacement continued at the time they were surveyed. When those who reported that their lives were still being disrupted by the hurricane were asked what they needed most in order to solve their problems, the most common answers were house and property repairs and financial assistance (Hamel et al., 2018).

In Harris County, which is the focus of this analysis, 37% of residents reported that their place of residence had sustained damage as a result of the storm. Within that group, 4% reported that their home was destroyed, 15% reported major damage and 19% reported that there was minor damage. Of this 37%, 14% reported that their home was "still in an unlivable condition". 20% of respondents who reported home damage in this region felt as though the place where they were currently living was not safe. In total, the study indicates that 8% of Harris County residents did not return to their pre-Hurricane home following the storm, which is the most accurate data currently available on Hurricane Harvey displacement, because FEMA does not maintain a count of how many Texans are still without permanent homes following the storm (Hamel et al., 2018).

67% of residents who were still displaced due to Hurricane Harvey indicated that they were not getting the help that they needed to recover. 53% said that they needed more help "apply[ing] for disaster assistance", 45% said they needed help

"finding someone to help navigate the different systems for receiving help", 42% indicated that they needed help "finding affordable permanent housing" and 28% said they needed help getting legal assistance. Many of these services are offered to the public; the FEMA helpline is designed to assist disaster victims in navigating aid systems and the government offers disaster legal services. The survey did not, however, indicate whether the problem is that those affected by Hurricane Harvey are unaware of these programs, or if they attempted to use them and did not find that they met their needs (Hamel et al., 2018).

The survey did specifically ask affected residents about whether they had applied for disaster assistance through FEMA or the US Small Business Administration, and 41% indicated that they had submitted applications. Of those who applied, 39% were approved for assistance and 42% were denied. In addition, 28% of affected residents received financial assistance from a charitable organization. Although low-income individuals were among the most likely to have received financial assistance following Hurricane Harvey, they were also the most likely to report that the amount of assistance was insufficient, with focus group participants indicating that FEMA repair estimates were very out of touch with real material and labor costs (Hamel et al., 2018).

5.1.2 311 Services During and After Emergencies and Disasters

Before, during and after a disaster, residents understandably have many questions about the status of relief efforts that are not appropriate for emergency services, which will likely be overwhelmed with more urgent requests and calls for

assistance. Further, it is to the government's benefit to maintain a line of communication with citizens during disasters because it gives them on the ground information about where services are most needed. 311 requests provide local governments with a mechanism for accessing information and providing non-emergency assistance. During hurricanes, 311 call volumes are observed to increase substantially from normal use. For example, during Hurricane Wilma in 2015, 311 use in Miami increased by 636%. Volume peaked the day after the storm when 24,000 requests were logged; a 1200% increase from the daily average (Schellong & Langenberg, 2007). Similarly high volumes have been linked to hurricanes in other cities as well, such as New York City during Hurricane Sandy (Wiseman, 2014) and Hampton during Hurricane Isabel (Fleming, 2008).

Soon after New York City launched their 311 services in 2003, the Northeastern United States experienced a major blackout. Although the internet and cell phones were without service, landline telephones remained functional, making the 311 lines one of the few sources of information available to New Yorkers until power was restored. It proved to be an incredibly valuable service. For example, it was reported that many calls were received from diabetics who were inquiring about whether their insulin was safe to use without refrigeration. Not only were the 311 operators able to get this information and relay it to the callers, but they also passed it on to the media so that it could be widely disseminated via radio throughout the city (Wiseman, 2014). Wiseman also notes that 311 lines can be helpful when local governments are seeking FEMA assistance. FEMA offers financial assistance to local

governments that declare a state of emergency, but in order for the assistance to be approved FEMA requires specific information about the location and severity of the damage. Chicago used 311 flood complaints as a data source that was submitted to the agency following flooding in the city, which helped them to efficiently and quickly secure recovery assistance.

In September 2017, a report was published that specifically analyzed 311 calls in New York City that were related to Hurricane Sandy, using these calls as a proxy for recovery within the city. Between when the storm hit the city in late October 2012 through to when the article was published almost five years later, over 80,000 calls had been placed that were directly related to the storm. The contact volume peaked at over 8000 on October 29 when the storm hit the city, and thousands more came in the following weeks. However, the calls persisted much longer than would have been expected; in 2017, 311 operators received almost 150 calls related to Hurricane Sandy (Wolfe & Roeder, 2017).

5.2 *Data*

The analyses in this paper use 311 data from the city of Houston Texas to build the dependent variables. This data was described in detail in the previous chapter. The spatial unit of analysis for this paper is Census ZIP Code Tabulation Area (ZCTA), and individual requests were assigned to their corresponding ZCTA by mapping their reported longitudes and latitudes in QGIS (QGIS Development Team, 2018), and then tagging each request with the ZCTA in which it is located, using the Census Bureau's 2010 ZCTA shapefile.

Although the majority of the 311 logs included a ZIP Code in the address column, this was not always the case, because some requests were linked to intersections rather than home addresses. However, nearly all of the logs included spatial information about the site of the complaint in the form of latitude and longitudinal coordinates. The coordinates were mapped and joined them to the Census Bureau's 2010 ZCTA shapefile.

In addition to the 311 data used to construct the dependent variables in the analysis, variables were included in order to control for demographic, spatial and meteorological conditions that would have impacted the volume of requests that were placed after Hurricane Harvey. These variables came from a variety of data sources as outlined in Table 4.2.

Table 5.1: Independent Variable Overview and Sources

Category	Description	Source	Use
Socio-economic	Median income	American Community Survey (ACS)	2,3
	% Below Poverty Line	ACS	2,3
	Total households	ACS	1
	Population density	TIGER/Line, ACS	1
	Queen's contiguity lag of dependent variable	TIGER/Line, Houston 311	1,2,3
Impact	Individual assistance payouts	FEMA	1,2,3
	FEMA assessed building damage	FEMA	1,2,3
	FEMA assessed building damage	FEMA	1,2,3
Other	Pre-storm government services requests	Houston 311 Logs	1,2
	% change in average daily government services requests	Houston 311 Logs	1
	Storm-related requests (August 23 – October 6)	Houston 311 Logs	3

5.3 Methods

5.3.1 Analysis 1: Storm-related Requests Following Hurricane Harvey

The first analysis uses a dependent variable that was constructed to include 311 requests that are specifically related to hurricane-related concerns. This was designed in order to focus on the way that ZCTAs used the 311 services during and after Hurricane Harvey to seek out information or to alert local government officials to problems. These categories are not unique to Hurricane Harvey, and appeared infrequently in the logs prior to the storm, but for the purposes of this analysis they are only being included in the dependent variable if the contact occurred immediately prior to, during or after the hurricane, which hit Houston on August 25, 2017. In order to establish that these categories were appropriate, t-tests were performed in order to test whether the average number of daily requests about these concerns was significantly higher in the period following Hurricane Harvey than it was before.

Table 5.2: Storm-Related Requests, August 23 - October 6, 2017

Department	Division	Type	Total
Emergency Management	Evacuation	Medical Evacuation	308
		Storm Damage	203
Housing Community Development	Disaster Recovery	Crisis Cleanup	1521
Parks and Recreation	Forestry	Storm Tree Removal	661
Public Works Engineering	Street and Drainage	Flooding	4416
Solid Waste Management	Collections	Storm Debris Collection	10432

Like the analysis performed on government services requests in the previous chapter, count data is used as the dependent variable. This data has a strong right-

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skew and is over dispersed. After testing multiple models and variable transformations for goodness of fit, it was clear the negative binomial regression model was the most appropriate option. The econometric specifications of the models are as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 W_{yi} + \varepsilon \tag{1}$$
$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \tag{2}$$
$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 W_{yi} + \varepsilon \tag{3}$$

Where Y is the count of storm-related 311 requests made in ZCTA i between the dates of August 23 and October 6, 2017.

X_1 represents the total number of households in ZCTA i, and X_2 represents covariates that estimate storm damages within ZCTA i in order to test whether ZCTAs that received the most damage made the most contact. Three different variables were introduced into the analysis to attempt to control for the amount of damage done by the storm in a given ZCTA: the amount of FEMA individual assistance issued to the ZCTA, and FEMA-assessed building damage counts of destroyed and affected buildings.

The building damage counts come from the FEMA Modeled Building Damage Assessment dataset. The information is generated by a model that used "building inventories and modeled flood depth grids to assess potential impacts and provide an estimate" of the damaged buildings (FEMA, 2017). The damages are categorized as affected, minimal damage, major damage, and destroyed, and each damaged building is categorized individually. This data was available as a shapefile, and QGIS was used to tag the individual buildings with the ZCTAs in which they

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were located in order to create count variables (QGIS Development Team, 2018). For the purposes of this analysis, minimal and major damages were grouped together to create a non-destroyed damages count variable, and destroyed buildings were counted separately.

X_3 is introduced into the model in equation 2 and 3. It represents the total number of government services requests made in a given ZCTA prior to the storm. This is the same measure as that which was used as the dependent variable in the previous chapter. This is included because it is likely that ZCTAs that used 311 more frequently prior to the storm will be more aware of and comfortable with the service, leading them to continue using it in higher volume when making storm-related complaints.

X_4 is introduced into the model in equation 3, and it represents the percent change in daily average government services requests, comparing the number of daily requests that were made in the period prior to the storm and the number of requests made in the period that followed. As discussed above, many homes in the Houston area were severely damaged or destroyed in Hurricane Harvey and as a result, many residents did not return to their prior residence immediately after the storm. Some did not return at all. This means that the storm caused a population decrease in some parts of the city, which can be expected to cause a decrease in 311 requests coming from these areas. This is potentially problematic, because one would expect that more severely storm-damaged ZCTAs would place more storm-related 311 requests as a response to the increased damage, but these effects may be muted or even cancelled

out entirely by a population decrease. In order to control for potential population changes, the model includes the percent change in daily government services requests between the six-week period under study and the same six weeks the previous year.

Table 5.3: Moran's I Test for Storm-related Requests

	Normal Approximation	Randomization
Moran's I	0.2582	0.2582
Mean	-0.0106	-0.0106
Std. deviation	0.0610	0.0562
Z-score	4.4051	4.7793
P-value	0.0000	0.0000

Finally, Models 3, 4 and 5 all include a spatial lag of the dependent variable Y. Spatial autocorrelation is a potential problem in any model that uses geographic spaces as units of analysis, and the literature indicates that spatial autocorrelation is often a factor when conducting an analysis using 311 requests (Minkoff, 2016). Similarities tend to be geographically clustered, meaning that the variables of interest in one ZCTA may be influenced by other ZCTAs in its proximity. This violates assumptions of independence. Moran's I tests were performed on the government services request count in order to test which confirmed that the dependent variable was positively and significantly spatially auto correlated (Table 5.3). To correct this, a spatial lag of the dependent variable was created using a first order queen's contiguity matrix.

