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The Weight of Administrative Burden: The Distributive Consequences of Federal Disaster Assistance on Recovery after Hurricane Harvey

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The Weight of Administrative Burden: The Distributive Consequences of Federal Disaster Assistance on Recovery after Hurricane Harvey

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The Weight of Administrative Burden: The Distributive Consequences of Federal Disaster Assistance on Recovery after Hurricane Harvey

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Dedication

I want to dedicate this work to my husband, Jonathan Malmin. He was my biggest supporter, advocate, and friend throughout this entire process. He gave me space to be a researcher, scholar, and mother. I also want to dedicate this work to my children, Henri James and Lauryn Sophia. They are my constant inspiration and challenge to leave this world better than how I found it. Lastly, to my source, drive, and invitation - Isa 9:6 | Lev 19:14.

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LIST OF ABBREVIATIONS

ACS – American Community Survey

HUD – U.S. Department of Housing and Urban Development

CDBG – Community Development Block Grant

EITC – Earned Income Tax Credit

FEMA – Federal Emergency Management Agency

FOIA – Freedom of Information Act

IA – Individual Assistance

ICE – Immigration Customs and Enforcement

IHP – Individuals and Households Program

OLS – Ordinary Least Squares

OR – Odds Ratio

pII – personally identifiable information

SBA – Small Business Administration

TSA – Transitional Sheltering Assistance

USGS – US Geological Survey

ZHVI – Zillow Home Value Index

SUMMARY

My dissertation identifies the impacts of administrative burden on individuals and communities through differential federal recovery assistance allocation. I present four essays that evaluate the Federal Emergency Management Agency (FEMA) direct-to-households grant program and the Small Business Administration (SBA) disaster home loan program. These are large federal programs directed at providing recovery assistance to individuals. I also utilize the Kaiser Family Foundation/Episcopal Health Foundation Harvey Anniversary Survey to assess perceptions of recovery by individuals who applied to FEMA and/or SBA for disaster assistance.

I find that disparities in funding exist for specific demographic profiles, particularly persons with disabilities. Moreover, administrative burdens vary along the process of interacting with federal agencies. Such burdens result in the lower allocation of federal resources, self-reported recovery, and negative perceptions of fairness and equity. Lastly, communities that experience lower administrative burdens in acquiring federal recovery dollars see faster growth in home equity after the disaster, presenting implications for burden presence and future wealth generation. My findings expand administrative burden theory by pointing to nuanced forms of onerous experiences which impact citizen outcomes. These experiences include procedural, exclusion, and delivery burdens at strategic points within the administrative process. These distinct forms of administrative burdens influence allocation of federal assistance, recovery, wealth, and perceptions of the broader society.

CHAPTER 1: INTRODUCTION

1.1 Overview

The purpose of my study is to assess whether disparities in federal recovery assistance persist for specific communities, the nature of citizen's interaction with the federal recovery apparatus, and how such interactions prove to shape recovery, wealth outcomes, perceptions of fairness, and equity. I evaluate administrative burden theory's sufficiency in providing a causal explanation for the observed citizen-state interactions and their outcomes. Through a thorough analysis of one major disaster event from multiple vantage points, I hope to fully understand how the administrative process hinders or catalyzes individual and community recovery trajectories. The findings have implications for how well communities recover from future disasters and how citizen-state interactions may influence governance.

Disasters have severe implications for life and property, often requiring large-scale collective action to facilitate recovery. One key determinant of recovery is access to resources that mitigate damage losses and slows the recovery trajectories associated with disasters. Often, the federal government may step in to assist communities through the provision of such resources. Dr. Dennis Mileti states

recovery is not just a physical outcome but a social process that encompasses decision making about restoration and reconstruction activities. This perspective highlights how decisions are made, who is involved in making them, what consequences those decisions have on the community, and who benefits and who does not (Mileti 1999 p. 230).

The Federal Emergency Management Agency (FEMA) provides grants and other forms of assistance to households impacted by disasters. The Small Business Administration (SBA) provides low-interest disaster home loans to impacted residents. There are legal requirements to ensure that persons with disabilities have equal access and reasonable accommodations to all federal recovery services after disasters (Americans With Disabilities Act of 1990., 1990; Kailes & Enders, 2007). Nevertheless, during the 2017 hurricane season (Harvey, Irma & Maria), over 1.3 million individuals with disabilities were denied federal recovery assistance tied to the federal bureaucratic process (GAO, 2019).

Administrative burden as a theory provides insight into bureaucratic inequities experienced by citizens, particularly for historically marginalized persons with disabilities. The foundations of administrative burden emerge from the red tape literature. Red tape focuses on rules, regulations, and procedures that constrain organizations' performance (Baldwin, 1990; Bozeman, 1993; Bozeman & Feeney, 2013; DeHart-Davis & Pandey, 2009; Heinrich, 2016; Pandey & Scott, 2002). If left unchecked, red tape costs may escape the public organization's bounds and begin to impose costs onto clients. When the clients are citizens interacting with the administrative state, the legitimacy of government actions under red tape's constraining forces poses a more significant concern (Moynihan & Herd, 2010). When red tape begins to impact citizens through costly access to services differentially, administrative burden emerges (Bozeman, 2000; Burden et al., 2012; Heinrich, 2016; Moynihan et al., 2014; Peeters, 2019).

Administrative burden theory includes the compliance, learning, and psychological costs borne by citizens in accessing government services (Moynihan et al., 2014). If already marginalized citizens encounter service delays and denials as forms of administrative burden, there is the potential to further exacerbate social inequity due to the burden encounters (Aizer, 2003; Brodkin & Majmundar, 2010; Heckman & Smith, 2003; Moynihan et al., 2014; Peeters, 2019; Peeters & Widlak, 2018). Moreover, marginalized citizens lack the political and financial resources needed to overcome administrative burdens; such little recourse or alternatives leads to implications on democratic norms and values (Kogan, 2017; Mettler & Soss, 2004; Moynihan & Soss, 2014).

Much of the red tape and administrative burden literature focuses on means-tested or income-based eligibility programs. I evaluated two universal federal disaster recovery programs. When disasters overwhelm local and state jurisdictions' capacity to respond, the federal government may step in and assist in recovery work. Through access to federal recovery programs, disaster-affected individuals and communities can regain a sense of place post-disaster. Administrative burdens within federal assistance for those already marginalized may exacerbate unequal recovery trajectories and proliferate social inequity. Public administrative theories on administrative burden provide insight into uneven disaster recovery trajectories, elucidate mechanisms to reduce administrative burden, and in turn, provide a path forward towards mitigating social inequity through administrative inclusion.

1.1.1 Main Findings and Contributions

My dissertation identifies differential resource allocations from federal recovery grants and low-interest loan assistance to individuals and communities impacted by Hurricane Harvey in Texas. I find that as the prevalence of disability increases in communities, those communities receive less grant funding, controlling for factors such as storm damage, poverty, and race/ethnicity. Moreover, the disability-related disparity widens as the amount of funding within communities increases. Individuals who self-identify as needing special accommodations on grant applications are more likely to receive grant assistance eligibility. Nevertheless, individuals coming from higher disability-prevalence communities are less likely to self-identify as needing special accommodations.

When individuals receive help in applying for disaster relief, there are lower odds of being delayed or denied federal assistance. Such individuals have positive perceptions of recovery, fairness, and equity. They are more likely to report a return to normalcy and higher confidence that wider rebuilding efforts help the middle class, the poor, those most in need, and persons like themselves. Such individuals receiving disaster application help are less likely to be African Americans or report a disability. Separately, individuals who face delays or denials in federal recovery assistance have significant negative perceptions of fairness and equity, as well as feelings of alienation one year after Harvey. Lastly, communities receiving federal recovery credit assistance with low administrative burdens experience faster rises in home values over time compared to communities with high administrative burdens. African American communities and communities with higher disability prevalence are at a particular disadvantage when experiencing lower administrative burdens associated with credit assistance, even when controlling for Harvey damage, pre-storm housing values, homeownership, and poverty.

I demonstrate that administrative burden in the form of procedural burdens (administrative processes that influence applying for services) and exclusion burdens (administrative process that influences denial of eligibility or services) are differentially experienced based on community and individual demographic profiles. Moreover, how communities receive services (i.e., delivery burdens) also present distinct influences on recovery trajectories. The negative outcomes of nuanced forms of burden (procedural, exclusion, and delivery) are not limited to allocating public resources. Procedural, exclusion and delivery burdens within the administrative recovery process influence longer-term recovery, wealth accumulation, and societal perceptions of fairness, equity.

While my empirically driven constructs of procedural, exclusion, and delivery burdens add to the literature on administrative burden, there are limitations to my work. I rely on one event, Hurricane Harvey, in my assessment of burdens. I also assess FEMA and SBA federal recovery assistance programs. There are other forms of assistance ranging from local to non-profit and the private market that facilitates recovery. While I do not assess these other forms of assistance and the internal burdens these structures may carry, the two federal programs are the most extensive and most immediate forms of assistance meant to start the post-disaster recovery process. Lastly, how I operationalize burden does not directly measure the original inputs of burden found in the literature (i.e., learning, compliance, and psychological costs). This challenge occurs due to the limitations of my secondary data and the quantitative methods of analysis that I use. I move from the theoretical learning, compliance, and psychological based cost- model of citizen-state interactions influencing citizen outcomes to an empirically driven model of administrative burden as onerous procedural, exclusion and delivery experience that influences citizen outcomes. My findings thus move administrative burden theory forward.

1.1.2 Dissertation structure

In my assessment of administrative burden and disaster recovery, I structure the dissertation using a four-essay format with introduction and conclusion chapters. Chapter two presents the literature on administrative burden, its expansion from red tape theory, the main costs associated with the burdens, and the implications of such burdens on historical program utilizations. I also present an overview of the disaster recovery literature, including a brief review of federal recovery policies and disaster-related social vulnerability. Chapter three (Essay 1) examines federal recovery assistance distributions based on underlying community demographic profiles using administrative and Census data. Through cross-sectional quantile regression, I use

FEMA Individual and Household Program (IHP) data at the zip code level regressed onto the community-level prevalence of disability. Chapter four (Essay 2) evaluates individual-level eligibility decisions through applicant-level FEMA administrative data using multivariate logistic regression. Through generalized logistic regression, chapter five (Essay 3) weighs how burden influences federal recovery assistance perceptions using survey data of the Harvey impacted region. Chapter six (Essay 4) presents an assessment of how the extent of federal recovery credit assistance influences home equity through a difference–in–difference study design. This chapter utilizes SBA disaster home loan data and Zillow market data to identify home value outcomes associated with burden.

Chapters three through six build upon each other, whereby I glean empirical insight into the nature of administrative burden. Within each essay chapter, I ground my findings within published government assessments and after-action reports of Hurricane Harvey to examine my findings within a larger context. Chapter seven presents a summative conclusion of the findings across all four essays and a discussion of overall study limitations. I construct a conceptual framework to contribute to the theory of administrative burden and future lines of research inquiry.