5.3.2 <u>Analysis 2: Time for Storm-Related Requests to Subside.</u>

This analysis examines the time that it takes for a ZCTA to significantly reduce the volume of 311 requests placed about storm-related concerns. The

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dependent variable is constructed in a similar way to the recovery time variables in

Chapter 3, Analysis 2. Storm-related requests were with the same method as the

previous analysis and sorted at the ZCTA level by the date that the request was made.

The number of days after Hurricane Harvey on which the 50th, 75th and 95th percentile

of total storm-related requests occurred within the ZCTA was calculated, and these

were used as the dependent variables in this analysis.

Unlike the time to recovery data used in Chapter 3, this data has a relatively

normal distribution. An OLS regression is the most appropriate model for the

analysis. The model specifications are as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_3 + \varepsilon \qquad (4)$$

Where Y is the length of time in days before storm-related 311 requests have reduced

by a given threshold in ZCTA i. X_1 represents the socio-economic variable of

interest; both median income and percent of the population below poverty level are

used in the model separately. X_2 represents the log transformation of government

services requests made in the period of study between 2016 and 2017, prior to

Hurricane Harvey. Finally, X_3 represents the three damage measures that were

included in Analysis 1: total FEMA individual assistance compensation, total

destroyed buildings, and total damaged buildings. A spatial lag was not included in

this mode because testing indicated that spatial autocorrelation was not present.

5.3.3 Analysis 3: Relative Long-term Storm-Related Request Volume

Zobel proposes a quantitative approach to estimating non-linear recovery in a

way that incorporates the shape of the recovery curve and thereby the nature of the

recovery process. By first plotting the recovery over time, one can calculate the area under the recovery curve, and then generate the ratio of the area under the curve to the area of the plot as a whole. This calculation can be taken as a representation of the recovery process. Using this method, he analyzed power outages in New York City post-Hurricane Sandy, and his model produced a point estimate for the recovery behavior as a whole (Zobel, 2014). Although Zobel noted that any time a system's performance is condensed into a single measure, certain characteristics and unique features will be lost in the process, this is a tradeoff inherent to the process of quantifying complex processes and systems.

This method was utilized in order to study the persistence of 311 requests made about storm-related concerns following Hurricane Harvey. In order to construct the dependent variable, the 311 data were used to generate the number of storm-related requests made per week in a given ZCTA per week following the storm. Storm-related requests persisted until twenty weeks following Hurricane Harvey. ZCYA level curves were plotted using this data, and then an integral was taken to measure the area under each curve. Then a ratio was created by dividing the area under each curve by the maximum total area of the graph, which is the peak number of weekly requests within the ZCTA multiplied by 21, the total number of weeks under study. This ratio acts as the dependent variable for this analysis. Larger ratio values indicate that request volume persisted within the ZCTA, whereas smaller ratios mean that the request volume decreased more quickly following the peak volume.

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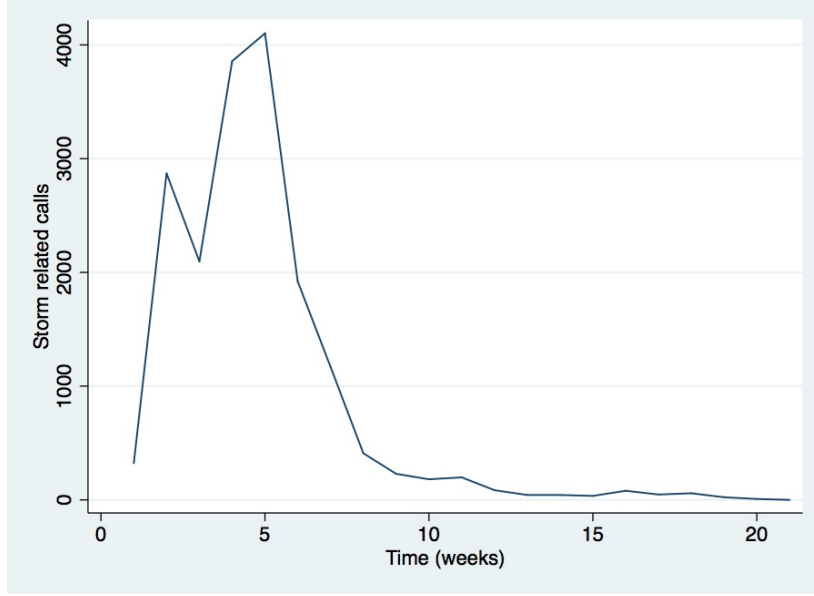
Figure 5.1: Storm-Related Requests Across Houston Over Time

As an illustrative example of the method used to construct the dependent variable, Figure 5.1 plots the number of storm-related requests across the entire Houston metro area per week. The peak request volume occurred in week 5, when a total of 4102 requests were placed, and they stopped entirely in week 21. Therefore, the total possible area of the graph is 4102*21 = 86412, and the integral of the curve is 17967.5. As a result, the curve ratio is 17967.5/86412, or 0.2079.

An OLS regression model is a good fit for this data, and the econometric specifications of the models are:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 W_{yi} + \varepsilon \tag{5}$$
$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 W_{yi} + \varepsilon \tag{6}$$
$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 W_{yi} + \varepsilon \tag{7}$$

Where Y represents the recovery ratio described above in ZCTA i. X_1 is the log transformed number of storm-related requests that was used as the dependent variable

for Analysis 1. X_2 represents the socio-economic variables of interest. Median income and percent below the poverty line were both used separately as potential variables in the model. Finally, X_4 represents the three damage-related covariates that were included in Analysis 2: FEMA individual compensation, total destroyed buildings and total damaged, non-destroyed buildings.

Table 5.4: Moran's I Test for Storm-Related Request Ratio

	Normal Approximation	Randomization
Moran's I	0.1806	0.1806
Mean	-00106	-0.0106
Std. deviation	0.0610	0.0610
Z-score	3.1343	3.1368
P-value	0.0017	0.0017

In addition, a Moran's I test was performed to test for spatial autocorrelation in the dependent variable in the model, and although it was not as highly correlated as was observed in Analysis 1 and Analysis 2, autocorrelation was still present. As a result, a spatial lag of the dependent variable was generated using a Queen's Contiguity Matrix and was included in all of the models.

5.4 Results

5.4.1 Analysis 1: Storm-related Requests Following Hurricane Harvey

Descriptive Statistics

The same 95 ZCTAs that were used in the analysis in the previous chapter were also included in this analysis. During the time period under study the total number of storm-related requests at the ZCTA level ranged from 0 to 1467. The mean number of requests was 162.39, and the median was 80. The data has a skewness

statistic of 3.3019, confirming that the data is right skewed, and the variance of

55721.18 means that it is over dispersed, thereby fulfilling the characteristics of a

dataset that is best modeled using a negative binomial regression model. A histogram

of the data distribution further confirms that the data takes the appropriate shape for

this model (Figure 5.2).
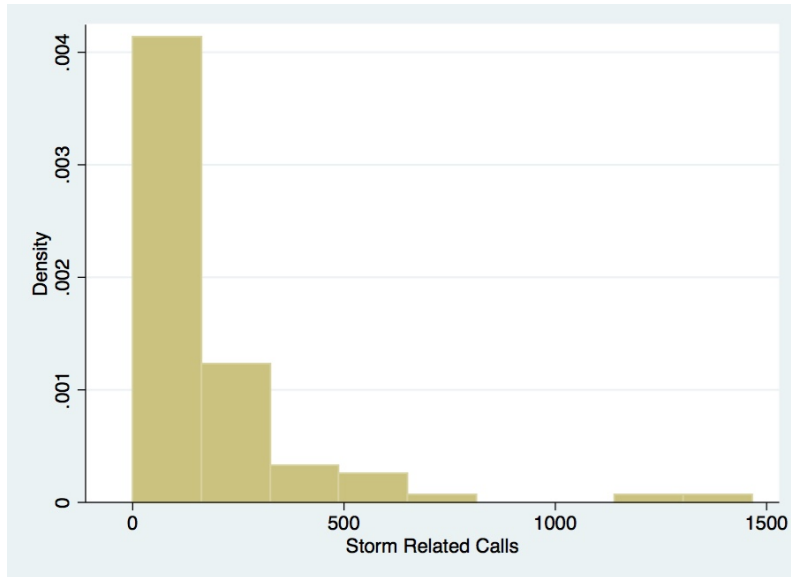
Figure 5.2: Storm-Related Requests by ZCTA, August 23 – October 6, 2017

A series of maps was produced in order to visualize and better understand the

way that 311 request volume, storm damage and FEMA compensation was

distributed across the city. All maps only include the ZCTAs for which 311 request

data is available. Figure 5.3 shows the distribution of storm-related 311 requests

across Houston between August 23 and October 6. As shown in the figure, high-

volume contacting neighborhoods are concentrated in the south-west quadrant of the

city. Similarly, Figure 5.4 shows the distribution of storm-related 311 requests per