CHAPTER 2: LITERATURE REVIEW

2.1 On the Origins of Administrative Burden: Seeing Red (Tape)

Administrative burden has its foundations in the red tape literature (Bozeman, 1993, 2000; Brodkin & Majmundar, 2010; Burden et al., 2012; Moynihan & Herd, 2010; Peeters, 2019). I begin with a brief overview of red tape to build a more robust discussion of administrative burden and its validity in my research questions. Specific aspects of red tape are discussed only through a limited lens to provide context for administrative burden theory. My brief summation of red tape theory includes definitions and constructs by notable scholars.

Red tape exists when internally or externally generated rules, regulations, and procedures (abbreviated to rule-constraints) negatively constrain the efficiency of organizations (Baldwin, 1990; Bozeman, 1993; Bozeman & Feeney, 2013; DeHart-Davis & Pandey, 2009; Heinrich, 2016; Pandey & Scott, 2002). The extent to which red tape endures within an organization is often task and institutional/sector dependent, with more red tape observed in government organizations compared to private and non-profit sectors (Bozeman, 1993; Bozeman et al., 1992; Feeney & Rainey, 2010; Pandey & Kingsley, 2000). Consequentially, red tape has potential implications for government performance, access to services, and citizen engagement (Pandey et al., 2007).

The origin and impact of red tape are dependent upon the bureaucrat's perspective, who must engage with the rule-constraints (Bozeman & Feeney, 2013). A bureaucrat's position and experience within a public organization influence whether they view the constraints of organizational rules as legitimate (Moynihan, 2012). If bureaucrats perceive that rule-constraints promote relative efficiency, then such rules have legitimacy (Bozeman, 2012; Kaufmann &

Feeney, 2013). When such rule-constraints lack legitimacy, negative perceptions of red tape emerge, which may be detrimental, counterproductive, lowers risk tolerance, and magnifies dysfunction within organizations (Bozeman et al., 1992; Bozeman & Kingsley, 1998; DeHart-Davis & Pandey, 2009; Pandey et al., 2007; Pandey & Kingsley, 2000; Pandey & Scott, 2002).

Bureaucratic-centered red tape focuses on the stakeholder impacts of red tape. Stakeholder red tape entails "organizational rules, regulations, and procedures that remain in force and entail a compliance burden but serve no object value by a given stakeholder group (Bozeman, 1993 p. 284)." Organizational stakeholders may range from legislative bodies and oversight agencies to clients of the organization. The large size of potential stakeholders poses operational challenges in overall red tape theory-building (Bozeman, 1993). Much of the red tape literature development focuses on how clients interact with the bureaucracy. However, legitimacy as a validating concept of whether rule-constraints are appropriate expands from the bureaucrat's purview to what Bozeman (1993) considers a far richer conceptualization than the original typology of organizational red tape. Legitimacy now considers the client's perception and perspective measured via the burden in which rule-constraints impose on the client (Bozeman, 1993).

Under classical economic theory, rational clients choose what they value. Incentives serve to promote a favorable action, whereas imposed costs deter unfavorable activity. The presence and constraining factors of red tape are forms of transactional costs. Of note, transaction costs may accrue through legitimate compliance burden within organizations. These costs, however, are still onerous and require resources from the client to respond appropriately (Bozeman, 2000; Bozeman & Feeney, 2013; Burden et al., 2012; Kaufmann & Feeney, 2013; Moynihan et al., 2014). More importantly, the legitimate costs are not under a strict literature definition considered red tape (Bozeman, 2000). The loss of legitimacy with transaction costs occurs when compliance burdens exceed the benefit of the rule's legitimate purpose. The results of such burdens manifest themselves in lower program access and higher financial costs to the client (Moynihan & Herd, 2010). When the client is the citizen, and the organization which imposes such transaction costs is the state, red tape theory contestably expands to that of administrative burden theory (Burden et al., 2012; Herd & Moynihan, 2018; Moynihan & Herd, 2010; Peeters, 2019).

2.2 Administrative Burden: The Citizen-focused Intentionality of Red Tape

Administrative burden theory expands on the red tape literature through its citizen-centered focus gleaned from the policy feedback tradition (Peeters, 2019; Wichowsky & Moynihan, 2008). Under a red tape – policy feedback linkage, the emergence of red tape begins with the policy process, includes programmatic implementation, and ends with the citizen experience (Moynihan & Herd, 2010). The policy feedback literature identifies the need for policy design to understand policy impact on citizenship among other scopes (Ingram & Schneider, 1993; Moynihan & Herd, 2010). Societal values on standing, worthiness, the expectation of fair treatment and power are often symbolically communicated through public policies and programs (Keiser & Miller, 2020; Mettler & Soss, 2004).

Linking red tape to the policy feedback tradition provides a potential administrative mechanism on how program design impacts the citizen-state interaction through bureaucratic discretion on policymaking (Burden et al., 2012; Moynihan & Herd, 2010; Soss, 1999). Consequential, distributive, and constructed administrative burdens emerges for citizens when rule-constraints result in differential costs in access to public resource allocation (Brodkin & Majmundar, 2010; A. M. Fox et al., 2020; Herd & Moynihan, 2018; Moreno & Mullins, 2017;

Moynihan et al., 2014; Peeters, 2019). Thus, the burden citizens face shapes their access to social, civic, and political rights through the administrative process (Moynihan & Herd, 2010). The legitimacy of rules central to the presence of red tape comes into play within administrative burden when the interpretation and implementation of rule-constraints, “limits access to citizen rights, fosters inequity, and negatively effects citizenship outcomes.” (Moynihan and Herd, 2010 p. 666).

In interacting with red tape, rule-constraints impose a compliance cost on citizens as they interact with the state. Administrative burden theory adds learning and psychological costs borne by the citizen in addition to the red tape-engendered compliance costs (Herd & Moynihan, 2018; Moynihan et al., 2014). Knowledge and information play a central role when individuals interact with the state. Citizens accrue learning costs when they lack the nuanced knowledge/information needed to navigate public programs (Herd & Moynihan, 2018; Moynihan et al., 2014). Psychological costs occur when the state imposes additional costs through the stress and social stigma citizens may endure in accessing services (Herd & Moynihan, 2018; Moynihan et al., 2014; Peeters, 2019). Whereas red tape may be an institutionally imposed environmental condition in which bureaucrats operate, administrative burdens may serve as an intentional policy tool used by administrators and policymakers in delivering public services (Bozeman & Feeney, 2013; Herd & Moynihan, 2018; Moynihan et al., 2014).

The administrative state may use red tape in a manner that differentially impacts and undermines the citizen's normative landscape of service eligibility, responsiveness, the minimum standard of living, and explicit equity (Herd, 2015; Herd et al., 2013; Keiser & Miller, 2020; Moynihan & Herd, 2010). Policy designs that limit public service utilization may come from discrimination of those who seek services, a desire for social control, value-based judgments on which citizens deserve services, or the results of constrained/limited resources (Brodkin, 1997; Goodsell, 1977; Heinrich, 2016; Lipsky, 1984; Moynihan & Herd, 2010; Scott, 1997; Soss, 1999; Soss et al., 2011). However, because the intentional and unintentional costs of administrative burdens emanate from administrators and are imposed on citizens, it is a construct of political means (Herd & Moynihan, 2018). The implicit and explicit exertion of authority from the bureaucracy is necessary for administrative burden (Peeters, 2019). Thus, due to the implied self-interest of organizations that promote administrative burden, the experience of administrative burden is of a political nature (Herd & Moynihan, 2018; Peeters, 2019).

Experience with administrative burden from the citizen's perspective manifest in service delays, loss of time and money, general exclusion, and cascading exclusion of other eligible services (Brodkin & Majmundar, 2010; Christensen et al., 2020; Hattke et al., 2019; Heinrich, 2016, 2018; Herd, 2015; Peeters, 2019). Furthermore, vulnerable populations are disproportionately impacted by administrative burdens due to limited political power and lack of affordable private-sector alternatives (Brodkin & Lipsky, 1983; Brodkin & Majmundar, 2010; Heinrich & Brill, 2015; Moynihan et al., 2014; Nisar, 2017; Peeters, 2019; Peeters & Widlak, 2018; Soss et al., 2011). Differential impacts based on class, race, educational attainment, and gender thus have the potential to exacerbate existing social inequities (Aizer, 2003; Brodkin & Majmundar, 2010; Heckman & Smith, 2003; Moynihan et al., 2014; Peeters, 2019; Peeters & Widlak, 2018). These bureaucratic hurdles lead to the often-observed low general participation in means-tested programs, as well as overwhelmingly negative encounters for socially disadvantaged citizens in which the programs initially target (Barnes & Henly, 2018; Bhargava & Manoli, 2015; Heinrich & Brill, 2015; Moynihan et al., 2014; Peeters, 2019). Lastly, developing research shows that in addition to the individual's costs, the presence of administrative burden may have negative collective impacts as individuals begin to relationally shift their interactions with the government (Mettler & Soss, 2004; Peeters, 2019; Peeters & Widlak, 2018). The collective impacts of negative government interaction occur around perceptions of citizenship, democratic participation, social capital, governmental trust by the citizen, and social mobility (Bruch et al., 2010; Heinrich, 2018; Moynihan & Herd, 2010; Peeters, 2019; Wichowsky & Moynihan, 2008).

2.2 Clear lines of distinction: Red Tape vs. Administrative Burden

Is it conceptually necessary to delineate between organizational red tape experienced by citizen-stakeholders and that of administrative burdens? In the media and political landscape, red tape is often framed from the citizen's perspective when it rises to national attention issues, such as in the case of natural disasters (Chen, 2015; Diaz, 2018; Epstein, 2012; Wallace, 2019). For instance, when citizens faced long wait times for flood insurance payouts to facilitate rebuilding after Hurricane Sandy, some residents and politicians cited "red tape" as the cause of delays (see Figure 2) (Spychalsky, 2013). During Hurricane Harvey, poorer residents reported feelings of mental stress and isolation associated with "red tape" in federal assistance (Fernandez, 2018). Theoretically, administrative burden focuses on the learning, psychological, and compliance costs for the citizen (i.e., citizens' stress due to service delays, the complicated navigation through multiple bureaucracies for services, and extensive paperwork). However, the larger narrative expressed by politicians, media, advocates, and citizens who seek to describe the administrative limitations and experiences with the federal recovery bureaucracy names red tape (Chen, 2015; Diaz, 2018; Epstein, 2012; Morris, 2018; Wallace, 2019).