household in the same time period. The distribution is very similar to the total number of requests.
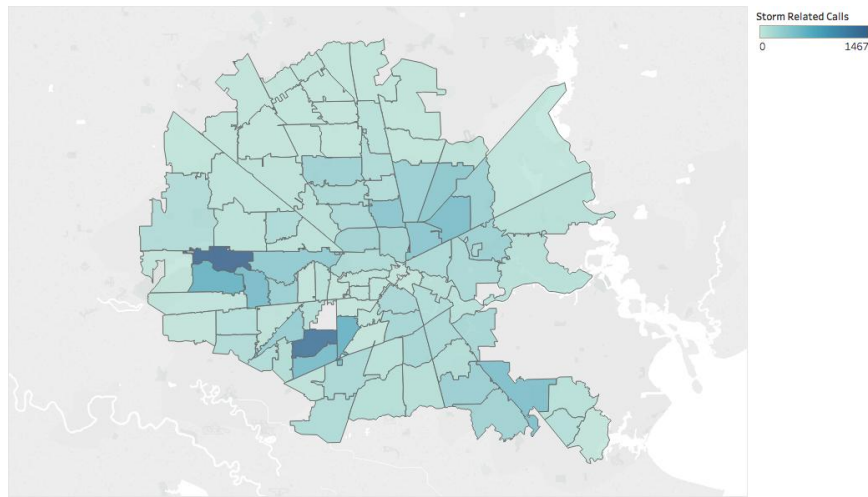
Figure 5.3: Distribution of Storm-Related Requests
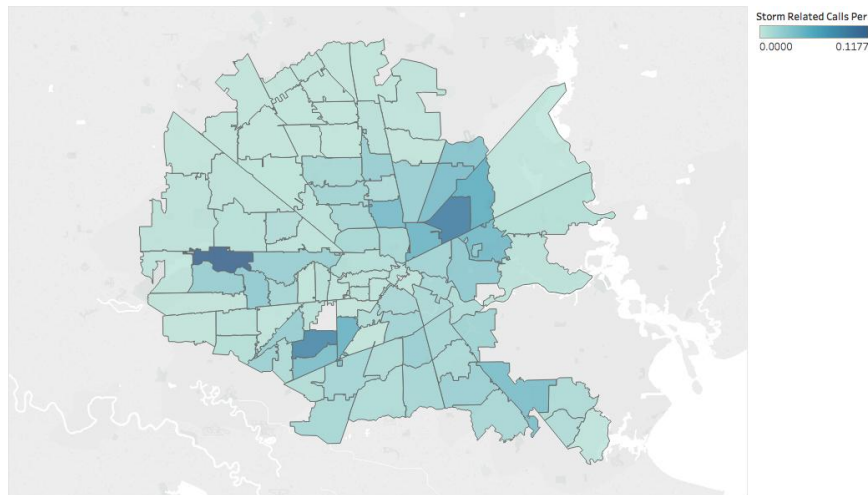
Figure 5.4: Distribution of Storm-Related Requests Per Household

Figure 5.5 shows the distribution of FEMA Individual Assistance payments across the City of Houston. Although there are some similarities to the distribution of storm requests, they are closely matched.
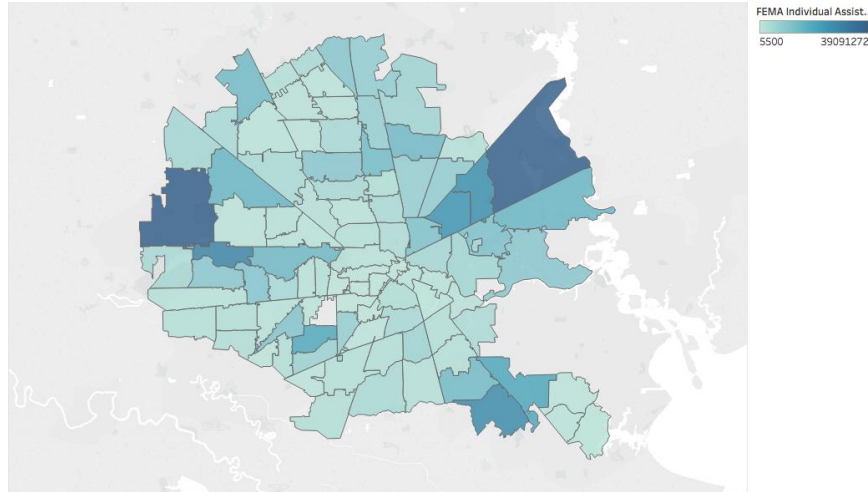
Figure 5.5: Distribution of FEMA Individual Assistance Payments

As might be expected, the channels by which people contacted the 311 service about storm-related concerns following Hurricane Harvey significantly from the channels by which 311 was generally contacted prior to Hurricane Harvey.

Table 5.5: Contact Channels Before and After Hurricane Harvey

	Pre-Storm Requests		Storm-Related Requests	
	Total	Percentage	Total	Percentage
Face2Face	158	0.03	32	0.18
Fax	5	0	0	0
Mail	65	0.01	0	0
SMS	625	0.11	7	0.04
Voice	486,137	86.41	15,163	86.32
WAP	50,324	8.95	2,013	11.46
WEB	23,012	4.09	305	1.74
e-mail	2,246	0.4	47	0.27

As seen in Table 5.5, people were significantly more likely to contact 311 over a mobile web browser and much less likely to contact using a website accessed by a computer. Face to face contact also represented a much larger proportion of the

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complaints. Voice calls decreased slightly as a relative proportion of total requests following the hurricane.

Regression Analysis

Table 5.6, Table 5.7 and Table 5.8 display the results of the negative binomial regression models that seek to identify the characteristics that influence the volume of storm-related requests at the ZCTA level within the city of Houston in the six weeks following Hurricane Harvey. All models were run both with and without spatial lags, because the literature indicates that the inclusion of a spatial lag can mute the impacts of other variables.

Table 5.6: Determinants of Storm-Related Request Volume (Model 3)

Total Households	0.00004571	0.00002357
	(-0.00002816)	(-0.0000278)
Destroyed Damages	-0.005149	-0.005607
	(-0.005209)	(-0.004592)
Non-Destroyed Damages	-0.0002313	-0.0001305
	(-0.0001775)	(-0.0001856)
FEMA Individual Assistance	9.708e-08***	5.345e-08**
	(-2.18E-08)	(-2.02E-08)
W_y		0.006502***
		(-0.001328)
Constant	3.9435***	3.1659***
	(-0.3324)	(-0.3634)
Log Alpha	0.3197*	0.1076
	(-0.1311)	(-0.1356)
Observations	95	95
Pseudo R2	0.02494	0.04618

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

The analysis begins with a simple model that seeks to explain the number of storm-related 311 requests by controlling for the total number of households and impact measures (Table 5.6). The results indicate that there is no statistically significant relationship between the total number of households within a ZCTA and the number of storm-related requests. We observe that neither the total number of households, the number of destroyed buildings nor the number of damaged buildings have a significant impact on the volume of storm-related requests. However, a small but significant increase in storm-related requests is observed when the amount of FEMA individual assistance paid within a ZCTA increases.

Table 5.7: Determinants of Storm-related 311 Request Volume (Model 4)

Total Households	0.00001297	-0.00001624
	(-0.00001984)	(-0.00001799)
Destroyed Damages	-0.002679	-0.001119
	(-0.00431)	(-0.003721)
Non-Destroyed Damages	-0.0002431	-0.0001898
	(-0.0001473)	(-0.0001413)
FEMA Individual Assistance	1.010e-07***	6.899e-08***
	(-1.77E-08)	(-1.48E-08)
Government Services Requests (pre storm)	0.0004517***	0.0004122***
	(-0.00006405)	(-0.00004933)
W_y		0.005440***
		(-0.0008692)
Constant	2.7576***	2.2734***
	(-0.264)	(-0.2418)
Log Alpha	-0.1004	-0.4623**
	(-0.1401)	(-0.1488)
Observations	95	95
Pseudo R2	0.06599	0.09783

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 5.7 displays the results of the negative binomial regression model when the volume of pre-storm government services requests is added into the equation. We observe that there is a significant positive relationship between the volume of government services requests placed prior to the storm and the number of storm-related requests at the ZCTA level following Hurricane Harvey. The positive significant relationship between FEMA individual assistance and storm-related requests persisted but controlling for pre-storm 311 use did not improve the significance of the number of destroyed and non-destroyed damages in the equation.

Table 5.8: Storm-Related Request Volume (Model 5)

Total Households	0.00001462	-0.00001626
	(-0.00002055)	(-0.00001857)
Destroyed Damages	-0.002774	-0.001119
	(-0.004316)	(-0.003722)
Non-Destroyed Damages	-0.00025	-0.0001897
	(-0.0001479)	(-0.0001442)
FEMA Individual Assistance	1.039e-07***	6.897e-08***
	(-2.00E-08)	(-1.63E-08)
Government Services Requests (pre storm)	0.0004454***	0.0004123***
	(-0.00006722)	(-0.00005186)
% Change in Government Services Requests	-0.06307	0.0003173
	(-0.1967)	(-0.1315)
W_y		0.005440***
		(-0.0008703)
Constant	2.7608***	2.2734***
	(-0.2643)	(-0.2420)
Log Alpha	-0.1011	-0.4623**
	(-0.1401)	(-0.1488)
Observations	95	95
Pseudo R2	0.06607	0.09783

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Finally, Table 5.8 displays the results of the model that controls for the percent change in government services requests before and after the storm in an attempt to control for the possibility that some Houston residents evacuated due to Hurricane Harvey and did not return to their homes afterwards. However, the inclusion of this covariate into the model had virtually no impact on the model results. FEMA Individual Assistance and the number of government services requests made prior to the storm remain significant, and the rest of the covariates continue to lack significance in both the lagged and unlagged models.

5.4.2 Analysis 2: Time for Storm-related Requests to Subside

Descriptive Statistics

A total of 92 ZCTAs were used in this analysis, and Table 5.9 provides an overview of the descriptive statistics for the number of time in days for the storm-related requests to reduce by 50%, 75% and 95% following Hurricane Harvey.

Table 5.9: Descriptive Statistics for Dependent Variables in Days

	Minimum	Maximum	Median	Mean	Std. Dev.
50%	30	88	48	48.44	8.89
75%	30	99	57.25	58.57	10.81
95%	30	142	78	82.52	21.17

The data takes on a fairly normal distribution, and total storm-related requests had completely subsided very shortly after the 142-day mark that represented the maximum number of days before a ZCTA had received 95% of its total storm-related requests.

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Regression Analysis

The results of the OLS regression analysis can be found in Table 5.10. At the 75% and 95% reduction thresholds, there is a positive and significant relationship between median income and request time, and the same thresholds exhibit a negative and significant relationship between request reduction time and the percent of the population below poverty level. The log transformation of number of government services requests is also positive and significant at the 75% and 95% threshold levels.

Table 5.10: Determinants of Storm-Related Request Reduction Time

	50%	75%	95%	50%	75%	95%
Median Income	5.0e-05	.00014***	.00029***			
	(3.5e-05)	(3.8e-05)	(7.3e-05)			
% Below Poverty				-.11455	-.30466**	-.53149*
				(.10006)	(.11332)	(.2192)
Government Services (log)	-.21398	1.2465*	4.5367***	-.21595	1.2114*	4.34***
	(.51453)	(.56596)	(1.0753)	(.52273)	(.59198)	(1.1451)
Total Compensation	-1.8e-07	-4.3e-07**	-4.7e-07	-2.0e-07	-4.7e-07**	-5.6e-07
	(1.4e-07)	(1.5e-07)	(2.9e-07)	(1.4e-07)	(1.6e-07)	(3.1e-07)
Damages (destroyed)	-.02798	-.04043	-.02608	-.0209	-.01871	.02499
	(.03608)	(.03968)	(.0754)	(.03532)	(.04)	(.07738)
Damages (non-destroyed)	.00114	.00315*	.00542	.0009	.00245	.00386
	(.00143)	(.00157)	(.00299)	(.00141)	(.0016)	(.0031)
Constant	48.353***	43.714***	34.779***	53.537***	58.23***	63.414***
	(4.6923)	(5.1614)	(9.8068)	(3.9996)	(4.5295)	(8.7617)
Observations	92	92	92	92	92	92
R2	0.058	0.229	0.274	0.050	0.176	0.196

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Total compensation is significant at the 75% threshold level in the models using both median income and percent below the poverty level, and the non-destroyed damages are significant at the 75% level only in the models using median

income. The 50% threshold model has a very low R-squared value and none of the covariates have any significance whatsoever.

5.4.3 Analysis 3: Relative Long-Term Request Volume

Descriptive Statistics

For analysis 3, observations were removed if the number of storm-related requests in the first six weeks following Hurricane Harvey were less than 50. This analysis is meant to measure the reduction in 311 requests as a proxy for progress in the recovery process so it is illogical to include ZCTAs in which the baseline is very low. After removal, 60 observations remained. Within this data set, the mean of the dependent variable, ratio, is 0.1664 with a standard deviation of 0.5217, and a median of 0.166758.
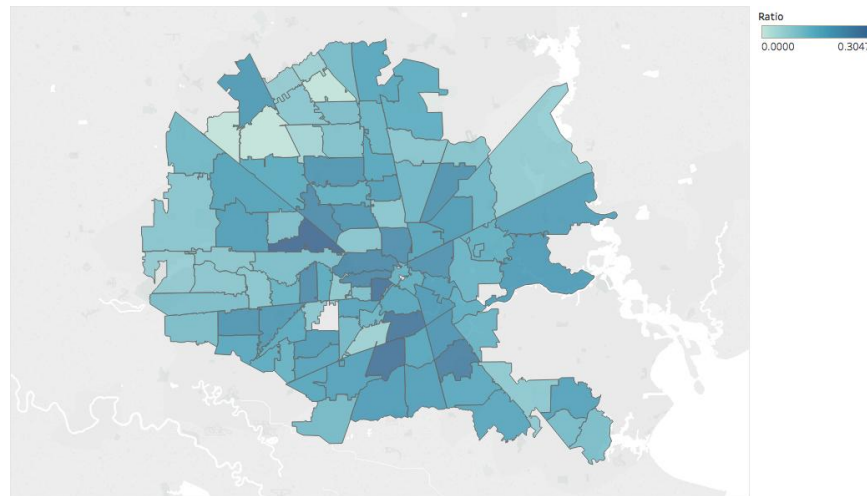
Figure 5.6: Distribution of Recovery Ratios

Figure 5.6 shows the distribution of recovery ratios across the city of Houston. Evidently, they are much more evenly distributed across the city than either the government services or storm-related 311 requests. This is because real volume of

requests is not relevant to the calculation, but instead the way that the requests diminished over time relative to the peak number of storm-related requests.

Regression Analysis

The results of the OLS regression analysis can be found in Table 5.11. There is a consistent and significant negative relationship between storm-related requests and the recovery ratio. No significant relationship between the recovery ratio and the socio-economic or hazard covariates was observed. The model was also run without spatial lags and using percent below poverty level as a socio-economic covariate rather than median income. The results were very similar.

Table 5.11: Determinants of Recovery Ratio

Storm-related requests (log)	-0.02449**	-0.02540**	-0.02540**
	(-0.008385)	(-0.008387)	(-0.008387)
Median Income		-3.27E-07	-3.27E-07
		(-2.72E-07)	(-2.72E-07)
W_y	0.02528	-0.07743	-0.07743
	(-0.2436)	(-0.2572)	(-0.2572)
Total Destroyed			-0.0001712
			(-0.0002269)
Total Compensation			-4.53E-10
			(-1.39E-09)
Total Non-Destroyed Damages			0.0001715
			(-0.0002316)
Constant	0.2890***	0.3265***	0.3265***
	(-0.06445)	(-0.0714)	(-0.0714)
Observations	60	60	60
Pseudo R2	0.137	0.159	0.159

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

5.5 <u>Discussion</u>

5.5.1 <u>Storm-Related Request Volume</u>

One of the primary goals of the 311 storm-related request analysis was to identify whether the amount of storm damage in a ZCTA following Hurricane Harvey had an impact on the number of storm-related requests placed at the ZCTA level. The results of this analysis were mixed. Neither the number of destroyed buildings nor the number of damaged buildings in a ZCTA had a significant relationship on the volume of storm-related requests recorded within a ZCTA. However, the total FEMA individual assistance paid out within a ZCTA had a significant, positive relationship with the number of requests related to storm-related issues in the neighborhood. This suggests that ZCTAs that received larger amounts of FEMA individual assistance also had more storm-related 311 complaints.

I hypothesize that there may be two separate forces that are driving these results. First, in ZCTAs with higher levels of destroyed and damaged buildings there would indeed be more reasons to contact 311 with storm-related complaints. However, in these same ZCTAs, people would likely resettle the ZCTA more slowly following the storm, and more people would be likely to permanently resettle. Fewer people in the ZCTA means that fewer requests will be placed. As a result, building destruction and damage may have both positive and negative impacts on the volume of storm-related 311 requests. The model attempted to control for this population change by including the percent change in daily government services requests before and after the storm as a covariate, hypothesizing that a decrease in relative contact

volume would indicate a population decrease. However, this measure was not significant when included in the model. Perhaps the disruption caused by the storm also changed the pattern of 311 use at the ZCTA level far beyond just shifts in population.

Unlike building damages, FEMA individual assistance is not a passive measure of hurricane impact. In order to receive this post-disaster aide, residents are required to go through an involved application process, which includes paperwork and a home visit. As a result, FEMA assistance does not simply measure damage, it is also a measure of a ZCTA's residents' willingness to engage with FEMA in order to secure funds. This means that in order to be granted this assistance, an individual must still be, to some degree, attached to their home and are likely to still be in the Houston area. With all this in mind, the relationship between storm-related requests and FEMA individual assistance is logically consistent. The types of people who successfully submit individual assistance applications are willing and motivated to engage with the government in order to advocate on behalf of their household. The same sort of person could be anticipated to make storm-related 311 complaints, inquiries and requests.

Similarly, there is a highly significant and positive relationship between the number of government service requests placed prior to Hurricane Harvey within a ZCTA and the number of storm-related requests made in the six weeks following the storm. This means that ZCTAs that use the 311 service more often in general also made more hurricane-specific requests. This is interesting because it means that a

major factor driving the number of storm-related requests isn't need, but rather a history of 311 service use. Perhaps some neighborhoods are less aware of the service, and this drives their lower usage rates.

Alternately, some communities may be aware of 311 services but share an increased skepticism about their efficacy. As a result, they might not perceive it to be worth their effort to contact 311 because they do not believe that it will make a difference. This could be an extension of the social capital theory that was proposed in the previous chapter to explain the lower rates of government services requests in wealthy ZCTAs prior to Hurricane Harvey. Perhaps those in wealthier neighborhoods have more efficient avenues for lodging complaints and advocating on behalf of their ZCTA, and therefore do not believe that it is worth their time to contact 311.

5.5.2 Time for Storm-related Requests to Subside

Analysis 2 found that as ZCTA income increased, it took longer for their 311 requests related to the hurricane to subside. Analysis 1 indicates that the opposite is true for total request volume: as median income increased, contact volume dropped. Perhaps this is simply because the higher volumes of storm-related requests early in the process in lower income ZCTAs meant that the problems they had contacted 311 about were addressed and there was no need to make contact again later on.

Another possible hypothesis is that residents in higher income neighborhoods were more likely to temporarily leave Houston after the storm, so they began making 311 requests about storm-related problems later in the recovery process, which caused them to take longer to reach the contact reduction thresholds. Some research does

indicate that when faced with severe storms, upper income households are more likely to evacuate, so these findings may be a result of this phenomenon (Dash & Gladwin, 2007).

5.5.3 Relative Long-term Contact Volume

Analysis 3 studied the way that relative contact volume changed over time within a given ZCTA. The model results indicate that there is a significant negative relationship between the dependent variable, recovery ratio, and the log of storm-related requests in the first six weeks following Hurricane Harvey. This means that ZCTAs that placed a higher absolute number of requests early in the recovery process experienced a faster decrease in the weekly rate of storm-related 311 requests. This falls in line with the findings from Analysis 2, which found that households with higher median incomes took longer to reach the 75% and 95% recovery thresholds.

These findings could indicate that 311 storm requests made earlier in the process had a positive impact on the recovery process within those ZCTAs, and as a result, fewer requests were required in the weeks that followed because the problems had been addressed. However, another possible explanation is that lower levels of storm-related requests in the early part of the recovery process is due to the fact that the residents within those ZCTAs evacuated in higher volumes, and it took them longer to return to Houston and begin to engage with the city about the recovery process. Therefore, their relative 311 contact volume persisted for longer because only then were people returning to their neighborhoods and observing the problems

for which they needed assistance. Without more data, it is difficult to determine which hypothesis is accurate.

5.5.4 The Unreached Potential of 311 Services and Disaster Recovery

As it currently stands and based on the available data it does not appear as though 311 services were being used to their full potential in Houston following Hurricane Harvey. 311 services provide a line of communication between communities and local government that could be an extremely valuable tool for post-disaster recovery. The primary way that this was being used following Hurricane Harvey was to alert the city to problems caused by the storm that needed local intervention. This is important, because it allows private citizens to act as the city's eyes and ears and keep it updated on problems related to the storm. However, as discussed above, it was being used inconsistently across the city, which may put some ZCTAs at a disadvantage during the recovery process.

One of the common complaints in post-disaster communities is a lack of information about available resources and recovery process. In the weeks following a major natural disaster, people do not know what help is available to them or how best to get it. In an optimal scenario, the 311 service could take on this role in recovering communities, and act as an intermediary between community residents and higher-level government agencies such as FEMA and the Department of Homeland Security. There was no category for storm-related inquiries, simply storm-related complaints. This would suggest that it is primarily being used as a way request the city's

intervention with material problems, rather than as a way of getting information about the recovery process of available resources.