Figure 2 Hurricane Sandy-impacted resident waiting on federal assistance. NOTE: Photo taken by Kristie Arden/Herald Pennsylvania Avenue resident Sam Kinsley placed red tape on her home in a display of frustration with her flood insurance company. Source: https://www.liherald.com/stories/cut-the-red-tape,46070

As such, the conceptual delineations between red tape and administrative burden are not as pressing from the citizen's point of view (Moynihan et al., 2016). Empirically separating red tape from administrative burden is also a challenge. For instance, red tape can be highly subjective and affectively driven. Emotional pathways linked to red tape may be underestimated and distorted when researchers separate red tape and administrative burden (Hattke et al., 2019). Outcomes of the rules, whether such outcomes are perceived as fair, and general knowledge of the political process influence red tape perceptions (Kaufmann & Feeney, 2013; Keiser & Miller, 2020; Moreno & Mullins, 2017; Tummers et al., 2016).

The separation of administrative burden from red tape provides a critique and focuses on citizens' differential costs. To build upon administrative burden theory is to depart from theories on operational efficiency within public administration and allows for an empirical study of where the presence of red tape violates public administration and democratic values (Keiser & Miller, 2020; Mettler & Soss, 2004; Moynihan & Herd, 2010; Moynihan & Soss, 2014). Clear separation and defining of administrative burden and red tape theories allow for a later rejoining of the two theories within the sphere of praxis. Identifying mechanisms of reducing red tape offers a practical application within administrative burden theory in alleviating the negative impact of citizens' interaction with the state (Moynihan & Herd, 2010).

My dissertation focuses on administrative burden in non-means-tested programs, specifically federal disaster recovery assistance programs. This work extends the proposition of several researchers that encounters with administrative burdens lead to lower resources allocations for segments of the population already in greatest need, creating a compounding effect on recovery, wealth, and perceptions of fairness and equity (Bruch et al., 2010; Heinrich, 2016; Soss et al., 2011).

2.3 The Impacts of Disasters and the Differential Recovery Trajectories

Disasters cause severe disruptions to life and property, resulting in the need for collective recovery efforts. One facet of disaster recovery is rooted in the differential impacts within communities, whereby disaster risk impacts population subgroups differently (Logan et al., 2016). Individual, family, and neighborhood characteristics that impact disaster recovery point to underlying vulnerabilities associated with lower socioeconomic distributions (Elliott & Howell, 2017). Such underlying vulnerabilities lead to post-disaster experiences of more significant displacement, out-migration, mental and physical injuries, and fewer benefits of government assistance (Boustan et al., 2017; Curtis et al., 2015; Elliott & Howell, 2017; Fothergill & Peek, 2004; Fussell et al., 2016; Howell & Elliott, 2018; Karim & Noy, 2015; Pais & Elliott, 2008; Pelling, 2003; Tierney, 2012; K. J. Tierney, 2007).

Marginalized communities and individuals are less likely to own property, are vulnerable to financial liabilities, require the use of their savings to stay afloat, and are subject to higher rent due to reduced housing stock associated with disasters (Elliott & Howell, 2017; Elliott & Pais, 2006; Howell & Elliott, 2018; Vigdor, 2008). Socially vulnerable populations, particularly African American and Latinx women, are also more likely to be impacted by residential instability after disasters (Abramson et al., 2010; Billings et al., 2019; Howell & Elliott, 2018). Moreover, across individual, social support, and neighborhood factors, age and disability may negatively suppress disaster recovery (Abramson et al., 2010). Poverty rates also experience an overall increase after a disaster, despite the increase in non-profit and commercial businesses after a catastrophic event (Cutter et al., 2003; Fothergill & Peek, 2004; Smiley et al., 2018).

When communities experience major disasters, the federal government may assist in the recovery efforts through the infusion of federal dollars into disaster-damaged communities (Appendix A). The Stafford Act provides authorization of federal assistance to state and local jurisdictions. The Act was initially created to achieve administrative efficiency, routinizing federal government support of state and local disaster recovery efforts (Smith & Birkland, 2012). As the federal government entered recovery work in the 1950s and expanded dramatically in the 1990s, the federal government came to take its place as the primary driver/funder of recovery efforts from natural disasters (Smith & Birkland, 2012).

With the increase in scale and frequency of disasters, recovery from large-scale events may be anywhere from immediate to decadal in timescale (Boustan et al., 2017; Cavallo et al., 2013). However, allocation of federal dollars shortens the recovery trajectory of households and communities (Billings et al., 2019; Deryugina et al., 2018; Gallagher et al., 2019; Gallagher & Hartley, 2017; McIntosh, 2008; Sacerdote, 2012). For instance, ten years after Hurricane Katrina, residents impacted by the storm in New Orleans had lower homeownership rates and higher insolvency rates (Bleemer & van der Klaauw, 2019). Yet, residents who participated in a federal recovery program had higher post-disaster homeownership rates and were less likely to face bankruptcy or foreclosure compared to those who did not participate in the federal recovery program (Bleemer & van der Klaauw, 2019). The use of public and private resources as recovery tools reduces adverse financial conditions associated with natural disasters (Billings et al., 2019; Deryugina et al., 2018; Gallagher et al., 2019; Gallagher & Hartley, 2017; McIntosh, 2008; Sacerdote, 2012). However, individuals with considerable pre-disaster resources such as property and income have greater entrée to such tools, often subsidized by federal recovery investments (Howell & Elliott, 2018; Peacock et al., 2014).

Social inequity within disaster management occurs when institutional structures prevent access to opportunities and resources to facilitate recovery (Emrich et al., 2019; Thomas et al., 2013). Marginalized communities have historically had limited access to government assistance after a disaster (Begley et al., 2018; Billings et al., 2019; Emrich et al., 2019; Grube et al., 2018; Howell & Elliott, 2018; Pelling, 2003; Rufat et al., 2015; Smiley et al., 2018; Tierney, 2012). Communities benefitting the greatest from federal disaster assistance aid are often wealthier, whiter, more educated, and have higher homeownership (Begley et al., 2018; Billings et al., 2019; Howell & Elliott, 2018). For example, when controlling for disaster damages, counties that received FEMA aid between 1993 and 2003 accumulated more wealth with the more assistance received, indicating government assistance exacerbates social inequality, and polarizes wealth trajectories (Howell & Elliott, 2018). How federal programs are implemented in the face of disasters may provide a unique narrative on how burdens are expressed or suppressed administratively, with implications on *who* recovers and *why* (Mileti, 1999).

Administrative burden involves institutional and bureaucratic processes which create differential resource distribution outcomes aligned along with pre-existing social inequities (Bullard, 2008; Cole & Foster, 2001; Domingue & Emrich, 2019; Harrison, 2014; Herd & Moynihan, 2018; Mohai et al., 2009; Morello-Frosch, 2002; Muller et al., 2018; Pellow, 2017; Pulido, 2015; Schlosberg, 1999, 2009; Shrader-Frechette, 2002). Within federal disaster recovery programs, burden will most likely occur through the allocation of assistance along the lines of race, gender, socioeconomic status, and age (Bullard & Wright, 2012; Domingue & Emrich, 2019; Thomas et al., 2013). However, in what manner burdens manifests within the disaster recovery policy arena may vary across geography, disaster, and time (Domingue & Emrich, 2019). More research is needed in understanding burden around disaster recovery and the role the federal government plays in either exacerbating or mitigating such inequities. Public administration theories may lend insight into the phenomenon of uneven disaster recovery coupled with administrative/bureaucratic outcomes. Such coupling through a public administration lens may serve to answer the call for more significant theoretical development around the disaster recovery process (Smith & Birkland, 2012).

In the next chapter, I begin to assess the consequential nature of administrative burden concerning federal disaster recovery funding distributions for specific communities, particularly communities with higher pre-disaster disabilities. Federal disaster recovery assistance is targeted to all US citizens impacted by disasters, regardless of income. However, persons with disabilities are accorded specific legal protections designed to promote equal access and reasonable accommodations to federal programs. I use Hurricane Harvey, which impacted the state of Texas, as a case study to assess the influence of administrative burden on a direct-to-household cash assistance program. I assess whether there are disparities in resource allocation of funds by disability prevalence, a potential outcome of administrative burden. I also create an indirect measure of learning costs to assess whether such costs explain why federal resource allocation disparities are present.

CHAPTER 3: ESSAY ONE

3.1 Significance and Justification

Through intersectional forms of vulnerability, persons with disabilities are often situated within public housing projects and located in segregated low-income communities with higher exposures to natural hazards (Chakraborty et al., 2019). For persons with disabilities, such social disadvantages to disasters are critically constructed through policy designs that create physical and social impediments to relief (Hemingway & Priestley, 2006). The results are often longer disaster recovery time spans for individuals with disabilities (Stough et al., 2015; Van Willigen et al., 2002). Disability-specific recovery issues encompass securing accessible temporary housing, loss of healthcare, inaccessible clinical and supportive health services, gaps in disability-specific insurance needs, and caregiver network disruptions (Adams et al., 2011; Davis & Phillips, 2009; Fox et al., 2010). Other contributions to incomplete or longer recovery time spans for persons with disability include newly developed health conditions from disaster-induced delays in medical treatment (Adams et al., 2011; Willams et al., 2005). Provision of federal assistance shortens the durations of such disaster recovery needs (Billings et al., 2019; Deryugina et al., 2018; Gallagher et al., 2019; Gallagher & Hartley, 2017; McIntosh, 2008; Sacerdote, 2012). Yet how well individuals with disabilities are situated within receiving federal disaster assistance given their intersectional forms of vulnerability requires further examination.

FEMA's Individuals & Households Program (IHP) provides financial assistance to households impacted by disasters (FEMA, 2016). Approved applicants may use the cash assistance to meet housing or medical-related costs, among other needs (Table 3.1) (FEMA, n.d., 2016; Lindsay & Webster, 2019; Torsell & Nagel, 2017).

Table 3.1 FEMA provided services within the Individuals and Household Programs (IHP)

Housing Assistance: Financial	**Housing Assistance: Direct**	**ONA: SBA - Dependent**	**ONA: Non-SBA-Dependent**
Lodging Expense Reimbursement Rental Assistance Home Repair Assistance Home Replacement Assistance	Multifamily Lease and Repair Transportable Temporary Housing Units Direct Lease Permanent Housing Construction	Personal Property Moving and Storage Transportation Assistance Group Flood Insurance Policy	Funeral Assistance Medical and Dental Assistance Childcare Assistance Assistance for Miscellaneous Items Critical Needs Assistance Clean and Removal Assistance

NOTES: Types of Housing Assistance and Other Needs Assistance (ONA). Source: FEMA, Individual Assistance Program and Policy Guide (IAPPG), FP 104-009-03, March 2019, p. 7 at https://www.fema.gov/sites/default/files/2020-07/fema_individual-assistance-program-policy-guide_2019.pdf . The different types of Housing Assistance may constitute either financial or direct assistance; however, all types of ONA are forms of financial assistance.