The 311 system could be more effectively harnessed as a non-emergency line for post-disaster information through proactive public education campaigns that brought the service to the public consciousness well in advance of a natural disaster, as well as by ensuring that 311 operators are given up to date information about the recovery process and resources to share with callers. However, none of these efforts will be successful if contacting 311 is ultimately not an effective way to bring problems to the city's attention, and the publicly available 311 data alone is insufficient to make a determination about the quality of the resulting service. This is an important avenue for future research and would likely require the collection of primary survey data to inquire about residents' perception of the 311 service, whether they have used it, and if so, whether they were satisfied with their experience.

6. Reflections and Conclusions

One of the most salient and frequently made points in the resilience and recovery literature is that these are processes that extend across multiple dimensions, spaces and time spans (Cutter et al., 2008a; Engle et al., 2014; Folke, 2006). As a result, these concepts are incredibly difficult to quantify because the majority of operationalizable proxies fail to capture the entirety of the recovery process. Instead, there are many examples in the literature of researchers opting to focus in on a single dimension, time period or spatial scale (Burton, 2014; Finch et al., 2010).

The interdependencies and interactions between the sub-processes and processes that drive recovery more broadly are certain to have an impact on the final outcome. From a system perspective, infrastructure recovery gives way to system recovery, which in turn leads to community recovery. Similarly, when considering multiple temporal scales, there are multiple different phases of recovery, each of which has different goals and different approaches. Meanwhile, recovery occurs simultaneously at the household, community, local, county and state levels. Success or failure in any of these systems, stages or spaces will reverberate throughout the process as a whole.

A siloed approach to resilience and recovery research will be blind to most of the process. This is the current status quo, and as a result there is a lack of clarity in the literature about the nature of these interactions and their likely outcomes. Questions arise about whether the determinants of recovery hold consistent at different phases, scales and dimensions of the process: will a community that excels

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at emergency cleanup efforts immediately after the disaster be similarly successful during the next phase of recovery? These shortcomings in the literature are of course, largely attributable to difficulties in measurement.

This research was designed with the primary goal of examining recovery at multiple scales, while simultaneously considering the social and economic forces and community behaviors that influence recovery outcomes. There is not one single quantitative measure or point of measurement that will comprehensively capture the complexities of the recovery process, so the analytical chapters that comprised the body of this work proposed a variety of new ways to conceptualize and quantify recovery in order to analyze the way that neighborhood characteristics and community engagement influence the recovery process at multiple dimension and temporal scales.

Throughout the process of writing this dissertation, I conceptualized and began data collection and cleaning on several papers are unfinished, but establish promising avenues for future research on interdependent, multi-scalar resilience and post-disaster recovery. In particular, school closures and school absences were identified as a potentially interesting metric for multi-system post-hurricane recovery. Public schools are designated as critical infrastructure by the Department of Homeland Security, and their functioning during times of environmental stress is a fascinating example of infrastructure interdependence (DHS, 2016). Schools rely on a wide variety of infrastructure systems in order to operate, and communities rely on schools for many functions beyond public education.

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Meanwhile, school attendance would be more effective in measuring slightly longer-term recovery as it does not simply measure the amount of time it takes for schools and the infrastructure systems upon which they depend to return to a baseline level of functioning. It instead expands the analysis to include the recovery process as it affects the students' households: issues such as displacement, damage, illness and trauma stemming from the disaster would be expected to drive down attendance numbers until circumstances normalized. Although time and data constraints prevented an analysis of this sort to be included in the dissertation, it is a unique approach to recovery that I hope to pursue in future research.

This research could also have been strengthened by primary data collection as a way of investigating long-term community-wide recovery and community perceptions of the recovery process. As discussed in Chapter 2, the literature indicates that mixed methods are the ideal approach for studying resilience and recovery. Open-ended interviews with community members could help to identify components of recovery that are not captured by more quantitative measures, such as collective action and social trust. Further, it would give insight into whether broader community-level recovery is perceived to be largely just a combination of the measurable component parts, or if there are other, more abstract factors that impact whether community members feel as though their community is recovered, even after the outages are fixed, debris is cleared, services are restored and buildings are repaired.

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A case study could also give insight into the way that social capital and social participation impacts the construction of narratives. Other studies on perceptions of recovery have indicated that the extent to which the recovery process was participatory has a significant impact on the way that community members feel about the recovery process in its aftermath (Kweit & Kweit, 2004). Primary data collection was ultimately not pursued due time and resource constraints but remains a promising avenue for potential research. Given the direction and results of the completed dissertation, it would be particularly interesting to gather primary data about the way that citizens used 311 requests during post-disaster recovery periods and whether or not they perceived these services as being useful and informative in this context.

One major limitation of this research is that each of the analyses were limited to only one hurricane in one region. Because of this, we cannot claim to know whether the results of this dissertation are a widespread phenomenon or limited to the specific setting that they describe. An important next step in this research is then to collect similar data from other regions and other hurricanes in order to develop a more detailed understanding of broader recovery trends throughout the United States.

In Chapter 3, power outage and power restoration data were used in order to consider the impacts of socio-economic status on power outages and power restoration time in the aftermath of hurricane-induced outages at the ZCTA level. This analysis focuses on a fairly short time scale and examines a portion of the recovery process that is thought by many to be very utilitarian and devoid of socio-economic biases. However, the results indicate that even when considering this very

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technical, very short-term recovery process, socio-economic inequalities play a role in the recovery outcomes.

The findings of this paper make a strong argument for the importance of thinking of resilience and recovery as being on a temporal continuum, rather than taking a snapshot of the process at a single point in time. In the early stages of the analysis, only the 95% recovery threshold was considered because that was the industry standard for assessing power restoration. When the analysis was broadened to consider multiple recovery benchmarks, a more robust and interesting narrative emerged about the way that power recovery is prioritized to the disadvantage of lower-income communities. The same principles can also be applied to assessing recovery at multiple spatial and systemic scales.

By considering impact as a component of recovery this paper also provides insight on the vulnerability resilience continuum. The process of building resilience and setting a community up for a successful recovery begins long before the declaration of a national emergency. The Hurricane Isaac analysis indicated that antecedent socio-economic conditions within a ZCTA had an impact on the number of power outages within that community. This in turn had a significant impact on the time it took for a ZCTA to reach 95% restoration.

The use of 311 data to analyze how communities behaved following Hurricane Harvey considered a different dimension of recovery. Rather than looking at the restoration of a specific system or system component, storm-related 311 requests were used in order to consider the way that communities interact with their

local government following natural disasters. Recovery is not something that happens to a community, it is a dynamic process in which community residents are involved and engaged. This chapter found that the way that citizens engaged with government throughout the recovery process with 311 is meaningfully different and distinct from the way that social capital typically manifests.

Although 311 requests function as a way of connecting communities with government officials, we observe that this service is used more frequently in lower-income neighborhoods that typically have lower levels of bridging social capital, leading to the potential conclusion that the use of 311 services is not a proxy for social capital because it ultimately serves as its less desirable replacement. Communities that do not have access to the bridging social capital necessary to advocate for their neighborhoods to local officials following a natural disaster might turn to 311 services to voice their complaints in lieu of more direct action.

While this finding was unexpected, it may contribute more to our understanding of unequal social capital and post-disaster recovery than if 311 requests had served as a more effective proxy. The fact that social capital is a tool that assists in post-disaster recovery but disproportionately benefits the wealthy and connected is well known in the disaster literature, but there are very few solutions to this problem that are being proposed. 311 services have the potential to be a way of sharing information, connecting residents to community groups, and generally providing them with the resources needed to guide them through the recovery

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process. This presents an exciting opportunity for the government to replicate the benefits of social capital in a way that is more egalitarian.

This research can be taken as further evidence of what was discussed in the prospectus that was written and defended two years ago. Researching resilience and recovery, particularly multi-scalar resilience and recovery, is a difficult task, largely because of limitations in data and measurement. The complexity of these processes makes it difficult to reduce them to a single data point or compresses them into a single model. However, when multiple measures and models are taken together, as in this dissertation, a clearer picture begins to emerge. As a result, focused efforts must be made to improve data tracking, collection and availability relevant to all scales of recovery. This dissertation contributed to these efforts by introducing novel recovery metrics, allowing for the examination of recovery at multiple scales and contributing to a better understanding of the way that inequalities in recovery outcomes present throughout the process.

7. Appendix

Table 7.1: Descriptive Statistics for Maximum Outages Analysis (Ch 3.3.1)

Variable	Mean	Std. Dev.	Min	Max
Maximum Outages	2620.183	4140.051	25	21343
Median Income	44970.96	14520.75	17300	100000
Percent Below Poverty	19.45228	9.880057	0.6	54.4
Percent with Bachelor's Degree	11.42218	6.397369	0.5	35
Total Customers	4857.369	5122.763	9	21744
Maximum Gusts	34.93196	8.792181	15.84287	51.1828
Sustained Wind Duration	1800.763	757.973	0	2520
Precipitation	82.05226	68.34489	1.369268	217.3865
Maximum Flood Ratio	0.3603915	0.2334049	0.0234523	1.382497
Soil Moisture	344.949	62.57341	142.51	410.6136

Table 7.2: Descriptive Statistics for Restoration Analysis (Ch 3.3.2)