Program eligibility is based on several factors, including damage assessments, a mandate not to duplicate insurance coverage, and social vulnerability (FEMA, 2016; GAO, 2018). Individuals must submit a registration form which includes a questionnaire on demographics, citizenship status, financial information, and level of disaster damage (FEMA, 2016). Registrants may apply using several approaches including disaster recovery centers, online or through a toll-free hotline, which includes Text Telephone Relay (TTY) and video relay services (GAO, 2019). [1]

[1] "TTY is for individuals who are deaf, hard of hearing, deaf/blind, or have speech disabilities and wish to communicate with a hearing person who uses a standard telephone. TTY relay calls are generally made using a text telephone, also known as TTY, which is a communications device equipped with a keyboard for typing messages and a screen for reading messages. A TTY device connects to a standard phone line. TTY callers call the Federal Relay TTY Toll-Free Number to reach a Communication Assistant (CA) who processes their call. Once connected, the TTY user types messages to the CA, who relays the conversation by reading it aloud to the hearing person. The CA then listens to the hearing person's reply and types it to the TTY user." Source: Text Telephone Relay or Telecommunications Relay Service (TTY/TRS). Federal Relay. Available at: https://www.federalrelay.us/tty.html

Within Texas, close to ninety-four percent of individuals with disabilities are situated within the home rather than in institutions, meaning that they rely on the same direct assistance to repair and recover from home damages as the wider community in which they reside (ADA-PARC, n.d.). Disability-relevant assistance under IHP grants include a one-time payment for the purchase of live-saving and life-sustaining items such as durable medical equipment (FEMA, 2018a). FEMA also provides direct housing assistance when persons with disabilities are unable to find accessible housing due to the disaster, or the available homes are not near accessible public transportation (FEMA, 2016). The housing may include an additional bedroom to meet reasonable accommodation requirements or meet uniform accessibility compliance standards if the housing is a manufactured unit. Lastly, individuals may acquire financial assistance to offset the costs of disaster-related disruptions in assistive care for their children with disabilities (FEMA, 2016).

Several regulatory mechanisms at the federal level mandate the inclusion of persons with disability in recovery programs and services. The Rehabilitation Act of 1973 (29 U.S.C. 701 et seq) and the Americans with Disabilities Act of 1990 as amended (42 U.S.C. 121010, et seq) requires equal access to federal funding, information, and services for disaster recovery. The Post-Katrina Emergency Management Reform Act of 2006 (Pub. L. 109-295) also addresses removal of disability-based discrimination through the assistance in disaster recovery services (GAO, 2019). The 2006 Post-Katrina Act created the Office of Disability and Integration and Coordination, whereby disability integration advisors deploy during disasters to work with staff to support accommodation services and inclusive practices. Accommodation services include providing American Sign Language interpreters and tracking service shortfalls for key demographic groups (GAO, 2017). However, despite federal laws and policies, persistent gaps in the utilization of disaster recovery services continue to emerge for persons with disabilities (GAO, 2019).

FEMA lacks standard procedures for disability integration staff, resulting in ineffective sharing and leveraging of information on disability integration needs (GAO, 2017). Specific service shortfalls and inconsistencies include not assigning disability integration staff to recovery efforts, exclusion of disability stakeholders in recovery groups, and inaccessible emergency alerts, evacuation and sheltering information (GAO, 2017). FEMA also remains understaffed, with the actual number of disability integration personnel in FEMA's incident workforce at only 40% during Hurricane Harvey (FEMA, 2018b). In addition, IHP registration processes are confusing and easily misinterpreted for persons with disabilities, with over one million individuals with disabilities denied assistance during the 2017 hurricane season (Harvey, Irma, Maria) (GAO, 2019). An executive director of a Texas coalition of community-based organization reports,

> *FEMA's system is not designed to serve those who need it most. It is better suited for folks that can navigate a very complicated system… After you do cross the hurdles and are able to get the golden ticket to get some assistance, you're met with another set of challenges of looking at how much assistance you're going to get and if it's really going to help you in the long run (Morris, 2018).*

Administrative burden theory contends that eligible individuals of program services face delays and denials of services through the application of differential costs (Moynihan et al., 2014). The theory emphasizes the experience of the citizen (Herd & Moynihan, 2018). The administrative state may use rule-constraints in a manner that differentially impacts and undermines the citizen's normative landscape of access, responsiveness, the minimum standard of living, and explicit equity (Keiser & Miller, 2020; Moynihan & Herd, 2010). Policy designs which limit public service utilization may come from discrimination of those who seek services, a desire for social control, passive statements on those deemed worthy of services, or the results of constrained/limited resources (Brodkin, 1997; Goodsell, 1977; Heinrich, 2016; Lipsky, 1984; Moynihan & Herd, 2010; Scott, 1997; Soss, 1999; Soss et al., 2011). However, because the intentional and unintentional costs of administrative burdens emanate from administrators and are imposed on citizens, it is a construct of political means (Herd & Moynihan, 2018; Peeters, 2019).

Administrative Burden theory identifies three components of costs which may be differentially imposed: learning costs, psychological costs, and compliance costs (Moynihan et al., 2015). Much of the theoretical understanding of administrative burden emanates from evaluations of means-tested programs (Heinrich, 2016; Moynihan et al., 2014; Peeters, 2019). Various state and federal policymakers may alter levels of administrative burden components through policy instruments based on competing policy agendas (Fox et al., 2020; Moynihan et al., 2016b). Variations in means-tested program participation may also be due to stigma, lack of information, and generic transaction/compliance costs (Chudnovsky & Peeters, 2020; Currie, 2006). The overall research trend among non-means tested programs also shows lowered participation rates based on variations in costs (Anderson & Meyer, 1997; Currie, 2006).

Higher learning costs come from a lack of information and knowledge (Moynihan et al., 2014). Several studies assess learning costs and program service utilization. Through a randomized control field experiment, Bhargava and Manoli (2012) find that low utilization of the Earned Income Tax Credit (EITC) for those eligible are often due to low awareness of eligibility and potential benefits. Providing households with simple information through mailings on eligibility and benefits increases their EITC filings (Bhargava & Manoli, 2012). Increases in information complexity reduces an individual's perceptions of eligibility and lowered attention, thereby suppressing enrollment up-take (Bhargava & Manoli, 2015). In another randomized field experiment, White et al. (2015) find that local election administrators provide different levels of voter information to citizens based on perceived racial/ethnic makeup (White et al., 2015). Boatman and Evans (2017) find greater knowledge of federal student loan programs and financial literacy associated with lower student aversion to borrowing for college. The study also finds that prior loan experience influences willingness to borrow for college (Boatman & Evans, 2017). The provision of information reduces learning costs associated with engaging administrative services (Boatman & Evans, 2017; Chudnovsky & Peeters, 2020; Jessoe & Rapson, 2014; Moynihan et al., 2014; White et al., 2015).

My study evaluates the presence of burden on communities with higher levels of disabilities present and test an indirect means of capturing zip code level learning as a protective factor against burden. I test four hypotheses:

Hypothesis 1.1: *As the proportion of disability grows within disaster-assistance eligible communities, these communities will receive less federal recovery funding.*

Hypothesis 1.2: *The disparity in recovery funding among communities with higher levels of disability will grow as the distribution of recovery funding increases.*

Hypothesis 1.3: *Communities receiving past federal disaster assistance eligibility will be more likely to receive present-day federal recovery assistance dollars.*

Hypothesis 1.4: *Disparities in federal recovery dollars by community-level disabilities will be moderated by past disaster assistance eligibility.*

Within hypotheses 1.1 and 1.2, I test whether there are differential availabilities of recovery assistance along pre-existing marginalization lines. One key aspect of administrative burden literature is the exclusion of individuals from services despite their eligibility or entitlement to such services. The main (not only) driving factor of service eligibility is disaster damage – regardless of income. Thus, in assessing federal recovery assistance, policies would dictate that disparities related to disabilities will not be present when controlling for the level of disaster damage. In addition, federal statutes require equal access and reasonable accommodations to recovery services, which translates to stated policies targeting persons with disabilities to ensure federal compliance (Americans With Disabilities Act of 1990., 1990). However, with administrative burden theory asserting that exclusion happens due to higher costs in utilizing program services, I contend that communities with higher levels of disability will experience more significant exclusion in the allocation of recovery resources due to administratively imposed costs.

Hypotheses 1.3 and 1.4 test learning costs via experience. Learning costs accrue when citizens must learn about the program, whether they are eligible, the nature of benefits, and how to access services (Moynihan et al., 2014; 2015). Information which is handicap accessible for persons with disabilities assists in navigating the recovery process (McCormack, 2019; Stough & Kelman, 2018; Wisner et al., 2003). I cannot observe to what extent individuals and communities receive accessible information related to Hurricane Harvey within this study. As an alternative, I measure past experience with disaster declarations as an indirect proxy for information on disaster recovery assistance eligibility. Previous researchers find that experiencing past disasters leads to increases in current day disaster preparedness actions (Malmin, 2020; Onuma et al., 2017). However, how does prior experience result in an uptake in present-day disaster recovery assistance? I contend that one form of recovery learning occurs through communities' experiences with prior disasters. In recovering from previous disasters, citizens (and communities) learn about recovery assistance by navigating the bureaucratic process to receive services. When disasters occur again, these citizens rely on their disaster histories and prior knowledge to reduce learning costs and increase access to recovery services. I attempt to measure the aggregate learning process of individuals as represented by zip codes with prior disaster assistance eligibility history. Thus, my study assesses whether previous experience with disaster eligibility influences greater present-day allocation of federal recovery assistance.

3.2 Methods

Hurricane Harvey developed into a tropical storm on August 17, 2017. On August 25, the storm made landfall on the Texas coast as a Category 4 hurricane (National Weather Service (NWS), n.d.). The storm first impacted the Port Aransas area then slowly moved inland. Significant rain bands developed as the storm moved over Harris, Fort Bend, and Brazoria counties resulting in heavy rainfall events and widespread catastrophic flooding (National Weather Service (NWS), n.d.). It was the first hurricane to make landfall in Texas since Hurricane Ike (Category 3) in 2008 and at the time of this research was the second-costliest US hurricane after Hurricane Katrina (Blake & Zelinsky, 2018; National Weather Service (NWS), n.d.). Rainfall totals during Harvey exceeded historical maximums, resulted in 68 deaths and an estimated $125 billion in damages (Appendix B) (Blake & Zelinsky, 2018; Walters, 2018). President Trump declared Hurricane Harvey a disaster on August 25, 2017, paving the way for the release of federal funds to the state of Texas (FEMA, 2018b; The White House, 2017). In total, forty-one counties in Texas received federal disaster declarations due to Hurricane Harvey.

The zip codes within the forty-one disaster declared counties served as my unit of analysis as they were eligible to receive federal disaster assistance (Appendix C).

Hurricane Harvey presented an important and clarifying study event in disaster recovery. First, Harvey's extreme rainfall event led to massive flooding outside of the designated 100-year floodplains (Smiley, 2020). The historic nature of the Harvey-induced floods however is expected to become more frequent, requiring changes to how researchers, government and the private sector assess risk (Emanuel, 2017; Smiley, 2020). In addition, Harvey occurred during a time when the United States faced multiple large-scale disasters including the 2017 California Wildfires, Hurricane Irma, and Hurricane Maria within a short time span (FEMA, 2020a). Such concurrent/serial hazards stress existing administrative systems, further exacerbating delivery of services. Yet, these stressors will become more prevalent under a changing climate, requiring systems to adapt and pivot as they meet their policy mandates in providing inclusive and accessible disaster-related assistance to communities.

I used total FEMA grant dollars distributed under IHP. FEMA provides publicly available data on total IHP awards for Housing Assistance (HA) and Other Needs Assistance (ONA) distributed by disaster declaration at the zip code level (Appendix D). Previous studies use IHP award amounts in assessing federal disaster aid distribution and social vulnerability (Drakes et al., 2021; Emrich et al., 2019; Kousky, 2013). In the 2008 Missouri floods and tornadoes, socially vulnerable groups were more likely to receive IHP assistance, but at lower dollar amounts (Kousky, 2013). In the case of the 2015 South Carolina floods, social vulnerability characteristics were neither a driver for disparity nor preferential receipt of average IHP assistance (Emrich et al., 2019). I assessed changes in allocation of total IHP grant assistance at the zip code explicitly by disability profiles.

I assessed the proportion of noninstitutionalized individuals with disabilities by zip code. I used the 2016 U.S. Census American Community Survey (ACS) survey to identify disability prevalence. Total disability included vision, ambulatory, cognitive, hearing, independent living, and self-care impairments difficulties. Persons with disabilities may be more likely to be exposed to flooding due to where their homes are located and the extent of disaster damage (Chakraborty et al., 2019). Exposure to flooding may have negative physical and mental health outcomes as well (Collins et al., 2013; Jiao et al., 2012; McLaughlin et al., 2011; Tong et al., 2011; Wade et al., 2004). Individuals with lower socioeconomic status and the elderly (whom have higher likelihoods of disabilities) are more at risk for negative health outcomes (Collins et al., 2013). Yet, such individuals may also be less likely to receive public assistance (Griego et al., 2020). I sought to assess whether disparities in FEMA assistance were conditional upon community-levels of disability prevalence for all Harvey-assistance eligible zip codes in Texas.

My second independent variable of interest termed *Prior recovery eligibility*, measured past disaster declaration eligibility as an indicator of experiential learning. *Prior recovery eligibility* determined whether communities at the zip code level received FEMA assistance eligibility for three recent disasters: the 2015 Memorial Day Floods, the 2016 Tax Day Floods and the June 2016 Floods (FEMA, n.d.-a, n.d.-b). The 2015 Memorial Day floods was declared a disaster on May 29th, 2015. FEMA approved 2,963 IHP applications and distributed fifty-seven million dollars. The 2016 Tax Day floods was declared a disaster on May 26th, 2016, with 10,618 approved FEMA IHP applications, and sixty-two million dollars awarded. Lastly, the June 2016 severe storms and floods was declared a disaster on June 11th, 2016. FEMA approved 5,697 IHP applications and awarded forty million dollars. All three disasters spatially overlapped the Harvey study area. I excluded other disasters declared between 2014 and 2017 in Texas from the analysis due to non-overlap with the study area.[2] I coded *Prior recovery eligibility* based on whether the zip code received assistance eligibility for at least 1 of the listed disaster declarations.

Models which do not control for disaster damage will severely bias estimate results when assessing FEMA IHP funding (FEMA, 2016; Lindsay & Webster, 2019; GAO, 2018). FEMA performs damage assessments through third party inspectors when registrants complete IHP applications for housing-related needs (FEMA, 2016). Relying on FEMA damage assessments however excludes individuals who may have been eligible for assistance but had low awareness or had applications rejected within the initial phase of registration. Sole reliance on FEMA damage assessments will underestimate potential disaster damage-related needs within communities. To overcome this bias, I relied on flooding data available from the US Geological Survey (USGS).

The USGS provides independent geospatial point data on the high watermarks (HWM) associated with large flooding events (USGS, 2020). High watermarks provide information on the highest elevation of floodwaters after an event due to storm tides, flash floods, or riverine flooding (Koenig et al., 2016). The data are traditionally used to inform flood inundation maps, flood warning systems, and other mitigation measures (Barlow et al., 2015). My proxy disaster damage variable measured the distance of the zip code centroid to the nearest high watermark. The smaller the distance between the centroid and high watermark point, the greater the Hurricane Harvey flood-related damages.

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[2] Counties may receive disaster declarations but aid does not include FEMA IHP as a form of disaster assistance. They can receive FEMA Public Assistance- which is assistance that goes to local governments and non-profit organization. Data collection/ public availability of IHP award amounts at the zip code level did not begin until July of 2014. Information available within the metadata of the FEMA public dataset: https://www.fema.gov/api/open/v1/IndividualAssistanceHousingRegistrantsLargeDisasters

Individuals who are socially vulnerable may possess lower coping capacity, and inability to navigate and understand eligibility criteria in applying for assistance (Drakes et al., 2021; Edgeley & Paveglio, 2017; Kamel, 2012; Kamel & Loukaitou-Sideris, 2004). To account for these factors, I controlled for additional socio-economic variables associated with uneven disaster recovery outcomes using the 2016 ACS. Control variables included the percentage of African American and Latinx, income, homeownership, limited English proficiency, population density (total zip code population per square mile area of the zip code), unemployment, and poverty.

3.2.1 Statistical Analysis

Recent studies show potential underestimates of population counts, with an urban/suburban bias present at the Census tract level and lower (Bazuin & Fraser, 2013; Chakraborty et al., 2019; Folch et al., 2016; Jung et al., 2019; Spielman & Singleton, 2015). As a result, I focused on the spatially larger zip code level, and exclude zip codes where ACS margins of error threshold exceeded population estimates (Chakraborty et al., 2019). I mapped counties with disaster declarations and identified zip codes which fell within the disaster declared counties meeting my ACS requirements. In the analysis I also included zip codes which fell partially within a disaster declared county.

Ordinary Least Squares (OLS) regression may provide an efficient unbiased estimator when several assumptions are met. OLS assumptions include normality and constant variance of the dependent variable, a linear relationship between the independent and dependent variables, and an uncorrelated error term with the independent variables. Due to the large fluctuations in FEMA assistance, OLS, however, would be inappropriate given its reliance on a normal distribution and sensitivity to outliers. On the other hand, quantile regression does not rely on an underlying distribution and is resistant to outliers through its reliance on the conditional median

(Angrist & Pischke, 2008). Quantile regression methods are often used within public health studies in understanding birth weight variability, within econometric studies on income inequality, and actuarial sciences around insurance risk premiums (Abrevaya & Dahl, 2008; Angrist et al., 2006; Heras et al., 2018; Ngwira, 2019). The use of quantile regression methods for disaster research is a novel approach and assists in the identification of population characteristics by the distribution of federal recovery funding. A quantile regression study design allowed me to assess variations in the percentile distribution of disaster assistance conditional upon community-level disability. Specifically, it allowed me to evaluate how the spread of Harvey FEMA recovery assistance changed based on the percentage of disabled within zip codes eligible to receive federal services.

To date, no research has assessed the distribution of recovery funding within communities, conditional upon social vulnerability factors. Regression quantiles are equivariant under monotonic transformations (Koenker & Hallock, 2001). Given the nonlinear relationship exhibited by FEMA IHP assistance and the percentage of total disability within zip codes, I assessed the conditional quantiles of (log)IHP award amounts, with the ability to exponential transform the data to convert back to IHP dollar amounts. I removed twenty-two zip codes from the study due to the margin of error exceeding the total population estimates (n = 15), or zero population (n = 7) as reported by the ACS. I assessed statistical significance at the alpha= 0.05 level. I analyzed spatial data using ArcGIS 10.8. All statistical analyses are performed using SAS software version 9.4. I provide descriptive statistics and cross-sectional quantile regression estimation results for the 10th, 25th, 50th, 75th, and 90th percentile distribution of disaster recovery assistance in the next section.

3.3 Results

In the aftermath of Hurricane Harvey, FEMA approved 373,150 applications, and distributed over 1.6 billion dollars in grants through the IHP (Appendix C) (FEMA, 2021). The maximum amount a household would be eligible to receive in IHP assistance was thirty-three thousand dollars in FY 2017 and generally limited to eighteen months (DHS, 2019). The average flood insurance payout for Harvey-related damages was eighty thousand dollars with average FEMA individual assistance grants at seven thousand dollars per household (Robinson, 2018). Within the study area, zip code received on average 3,472,172 dollars with a median of 739,201 dollars (n= 470). Communities within or adjacent to large cities received the most recovery funding, specifically Houston and the surrounding metroplex. Smaller cities such as Port Arthur and Rockport, which were directly in the path of Hurricane Harvey also received substantial sums. In contrast, largely unincorporated communities received little funding (Figure 3).

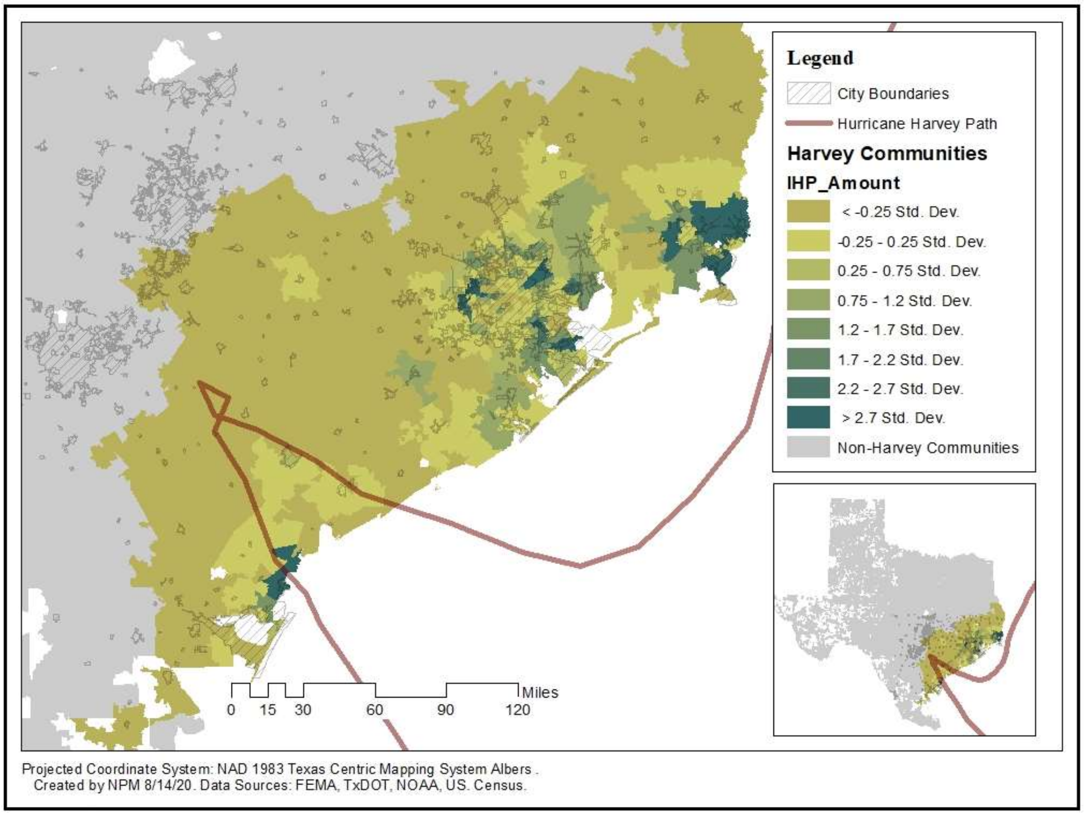


Figure 3 Map of federal disaster assistance eligible zip codes by FEMA IHP amounts received.[3]