Variable	Mean	Std. Dev.	Min	Max
Maximum Outages	2620.183	4140.051	25	21343
Median Income	44970.96	14520.75	17300	100000
Percent Below Poverty	19.45228	9.880057	0.6	54.4
Percent with Bachelor's Degree	11.42218	6.397369	0.5	35
Total Customers	4857.369	5122.763	9	21744
Maximum Gusts	34.93196	8.792181	15.84287	51.1828
Sustained Wind Duration	1800.763	757.973	0	2520
Precipitation	82.05226	68.34489	1.369268	217.3865
Maximum Flood Ratio	0.3603915	0.2334049	0.0234523	1.382497
Soil Moisture	344.949	62.57341	142.51	410.6136
Emergency Services	3.162712	2.504547	0	13
Health Services	0.4745763	0.8681032	0	6
Grocery Stores	3.640678	2.964594	0	14
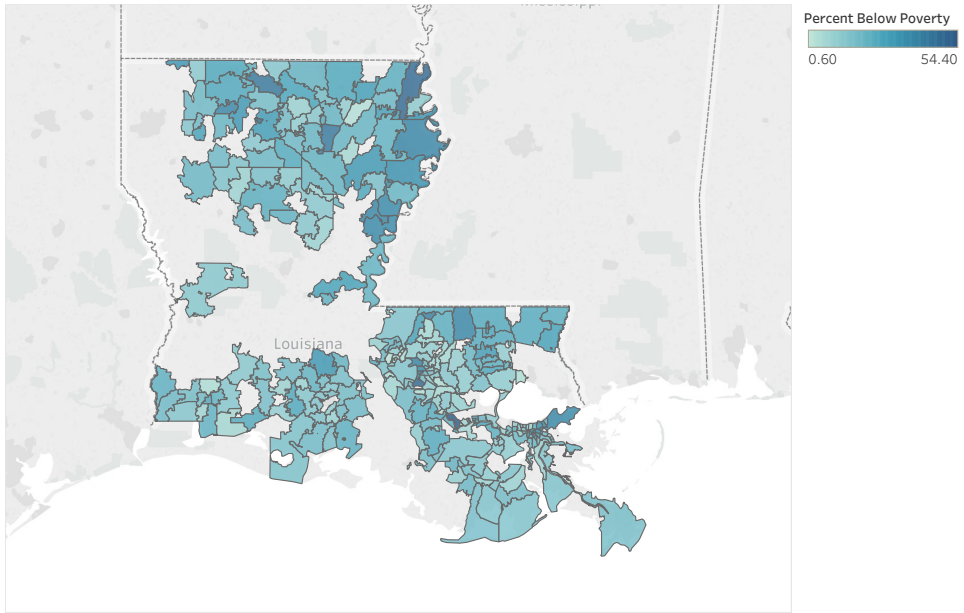
Figure 7.1: Percent Below Poverty Distribution
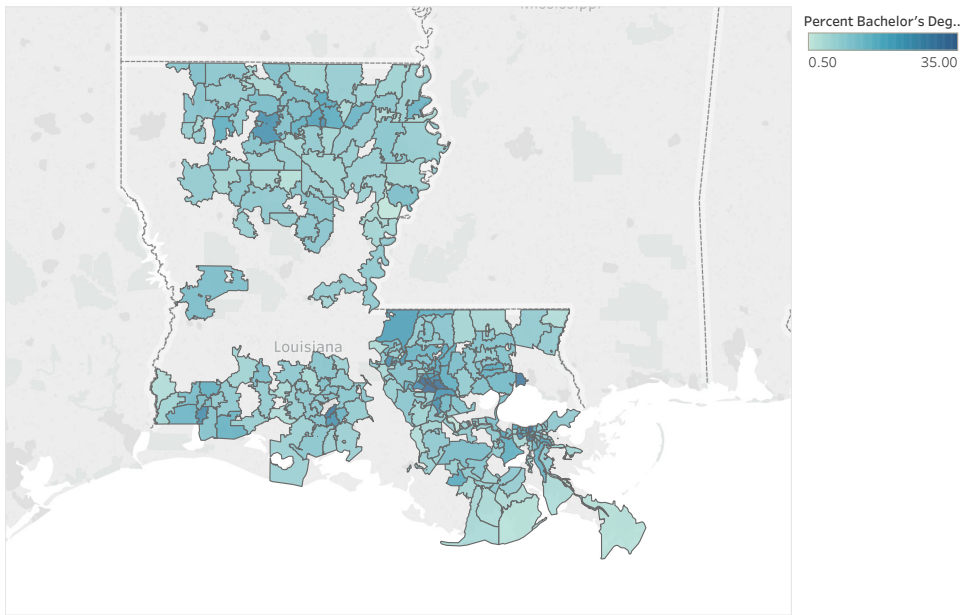
Figure 7.2: Percent With Bachelor's Degree Distribution

Figure 7.3: Wind Duration Distribution
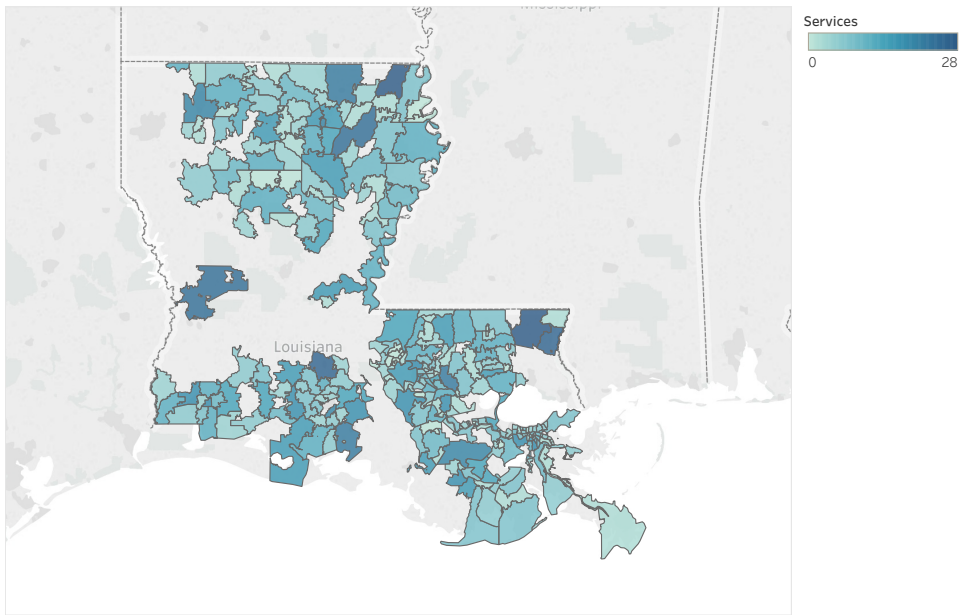
Figure 7.4: Health, Emergency and Grocery Services Distribution

Table 7.3: Percent With Bachelor's Degrees as a Determinant of Recovery (Ch. 3.4.2, Model 3)

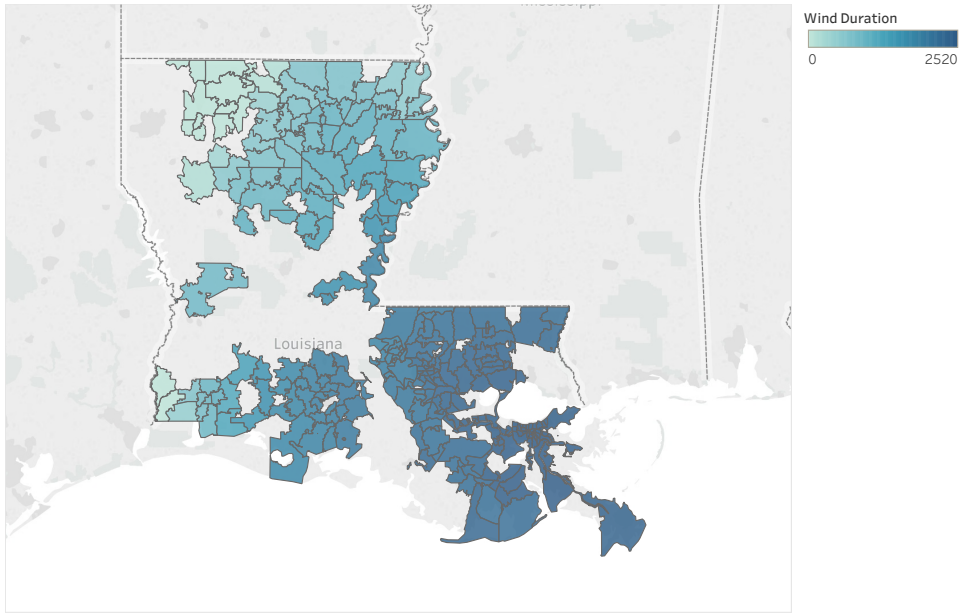|	95%		80%		50%	
% Bachelor's Degree	.00253	.0052	-.0032	.00251	-.01363	-.00257
	(.01091)	(.01134)	(.01085)	(.01175)	(.01108)	(.01197)
Maximum Outages	.00018***	5.7e-05*	.00014***	1.9e-05	.00011***	-2.5e-05
	(2.1e-05)	(2.3e-05)	(1.8e-05)	(2.2e-05)	(1.7e-05)	(2.1e-05)
W_y		.00053***		.00068***		
		(4.2e-05)		(5.1e-05)		.00077***
/cut 1	-.68107***	3.1645***	-.35631**	4.3016***	-.13864	4.7397***
	(.14166)	(.33532)	(.13777)	(.3683)	(.13951)	(.40399)
/cut 2	.1886	4.4169***	.43853**	5.6248***	.73555***	6.1344***
	(.13853)	(.36724)	(.14004)	(.41541)	(.14392)	(.45141)
/cut 3	1.0425***	5.858***	1.3172***	7.2811***	1.4992***	7.6537***
	(.14699)	(.4321)	(.15299)	(.49954)	(.15995)	(.54173)
/cut 4	2.0112***	7.2778***	2.5903***	9.4099***	2.444***	10.113***
	(.17325)	(.48439)	(.21425)	(.60023)	(.22102)	(.78826)
Observations	284	284	284	284	284	284
Pseudo R2	0.119	0.325	0.087	0.375	0.055	0.359

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 7.4: Percent With Bachelor's Degrees as a Determinant of Recovery (Ch. 3.4.2, Model 4)

	95%		80%		50%	
% Bachelor's Degree	.00324	.00509	-.00387	.00202	-.01672	-.00473
	(.01101)	(.01134)	(.01101)	(.01173)	(.01131)	(.01202)
Maximum Outages	.00013***	5.6e-05*	8.5e-05***	1.6e-05	5.4e-05**	-3.2e-05
	(2.1e-05)	(2.3e-05)	(1.9e-05)	(2.2e-05)	(1.8e-05)	(2.1e-05)
Sustained Wind Duration	.00089***	.00016	.00098***	.0002	.00092***	.0003*
	(.0001)	(.00013)	(.00011)	(.00013)	(.00011)	(.00012)
W_y		.0005***		.00064***		.00071***
		(5.0e-05)		(5.7e-05)		(6.4e-05)
/cut 1	.52826**	3.1354***	1.0806***	4.2915***	1.3022***	4.8114***
	(.20179)	(.33619)	(.21349)	(.36712)	(.23137)	(.40267)
/cut 2	1.5921***	4.4026***	2.1097***	5.6474***	2.3529***	6.2438***
	(.22007)	(.36805)	(.24013)	(.41662)	(.25279)	(.45264)
/cut 3	2.6549***	5.8585***	3.1612***	7.2964***	3.2163***	7.7449***
	(.24807)	(.43372)	(.26377)	(.49869)	(.27271)	(.53905)
/cut 4	3.7182***	7.2652***	4.5108***	9.3801***	4.2371***	10.074***
	(.27318)	(.48503)	(.30907)	(.59728)	(.32178)	(.77)
Observations	284	284	284	284	284	284
Pseudo R2	0.205	0.327	0.195	0.378	0.154	0.367