As a dependent variable, total cash assistance showed an exceptionally large right tailed, non-normal distribution (skewness = 4.11; kurtosis = 21.06). Table 2.3 provides summary statistics of the population within the study area. Across the varying communities, the average total disability within the study area was 14.8% (Table 3.2). However, communities with no prior recovery eligibility experience had higher proportions of total disabled present compared to communities with prior eligibility experience (18.8% vs.12.7%) (Table 3.2).

[3] FEMA IHP grant assistance had a Global Moran's Index of 0.21, with statistically significant clustering effects (z-score = 14.99; p-value = 0.000) using inverse-distance spatial weights.

Table 3.2 Descriptive statistics of study area at the zip code level

	Study Mean	***Prior Disaster(s) Eligibility***	***No Prior Disaster(s) Eligibility***
Median Income ($)	58544.7	61014.4	53132.3
Limited English Proficiency	6.0	7.4	3.1
Poverty (%)	15.1	15.5	14.4
Total Disability (%)	14.8	12.7	18.8
Unemployment (%)	3.7	3.6	3.9
Black (%)	12.9	14.3	10.0
White (%)	51.0	45.6	62.0
Latinx (%)	32.0	34.8	26.3
Homeowners (%)	69.1	66.3	74.7

NOTE: Summary statistics on demographics in the ACS-linked FEMA Individual Household Program dataset for zip codes eligible to receive Hurricane Harvey assistance (N = 470). Prior disaster eligibility (n = 314) indicates communities experienced recovery eligibility for at least one prior declared disaster event (2015 Memorial Day Floods, 2016 Tax Day Floods or the June 2016 Floods). No prior disasters (n = 156) indicate that the communities within the sample did not receive federal disaster declarations for the prior events listed.

In performing a simple unadjusted quantile regression, as the proportion of disabled increased one percent in minor recovery funded communities (10th percentile), total FEMA cash assistance decreased by 8.0 percent. The suppressing effect of community-level disability strengthened within substantial recovery funded communities (90th percentile), decreasing total FEMA grants received by 9.3 percent (tables not shown). The unadjusted disability effects on both the lower and upper quantile FEMA assistance distribution were statistically significant at the alpha 0.05 level.

The assessed variables had a correlation of less than 0.8, variance inflation factors of less than 10, with no threat to tolerance below 0.1 indicating no issues in multicollinearity. Table 3.3 reports the adjusted cross-section results of the quantile regression. When adjusted for socioeconomic factors, level of disaster damage, and prior recovery eligibility, the statistically significant disparity in FEMA grants for communities with higher proportions of disabled disappeared at the 10th and median percentile distributions (Table 3.3). However, the disparity reappeared beginning at the 60th percentile level and widened. Within substantially funded communities (90th percentile), total FEMA cash assistance decreased by 8.4% with every one percent increase in total disability (Table 3.3).

Table 3.3 Cross-sectional Quantile Regressions FEMA Cash Assistance by (total) Disability Prevalence and Prior Recovery Eligibility

	Percentile Distribution					
Effect	*10th*	*50th*	*60th*	*70th*	*80th*	*90th*
Disability	-0.01 (0.82)	-0.03 (0.39)	**-0.06*‡** **(0.03)**	**-0.06*‡** **(0.02)**	**-0.07*‡** **(0.01)**	**-0.08*‡** **(0.01)**
Prior recovery eligibility	0.53 (0.13)	0.06 (0.86)	-0.14 (0.57)	-0.14 (0.58)	-0.14 (0.61)	-0.27 (0.36)

NOTE: Cross-sectional Quantile Regression Estimation Results N = 434. Smaller sample size due to missing dependent data points. The dependent variable is (log) total IHP grants per zip code. Population density is measured in total population estimates/ zip code square miles. I present coefficient estimates (p-values). ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. I control for population density, unemployment, poverty, limited English Proficiency, homeownership, minority presence, level of disaster damage, and income.

The effects of community-level disability should be relatively stable in the form of constant coefficients across the percentile distributions, as FEMA grant totals move in tandem with disability through location shifts (Angrist & Pischke, 2008). This occurs only if within-group inequality remains constant (Angrist & Pischke, 2008). However, Table 3.3 demonstrates that disability-based disparity in community level funding did not remain constant but instead widened. Community level disability played an insignificant role in low levels of funding, but then served a suppressing effect for community level funding above the median percentile of FEMA aid distribution. A one percent increase in total disability decreased FEMA grant assistance at the 60th percentile by 6.0 percent, with the effects strengthen across the upper quantiles of the conditional recovery funding distribution (Table 3.3). The statistically significant trend in deepening disparity for communities with the disabled present remained present during the sensitivity analysis as well (Appendix Table E.1 – E.3). The forms of disability which appeared to have the greatest effect on the disparity in FEMA grant allocation were communities with greater proportions of hearing disability and independent living disability present (Table 3.4).

Table 3.4 Cross-sectional Quantile Regressions FEMA Cash Assistance by Disability-type Prevalence

	Percentile Distribution					
Effect	*10th*	*50th*	*60th*	*70th*	*80th*	*90th*
Model (1): Ambulatory	0.08 (0.03)	0.01 (0.75)	-0.02 (0.59)	-0.04 (0.17)	-0.08 (0.03)	-0.04 (0.40)
Model (2): Cognitive	0.03 (0.41)	-0.00 (0.97)	-0.00 (0.92)	-0.03 (0.53)	-0.04 (0.43)	-0.08 (0.31)
Model (3): Hearing	-0.01 (0.84)	**-0.08*‡ (0.05)**	**-0.12*‡ (<0.01)**	**-0.13*‡ (<0.01)**	**-0.12*‡ (0.01)**	**-0.16*‡ (0.01)**
Model (4): Independent Living	-0.00 (0.92)	-0.01 (0.84)	-0.05 (0.27)	**-0.10** (0.03)**	**-0.10** (0.05)**	-0.06 (0.38)
Model (5) Self-Care	0.15 (0.03)	-0.06 (0.29)	-0.01 (0.90)	-0.06 (0.37)	-0.07 (0.44)	-0.11 (0.35)
Model (6): Vision	-0.02 (0.69)	0.00 (0.90)	-0.08 (0.26)	-0.13 (0.12)	-0.08 (0.50)	-0.08 (0.58)
Model (Base): Total Disability	-0.00 (0.82)	-0.03 (0.39)	**-0.06*‡ (0.03)**	**-0.06*‡ (0.02)**	**-0.07*‡ (0.01)**	**-0.08*‡ (0.01)**

NOTE: N = 434. The dependent variable is (log) total IHP grants per zip code. I present coefficient estimates (p-values). Each disability model controlled for income, African Americans, Homeowners, Limited English Proficiency, Poverty, disability, unemployment, population density and recovery experience at the zip code level. ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. ACS-defined types include - Hearing difficulty: deaf or having serious difficulty hearing. Vision difficulty: blind or having serious difficulty seeing, even when wearing glasses. Cognitive difficulty: Because of a physical, mental, or emotional problem, having difficulty remembering, concentrating, or making decisions. Ambulatory difficulty: Having serious difficulty walking or climbing stairs. Self-care difficulty: Having difficulty bathing or dressing. Independent living difficulty: Because of a physical, mental, or emotional problem, having difficulty doing errands alone such as visiting a doctor's office or shopping. Independent living difficulty: Because of a physical, mental, or emotional problem, having difficulty doing errands alone such as visiting a doctor's office or shopping. Source: US Census (2020). American Community Survey Information Guide. Available at: https://www.census.gov/content/dam/Census/programs-surveys/acs/about/ACS_Information_Guide.pdf]

Prior recovery eligibility did not prove to be a statistically significant predictor of FEMA grant allocation across any portion of the recovery funding distribution (Table 3.3) (Appendix

F).[4] Yet, in assessing prior recovery eligibility as a learning effect modifier, there was a small statistically significant relationship. The decrease in FEMA grant allocation by disability significantly diminished a further 13.4% for communities with prior recovery eligibility. The additional decline occurred at the 10th percentile of the FEMA funding distribution alone (Table 3.5). Interestingly, when the prevalence of disability in minor recovery funded communities (i.e., the 10th percentile funding distribution) was zero, prior recovery eligibility was a significant predictor in receipt of funds. The positive effect declined rapidly with the increase in disability prevalence, again showing disability as a suppressing factor in recovery funding allocations

Table 3.5 Cross-sectional Quantile Regressions FEMA Cash Assistance with Prior Recovery Eligibility effect modifier

	Percentile Distribution					
Effect	*10th*	*50th*	*60th*	*70th*	*80th*	*90th*
Disability	0.03 (0.31)	-0.02 (0.52)	-0.06 (0.07)	-0.09 (0.02)	-0.08 (0.03)	-0.09 (0.15)
Prior recovery eligibility	2.91 (<0.01)	0.06 (0.95)	-0.52 (0.44)	-0.63 (0.33)	-0.44 (0.53)	-0.65 (0.58)
Disability x Prior recovery eligibility	**-0.13*‡** **(<0.01)**	-0.00 (0.99)	0.02 (0.58)	0.02 (0.55)	0.02 (0.68)	0.03 (0.69)

NOTE: N = 434. The dependent variable is (log) total IHP grants per zip code. I present coefficient estimates (p-values). The regression model controlled for median income, African Americans, Homeowners, Limited English Proficiency, Poverty, disability, unemployment, population density and recovery experience at the zip code level. ‡ statistically significant Wald test. *statistically significant Likelihood Chi-square test.