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 7.5: Percent With Bachelor's Degrees as a Determinant of Recovery (Ch. 3.4.2, Model 5)

	95%		80%		50%	
% Bachelor's Degree	.00273	.00513	-.00521	.00344	-.02063	-.00723
	(.01127)	(.01144)	(.01131)	(.01185)	(.01171)	(.01223)
Maximum Outages	6.2e-05**	4.5e-05	3.5e-05	1.8e-05	4.4e-07	-3.8e-05
	(2.3e-05)	(2.3e-05)	(2.1e-05)	(2.3e-05)	(2.1e-05)	(2.2e-05)
Sustained Wind Duration	-.00061*	-.00043	-.00067*	-.00041	-.00078**	-.0004
	(.00026)	(.00026)	(.00027)	(.00027)	(.00029)	(.0003)
Maximum Flood Ratio	1.4918***	.78703	1.0863**	.57964	.64642	.32617
	(.41352)	(.43414)	(.4141)	(.43419)	(.42137)	(.4392)
5-Day Precipitation	.01495***	.00652**	.01324***	.00116	.01439***	.00535*
	(.00195)	(.00238)	(.00192)	(.0024)	(.00197)	(.0023)
Maximum Wind	.04521*	.02837	.07195***	.04709*	.07187***	.04037
	(.01892)	(.01944)	(.01909)	(.01986)	(.01973)	(.02091)
W_y		.00038***		.0006***		.00062***
		(6.1e-05)		(6.8e-05)		(7.0e-05)
/cut 1	.69771	2.755***	1.7422***	4.8066***	1.8652***	4.8209***
	(.38153)	(.51066)	(.39177)	(.53949)	(.40944)	(.54913)
/cut 2	1.9463***	4.0752***	2.9973***	6.224***	3.1646***	6.3125***
	(.40644)	(.53976)	(.4268)	(.58333)	(.43226)	(.58295)
/cut 3	3.2898***	5.5893***	4.2573***	7.8641***	4.2006***	7.8253***
	(.43652)	(.58853)	(.44488)	(.63781)	(.44492)	(.64195)
/cut 4	4.5256***	6.9902***	5.7096***	9.8785***	5.2807***	9.9437***
	(.44419)	(.61205)	(.47236)	(.71682)	(.4828)	(.84366)
Observations	284	284	284	284	284	284
Pseudo R2	0.294	0.339	0.281	0.386	0.251	0.379

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 7.6: Percent With Bachelor's Degrees as a Determinant of Recovery (Ch. 3.4.2, Model 6)

|	95%		80%		50%	
% Bachelor's Degree	.0085	.01249	-.00105	.00945	-.0247	-.01166
	(.01266)	(.0129)	(.01282)	(.01347)	(.01332)	(.0139)
Maximum Outages	4.9e-05*	2.1e-05	3.5e-05	1.4e-06	1.2e-05	-4.0e-05
	(2.5e-05)	(2.5e-05)	(2.3e-05)	(2.5e-05)	(2.3e-05)	(2.5e-05)
Sustained Wind Duration	-.00065*	-.0005	-.00067*	-.00045	-.00075**	-.00041
	(.00026)	(.00027)	(.00027)	(.00028)	(.00029)	(.0003)
Maximum Flood Ratio	1.4898***	.74263	1.0694*	.54505	.65453	.3261
	(.41412)	(.43521)	(.41522)	(.43598)	(.42307)	(.44062)
5-Day Precipitation	.0155***	.00706**	.01319***	.00149	.01393***	.00551*
	(.00201)	(.00239)	(.00197)	(.00241)	(.00201)	(.00232)
Maximum Wind	.0478*	.0326	.07203***	.04961*	.0706***	.04088
	(.01904)	(.01955)	(.01917)	(.01992)	(.01981)	(.02093)
Emergency Services	-3.863	-3.9555	.11139	-.41286	.47858	.28342
	(119.58)	(105.43)	(1.1578)	(1.2589)	(1.1142)	(1.1762)
Health Services	-3.9602	-4.0772	.02597	-.50629	.53982	.36362
	(119.58)	(105.43)	(1.1694)	(1.2703)	(1.128)	(1.1904)
Grocery Stores	3.9078	4.033	-.09721	.47263	-.51856	-.285
	(119.58)	(105.43)	(1.1601)	(1.2613)	(1.1167)	(1.1791)
W_y		.00041***		.00062***		.00063***
		(6.2e-05)		(7.0e-05)		(7.1e-05)
/cut 1	.90518*	3.2679***	1.7904***	5.2065***	1.6915***	4.8606***
	(.40685)	(.55253)	(.41678)	(.58335)	(.43105)	(.58137)
/cut 2	2.169***	4.6239***	3.0483***	6.641***	2.9964***	6.3525***
	(.43444)	(.58612)	(.45137)	(.62794)	(.45163)	(.61303)
/cut 3	3.5164***	6.1598***	4.3087***	8.2851***	4.0407***	7.8741***
	(.46392)	(.63623)	(.4676)	(.68055)	(.46217)	(.67063)
/cut 4	4.7473***	7.5576***	5.7625***	10.303***	5.1326***	10.014***
	(.47005)	(.65776)	(.49228)	(.75577)	(.4973)	(.87076)
Observations	284	284	284	284	284	284
Pseudo R2	0.297	0.347	0.281	0.390	0.253	0.380

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

**Table 7.7: Descriptive Statistics for Government Services Analysis (Ch. 4.3.1)**

Variable	Mean	Std. Dev.	Min	Max
Government Services Requests	2703.663	2101.825	3	7831
Total Households	11569.58	5777.581	782	33717
Population Density	0.0017741	0.0009236	0.0002348	0.0058396
Median Income	55275.49	28215.31	25354	174153
% Below Poverty	20.36947	9.893347	2.6	43.2
% Limited English	14.45789	11.98162	0.7	58.8
Proportion Over 65	0.1004648	0.0380102	0.033873	0.268714
% With Children	31.50824	10.53929	2.557545	50.65862
% Single Units	59.28316	21.43982	0	97.4
Distance From City Center	15948.84	7789.782	1094.585	39543.14
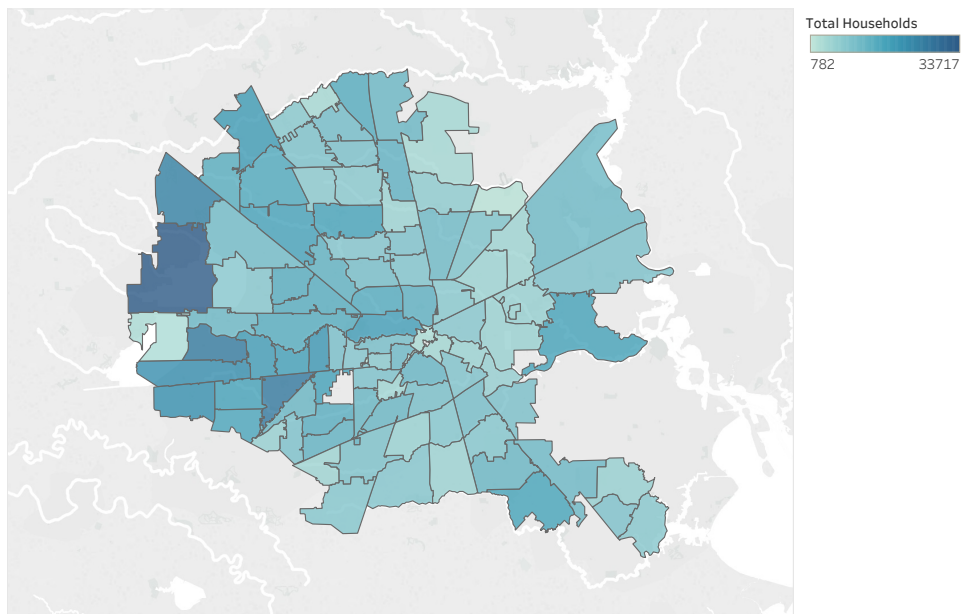
Figure 7.5: Total Households Distribution
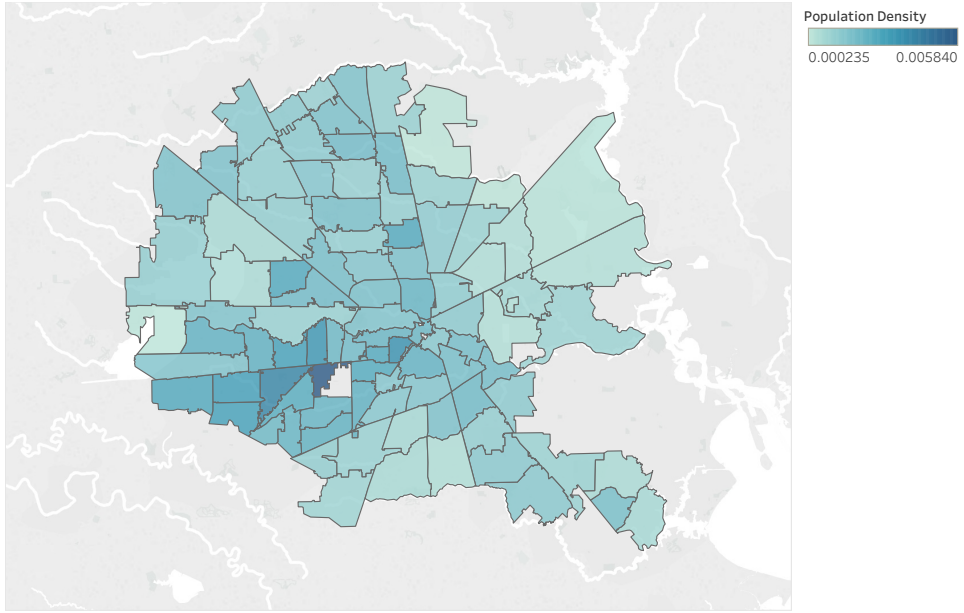
Figure 7.6: Population Density Distribution
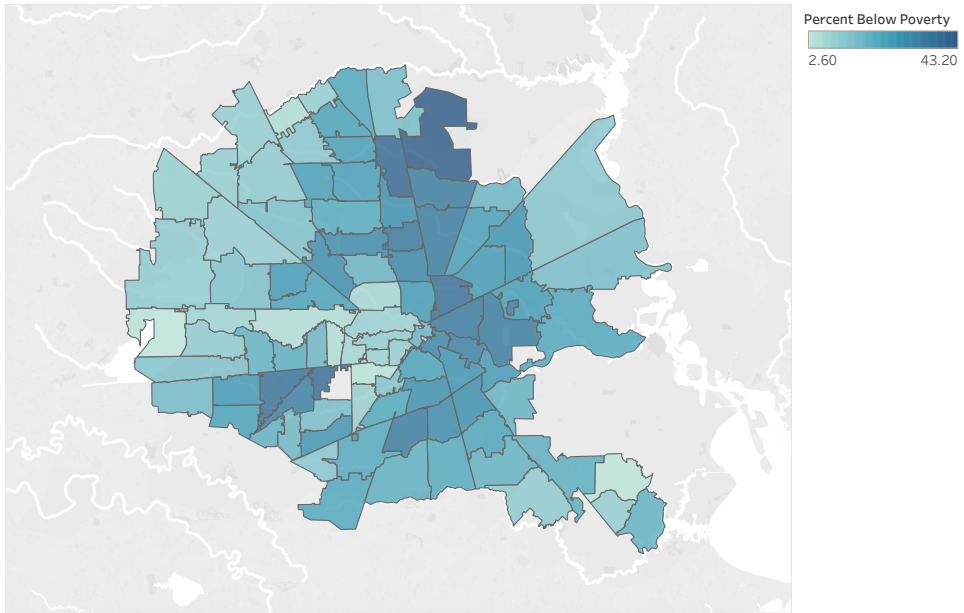
**Figure 7.7: Percent Below Poverty Distribution**