[4] In a separate analysis, I remove the June 2016 floods and assess the two largest events based on IHP assistance delivered, the 2015 Memorial Day Floods and the 2016 Tax Day Floods. When deconstructing recovery experience, I find a statistically significant effect of prior experience on the 10th percentile distribution of FEMA recovery funding. Zip codes with prior eligibility to both the 2015 Memorial Day Floods and the 2016 Tax Day Floods recovery assistance receive greater Hurricane Harvey grant dollars (Appendix F).

3.4 Discussion

Hurricane Harvey made landfall in Texas on August 25, 2017, leading to historic rainfall and catastrophic flooding in impacted areas. The large-scale devastation brought on by the storm led to massive federal emergency response and recovery efforts in the state. I assessed administrative burden in Harvey federal recovery assistance among communities with higher proportions of disability. Separately, I assessed whether prior recovery eligibility could serve as a proxy for lowered learning costs, thereby explaining an increase in the allocation of federal recovery assistance dollars received by communities.

I used a cross-sectional quantile regression study design to assess variations in the percentile distribution of disaster assistance. FEMA provided IHP data which I used to evaluate recovery dollars invested at the zip code level. The 2016 ACS 5 - year estimates provided the proportion of total disability. I created a proxy learning costs measure in prior recovery eligibility. Prior recovery eligibility measured whether communities received disaster declarations for the three most recent disasters before Harvey: the 2015 Memorial Day Floods, the 2016 Tax Day Floods, and the June 2016 Floods. I controlled for Harvey-flood damage using USGS data. I also controlled for additional socio-economic factors such as race/ethnicity, poverty, income, and homeownership status.

Despite policies that state explicit consideration in funding allocation, communities with higher proportions of disabilities experienced disparities in receipt of FEMA recovery dollars. Moreover, the disability-based disparities in funding widened as communities received more federal recovery dollars. The proportion of individuals with hearing impairments within the community drove much of the disability-based funding inequality. Prior recovery eligibility provided a minor but inconsistent explainer for increased Harvey funding allocation within communities, decreasing in effect with every one-percentage-point increase in disability for minor recovery (10th percentile) funded communities.

My disability-related disparity findings in recovery assistance were overall consistent with previous literature findings (Stough, 2017; Stough & Kelman, 2018).[5] Persons with disabilities face higher disaster exposures, greater loss of homes and support networks, and exacerbated adverse health outcomes due to disasters (Hemingway & Priestley, 2006; Peek & Stough, 2010; Stough, 2017; Stough et al., 2017). The differential disparities in federal assistance for such specific communities' points towards gaps in policy implementation and special accommodation constraints, confirming the indirect presence of administrative burden in federal recovery assistance for persons with disabilities (GAO, 2017, 2019; Stough et al., 2020).

Nevertheless, how can the theory of administrative burden explain the disparity in funding experienced by communities with higher proportions of disability? The most direct line of association is that of imposed learning costs. Citizens must learn about the program, whether they are eligible, the nature of benefits, and how to access services (Moynihan et al., 2014). However, higher learning costs accrue for citizens when they must overcome educational and language hurdles to interpret program information, with higher learning costs leading to lower program utilization. The identification of hearing impairment as the consistent driver of federal funding disparities indicates a language barrier administratively left unaddressed by FEMA, despite the mandate for equal access and reasonable accommodations.

For communities with a higher prevalence of disabilities, it may be that individuals are less likely to receive eligibility, or in receipt of eligibility they receive fewer recovery dollars.

[5] My findings contradict Griego et al. (2019), which found no significant difference in receipt of government assistance by disability, only non-government assistance. However, the study includes public forms of assistance from local to federal government entities. It is not specific to the FEMA grant program I assess and is limited to the Houston area.

They may also be less likely to apply for services at all. While learning costs may accrue within each of these points in the administrative processes, what construes as learning costs varies based on where the citizen is situated. Thus, burden takes on different forms: procedural (i.e., applying for services) or exclusionary (being denied or facing decision delays).

Government reports identify FEMA's lack of standard procedures around the use of disability integration staff, excluding disability stakeholders in recovery efforts, understaffing of disability integration personnel, long wait times during the FEMA application process, and easily misinterpreted and non-508 compliant IHP applications (GAO, 2017, 2019). These structural limitations may result in higher learning costs for persons with disabilities in acquiring FEMA application information, pointing to forms of procedural burdens. In assessing FEMA assistance for the disabled during Hurricane Harvey, the GAO reports,

> *Disaster-related information … was inaccessible to people with certain disabilities, according to local and non-profit officials we interviewed …. In interviews with these officials we heard multiple examples of the challenges faced by people with hearing impairments to getting timely and accurate information (GAO 2019 p. 22).*

The community-level disparities that I uncovered echo the GAO findings, with administrative burden theory identifying the mechanism as to how the disparity occurs. Moreover, it is a specific form of burden, procedural burden, which I theorize is occurring.

Interestingly, I found that disability-related disparities grew as more funds were distributed within communities, even when controlling for the level of damage and population density. One would expect that there would be less disparities in allocation with the more significant provision of resources, or at most, such disparities would remain constant. This was not the case for Harvey. More work is needed to disentangle the relationship between substantially funded recovery communities and the inclusion of disabled households.

While my disability measure served as an indicator for the direct outcome of administrative burden, I designed prior recovery experience as an indirect measure of administrative burden through learning costs. Lowered learning costs translate to lower administrative burden and thus greater resource allocation. I assume learning occurs with residents and community-based organizations present during past disasters with my prior recovery experience variable. These actors learn from navigating federal bureaucracies (i.e., who is eligible for services and how to apply) and use the experiential knowledge from prior disasters to interact with current-day public administrators successfully. My proxy learning cost measure did yield greater resource allocation, only when FEMA distributed less total funds. It may be the case that FEMA provided less rule-constraints for applicants in communities receiving lower federal dollars as attention and resources were turned towards communities receiving substantial federal investments. Any additional information or knowledge provided through shared community experiences increased a community's chance of receiving federal monies. As investments increased, the effect of shared community experience was not enough to overcome the administrative processes which determined receipt of services.

In addition, FEMA was critically understaffed, particularly with disability integration staff, headed into the 2017 hurricane season. The agency faced further strain due to Hurricane Maria and Irma shortly after Harvey. This structural impediment may explain why disability served to suppress prior recovery experience's positive effect when assessing federal recovery assistance. How persons with disabilities traverse federal bureaucratic recovery systems consistently present challenges through the lower allocation of financial resources for recovery and lower programmatic resources to effectively engage public administrators. Such challenges will interrupt how well persons with disabilities will recover from disasters, with implications on social, political, and civil rights.

3.4.1 Limitations

This study contained several limitations. The first limitation was the generalizability of the findings. I provided an in-depth assessment of FEMA's IHP allocation during one major event, Hurricane Harvey, in Texas. While the findings were statistically significant concerning disability and confirmed by federal assessment reports, comparing IHP allocations for other disaster events are needed. Such assessments of IHP funding across multiple disaster events would increase the external validity of the findings. The assessments would also have to account for disability-specific FEMA services offered through the Office of Disability Integration and Coordination and the changing nature of how FEMA deploys accommodation resources across disasters (GAO, 2019; Shapiro, 2020).

I did not measure delays or denials in FEMA services, but the quantity of FEMA services received by dollars allocated. The study did not assess the extent to which communities applied for and were denied services. While it was clear there were disparities in the allocation of funds, even when controlling for level of damage, I did not assess in what manner communities as a whole interact with the bureaucracy (i.e., whether or not they faced delays and denials, versus no interaction). In review of government reports, official documents attested to persons with disabilities interacting and experiencing administrative burden (GAO 2019). Analysis of individual-level applications to FEMA's IHP would strengthen my findings, particularly if disability-related needs are properly identified in the program eligibility process. I begin to undertake such a study in the next chapter.

The assessment of disability on recovery assistance captured disparities in government funds allocation, a measure of administrative burden presence. My proxy measure of learning costs in the form of prior recovery eligibility was not consistently influential. Prior recovery eligibility assumed that communities eligible to receive prior disaster assistance did successfully navigate the bureaucracy and carried such knowledge to current administrative interactions with federal recovery services. I also assumed under this metric that community learning was diffuse, whereby it was shared throughout the community and retained collectively among individual residents navigating recovery aid. In addition to not directly capturing such learning interactions, other forces such as the presence of non-profit and local governments, the extent of damage of the prior disasters, and shifts in the populations between the events and Harvey conceivably influenced how well communities learned from past events. While my analysis on disability demonstrated the presence of administrative burden, my prior recovery eligibility variable may have been too coarse and a poorly operationalized form of learning costs, presenting an information bias toward the null. Though administrative burden was present, to what extent the presence was due to learning costs, I could not empirically/definitively state.

Lastly, the study did not capture other disability-specific information, services, or resources available within communities. For instance, Portlight Strategies, a non-profit committed to inclusive disaster strategies, works to coordinate local organizations that provide durable medical equipment and assistive technology with those in need during Hurricane Harvey (Perry, 2017). How well Portlight Strategies can connect with disability needs varies within an impacted region. Community-based services that persons with disabilities often rely on for support and resources can contribute to aspects of disaster recovery. These disability-centered services too require support to meet the inclusive recovery needs of persons with disabilities after disasters (Subramaniam & Villeneuve, 2019). The extent to which those services are active and able to meet the needs within communities is not accounted for within my study. Data on the needs identified and to what manner services are linked and by whom (i.e., public and/or non-profit entities) would strengthen the findings on how communities with greater levels of disability are able to utilize recovery assistance.

3.4.2 Future Research

Future research should focus on how recovery assistance information spreads. Qualitative methods in the form of in-depth interviews and focus group discussion with local community groups active during disasters may capture the effect of learning and reduced administrative burden in communities receiving federal assistance. Instead of a temporal learning effect occurring with prior recovery experience, a spatial component to learning may occur at the community-level not fully captured in this study (i.e., neighbor to neighbor). Qualitative methods could be combined with spatial clustering analysis and participatory geographic information systems in identifying the quality, quantity, and spread of information as learning. Research endeavors should also be participatory, including people with disabilities and caregivers' voices when understanding how to create and navigate more inclusive bureaucratic systems. Research may include assessments of where inconsistencies in accessible and inclusive information emerge along the disaster recovery process and where local disability-based organizations' support may have an additive effect on recovery service utilizations.

3.4.3 Policy Recommendations and Conclusion

Given the findings, I identify several policy recommendations. First, FEMA should provide clear standards and procedures on the role that disability integration advisors should play during recovery activities on the local level. In addition, recent FEMA policy decisions to remove disability integration advisors from field deployments should be rescinded, with advisors playing a pivotal role in information dissemination and application processing (Shapiro, 2020). Ideally, the level of disability integration staff deployment into disaster impacted areas should be tied to both damage assessments and the level of pre-existing disability within the community. Such decisions on the deployment level should also be transparent and standard, with input from disability-rights organizations active during disasters. Training modules on FEMA policies, procedures, and application processes should also be developed so that local disability-based organizations can rapidly utilize the information to quickly augment FEMA's disability integration advisors on the ground during disasters.