Table 7.8: Determinants of 311 Request Volume (OLS Regression, Ch.4.4.1, Model 2)

|				
Total Households	.00064	.00066	.00093*	.00088*
	(.00041)	(.00036)	(.0004)	(.00037)
Population Density	5967.7	6743.7*	5394.7	6027.6*
	(3167.4)	(2822)	(3115.6)	(2856.9)
Median Income	-.00037***	-.0003***		
	(8.0e-05)	(7.3e-05)		
Percent Limited English	-.54627*	-.46102	-.61947*	-.46407
	(.26713)	(.23826)	(.26924)	(.24932)
Percent Over 65	24.652	54.818	50.577	67.998
	(64.744)	(57.924)	(64.742)	(59.43)
Percent With Children	-.12472	.02472	-.29037	-.13041
	(.36704)	(.32794)	(.36023)	(.33206)
Percent Single Units	47.896***	37.365**	45.602***	36.095**
	(12.684)	(11.488)	(12.514)	(11.681)
Distance from City Center	-.0018***	-.00072	-.00142***	-.00053
	(.00034)	(.00037)	(.00033)	(.00037)
W_y		.00121***		.0011***
		(.00025)		(.00026)
Percent Below Poverty			1.2539***	.90177***
			(.25825)	(.25096)
Constant	57.149***	13.192	7.8088	-19.854
	(14.317)	(15.613)	(15.562)	(15.705)
Observations	95	95	95	95
Pseudo R2	0.505	0.613	0.515	0.598

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 7.9: Descriptive Statistics for Storm Related Requests (Ch. 5.3.1)

Variable	Mean	Std. Dev.	Min	Max
Storm Related Requests	167.6848	238.0345	1	1467
Government Services Requests	2790.772	2078.55	3	7831
Total Households	11486.76	5841.616	782	33717
Median Income	55281.98	28621.88	25354	174153
% Below Poverty	20.54457	9.940254	2.6	43.2
Damaged Buildings	470.6087	994.3987	0	6151
Destroyed Buildings	19.13043	39.86549	0	327
FEMA Assistance	6175569	8037707	5500	3.91E+07
% Change Govt. Services Requests	0.2006134	0.8151201	-1	4.272727
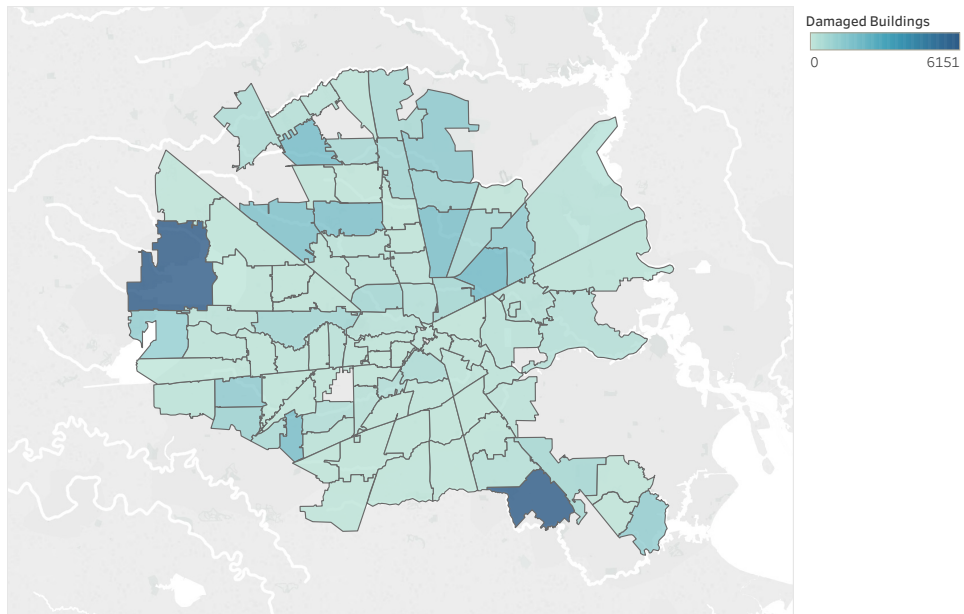
Figure 7.8: Distribution of Damaged Buildings
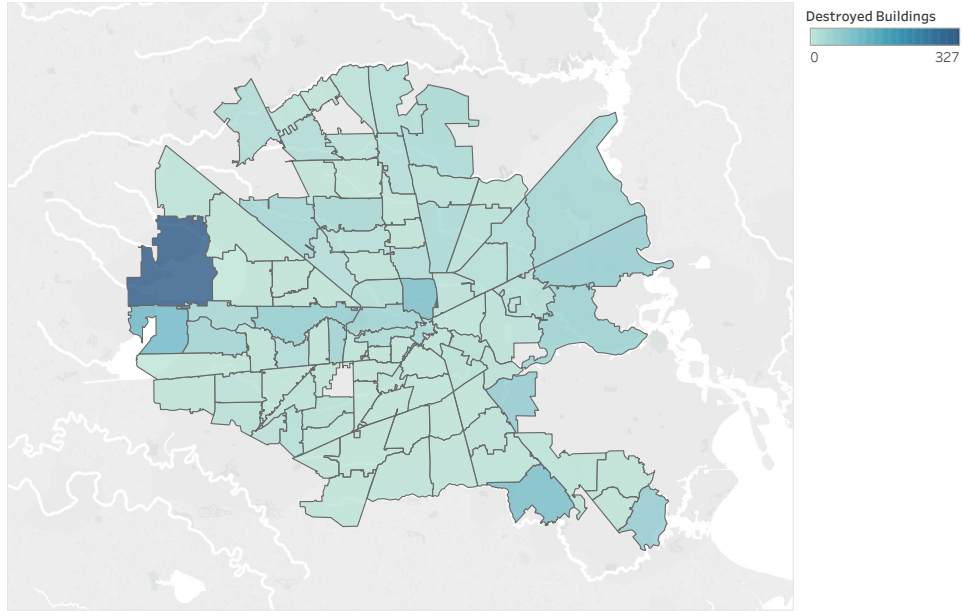
Figure 7.9: Distribution of Destroyed Buildings

Table 7.10: Descriptive Statistics for Request Reduction Analysis (Ch. 5.3.2)

Variable	Mean	Std. Dev.	Min	Max
Days to 50%	48.44022	8.894943	30	88
Days to 75%	58.57065	10.81299	30	99
Days to 95%	82.52174	21.17353	30	142
Median Income	55281.98	28621.88	25354	174153
Percent Below Poverty Level	20.54457	9.940254	2.6	43.2
Government Services (Log)	7.180285	1.859165	1.098612	8.965845
Total Destroyed	19.13043	39.86549	0	327
Total Damaged	470.6087	994.3987	0	6151
Total Compensation	6175569	8037707	5500	3.91E+07

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Table 7.11: Descriptive Statistics for Recovery Ratio Analysis (Ch 5.3.3)

Variable	Mean	Std. Dev.	Min	Max
Recovery Ratio	0.153115	0.0560873	0.0456349	0.3046537
Storm Requests (log)	4.189071	1.639744	0	7.290975
Median Income	55281.98	28621.88	25354	174153
% Below Poverty	20.54457	9.940254	2.6	43.2
Total Destroyed	19.13043	39.86549	0	327
Total Damaged	470.6087	994.3987	0	6151
Total Compensation	6175569	8037707	5500	3.91E+07

Table 7.12: Median Income as a Determinant of Discovery Ratio Models 5-7, No Weights (Ch 5.4.3)

Storm-related requests (log)	.01006**	.00935**	.01239**
	(.00345)	(.00354)	(.00365)
Median Income		-1.8e-07	-1.4e-07
		(2.0e-07)	(2.1e-07)
Total Destroyed			-3.5e-05
			(.00021)
Total Damages			1.3e-06
			(8.5e-06)
Total Compensation			-1.9e-09*
			(8.7e-10)
Constant	.11096***	.1239***	.12078***
	(.01549)	(.02131)	(.02115)
Observations	92	92	92
Pseudo R2	0.087	0.095	0.165

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 7.13: Percent Below Poverty as a Determinant of Recovery Ratio Models 6-7 (Ch.5.4.3)

Storm-related requests (log)	.00877*	.00745	.01181**	.0113**
	(.0035)	(.00377)	(.00364)	(.00406)
% Below Poverty	.00095	.00078	.00073	.00068
	(.00058)	(.00061)	(.00059)	(.00061)
		.01843		.00579
		(.0194)		(.0201)
Total Destroyed			-2.4e-05	-2.9e-05
			(.00021)	(.00021)
Total Damages			1.3e-06	1.7e-06
			(8.3e-06)	(8.4e-06)
Total Compensation			-1.9e-09*	-1.8e-09*
			(8.6e-10)	(8.9e-10)
Constant	.09685***	.09098***	.10009***	.09818***
	(.01758)	(.01864)	(.0176)	(.0189)
Observations	92	92	92	92
Pseudo R2	0.113	0.122	0.176	0.177

Standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$

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