In this chapter, I identified community-level disparities in IHP funding by disability prevalence. As disability increased, FEMA funding decreased. The funding gap was not consistent but widened as disaster-impacted communities received substantial funding. The disparity in federal recovery assistance was evidence of administrative burden, which I theorize to be distinctly procedural in nature and not an exclusionary burden. In chapter four, I move from community-level experiences of administrative burden to individual-level experiences of burden. I begin to pull out the different forms of burden initially identified as procedural and exclusionary in nature and see if demographic profiles, mainly persons with disabilities, experience the two forms of burdens equally. My findings are an essential step to reducing uneven trajectories in recovery for individuals and communities and aligns with federal mandates on preventing the violation of an individual's civil rights to equal access and reasonable accommodations.

CHAPTER 4: ESSAY TWO

4.1 Significance and Justification

Chapter three demonstrated that allocation of FEMA recovery funds varied significantly by community-level factors, specifically disabilities. Yet, the extent to which individuals with disabilities and/or their caregivers navigated FEMA's IHP application process and received eligibility for assistance is not fully known. An initial small-scale survey of the Houston MSA finds that persons with at least one disabled person in the household are less likely to receive assistance from non-government organizations but there is no statistically significant difference in the receipt of government assistance (Griego et al., 2020). However, the study does not differentiate between local and federal assistance.

Program uptake is the most common assessed administrative burden outcome (Brodkin & Majmundar, 2010; Chudnovsky & Peeters, 2020; Fox et al., 2020; Heinrich, 2016, 2015; Herd et al., 2013; Herd, 2015). Variations in rule-constraints which shorten eligibility decisions are associated with increases in Medicaid enrollment (Fox et al., 2020). Other state process changes such as auto-enrollment and form simplification also increase enrollment (Herd et al., 2013). Issues of documentation, sources of information eligibility, and changes to eligibility criteria are associated with disconnection of child welfare cash programs (Heinrich, 2016). The move to electronic filing increases enrollment for the Earned Income Tax Credit (Kopczuk & Pop-Eleches, 2007). Citizen factors such as decision-making bias, poverty and lack of information/knowledge also prevent eligible enrollment in services (Chudnovsky & Peeters, 2020). In line with other administrative burden research, I measure program uptake in the form federal recovery service eligibility at the application level by applicant characteristics. While I cannot measure directly whether learning, psychological or compliance costs are the result of differential service eligibility, I can infer the presence of administrative burden through review of government assessments and after action reports (FEMA, 2018b; GAO, 2018; 2019).

I evaluate whether individuals who self-identify as needing special accommodations are more likely to experience denials in FEMA eligibility for Hurricane Harvey. I seek to understand differential recovery assistance along pre-Harvey lines of socio-economic vulnerability. I focus on differential recovery service eligibility decisions for individual applicants. Due to non-inclusive application processes and lower allocation of FEMA funding in communities with higher disabled populations, I expect to see individuals who report special accommodations needs less likely to receive FEMA grant eligibility.

4.2 Methods

To assess program service eligibility for IHP grants, FEMA requires a complete application with specific information such as social security number, pre-disaster and current application address, insurance coverage information, income and losses caused by the disaster (FEMA, 2016). Once an application is complete, FEMA then performs an in-home inspection to verify disaster-related losses. Applicants may be denied eligibility for a variety of reasons including issues with verification of identity, ownership, or occupancy of property (FEMA, 2016). Other denial reasons may include damage not caused by the disaster, insufficient damage amount, or the registrant has insurance which may cover the damage amount. Applicants are also able to appeal their denials.

I used FEMA's publicly available, non-personally identifiable individual-level information on IHP registrants for Hurricane Harvey. The dataset consisted of 895,529 unique applicants.[6] The data also provided information on type of IHP assistance received and type of damage to the residence, if any (Appendix G). I restricted the sample to registrants who sought assistance for their primary residence. To determine applicant denial of services, I created a dichotomous variable (FEMA denial) based on whether registrants received eligibility for at least one type of IHP assistance: temporary sheltering assistance, rental assistance, repair assistance, or replacement assistance (Appendix G). If the applicant did not receive FEMA eligibility for any of the above forms of assistance, I code denial = 1. If FEMA deems the applicant eligible for at least one form of assistance, I code denial = 0. This approach mirrored the study of Billings et al. (2019) and their assessment of FEMA assistance to Harvey-impacted Houston areas minority and credit-limited communities.

Within the Individual and Household Unified Program Guidance, FEMA states, "[w]hen providing assistance, FEMA … considers the specific needs of applicants with disabilities or other access and functional needs (FEMA 2016 p. 38)." FEMA relies on registrants identifying whether they needed special accommodations through one question on the application process. Registrants are asked:

> *Did you, your co-applicant, or any dependents have help or support doing things like walking, seeing, hearing, or taking care of yourself before the disaster and have you lost that help or support because of the disaster (GAO 2019 p. 40)?*

Registrants who respond "Yes" then identify the form of disability (mobility, cognitive/developmental, mental health, hearing or speech, vision, other). With the reasonable accommodations identified, FEMA intends to align targeted resources for individuals with

[6] Data were accessed or retrieved from https://www.fema.gov/openfema-dataset-individual-assistance-housing-registrants-large-disasters-v1. FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

disabilities, such as assisting with the application process through individualized calls (GAO, 2019).

The dichotomous special accommodations request in the FEMA dataset served as my independent variable of interest. I created a dichotomous variable (special accommodations) based on whether registrants request special accommodations. The available data did not specify the form of disability or how the disability was impacted by Hurricane Harvey. While I could not distinguish *why* and *how* accommodations were requested by individual registrant, I could assess the impact such identified accommodation requests had on FEMA IHP eligibility.

Assessment of disaster damages is a requirement for FEMA assistance, known as verification of losses (FEMA, 2016). FEMA verifies losses first through physical inspection of applicant property by a FEMA representative. Where in-person inspection cannot occur, FEMA then relies on geospatial damage assessments or receipt of damage-related expense documents (i.e., medical bills, auto repair receipts) as forms of loss verification (FEMA, 2016). Of registrants within the dataset with FEMA verified damages, types of damage included: roof damage, foundation damage, repairs required to make the dwelling habitable, flood damage, or home destroyed (FEMA, 2016). However, there is growing concern around the inspection process for the verification of losses.

Individuals may be denied eligibility if FEMA inspectors fail to make contact after three attempts to complete inspections, with greater chances of such occurrence if individuals are displaced from their homes due to the disaster (Martín & Teles, 2018). Martín and Teles (2018) find that inspectors failing to make contact results in 9.6% of homeowners and 14.4% of renters becoming ineligible for FEMA services. Moreover, inspectors are not always aware of applicants who report needing special accommodations during the registration process, and thus are unable to communicate with individuals during the inspection process (GAO, 2019). Other reports note lack of consistency across inspections, under-estimation of damage, as well as potential inspection fraud (GAO, 2019; Massarra, 2012; "The Storm after the Storm," 2017). To adjust for inspection bias, I built separate models based on whether registrant applications note at least one type of FEMA verified damage.

4.2.1 Statistical Analysis

Given the dichotomous nature of the dependent variable (FEMA denial), I used multivariate logistic regression to understand the relationship between special accommodations and FEMA assistance eligibility. I used stepwise regression models as a discriminant analysis technique to identify relevant registrant-level confounding characteristics, improve model fit, and provide a robust estimate of my special accommodations variable (Hair et al., 2010; Wooldridge, 2006). I ran separate models based on whether applicants have assigned Harvey-related damage to their primary residency (i.e., no-damage and damage models).[7]

For the no-damage applicant models, the initial discriminating variables included FEMA inspection completion, flood insurance, homeowner's insurance, eligibility for a SBA loan, renter's status, size of the household, and housing type. Due to the large fluctuations in self-reported income, I created a binary median income variable based on whether registrants had above the median self-reported income of $30, 000. For the damage models, the analysis did not include FEMA inspection because all registrants who report at least one type of damage undergoes a FEMA inspection. The damage-assessed stepwise regression variables included flood insurance, homeowners' insurance, SBA loan eligibility, renter status, household size,

[7] A review of the predicted probabilities where damage is added as a confounder reveals a bimodal distribution, indicating two separate populations (Long & Freese, 2014). I run models according to whether applicants were identified as having at least one FEMA-inspected damage because the conditional probability of FEMA denials is different based on whether the applicant had assessed damage.

housing type, and the binary median income variable. The damage model also included the specific binary damage variables: roof damage, foundation damage, repairs required to make the dwelling habitable, flood damage, home destroyed.

For the non-damage-assessed and damage-assessed stepwise regressions, I retained the independent variables which had an alpha of 0.30 in the models as well as the variable of interest (special accommodations). I trained the stepwise regression models on a randomly selected thirty-percent subsample of the damage and no-damage populations to prevent overfitting of the data (Harrell, 2015). I tested the variables included in the final models for multicollinearity, fit, and influential observations and outliers (Long & Freese, 2014). I present descriptive statistics as well as odds ratios (OR) with 95% Confidence Intervals in the next section. I assessed statistical significance of my postestimation analyses at alpha 0.05 level.

4.3 Results

Within the IHP applicant population, 3.28% (n = 27,544) of registrants self-identified as needing special accommodations, well below the 14.8% prevalence of disability within Harvey's impacted communities. In addition, a larger portion of those who self-identified were renters compared to homeowners (57.39% vs. 42.51%). The largest form of eligible assistance for which those requesting accommodations received was transitional sheltering assistance (48%; n=13, 221) (Table 4.1).

Table 4.1 Eligibility received for registrants who identified as needing accommodations by renter's status

	Total		*Owners*		*Renters*	
	N	%	N	%	N	%
Personal Property	4143	15.04	1490	12.73	2653	16.78
Rental Assistance	5057	18.36	3021	25.8	2036	12.88
Repair Assistance	2645	9.6	2643	22.57	2	0.01
Replacement Assistance	21	0.08	20	0.17	1	0.01
Transitional Shelter Assistance	13221	**48**	6465	**55.21**	6744	**42.66**

NOTE: Special accommodations defined within FEMA IHP application as: Did you, your co-applicant, or any dependents have help or support doing things like walking, seeing, hearing, or taking care of yourself before the disaster and have you lost that help or support because of the disaster (GAO 2019 p. 40)

Transitional sheltering assistance allows for direct payment to hotels/motels when residents cannot return to their homes due to the disasters and is a means of reducing shelter populations (FEMA, 2017b). The assistance does not count towards maximum awards registrants may receive, with registrants responsible for ensuring the temporary lodging is accessible. Among accommodation-requested homeowners eligible for transitional sheltering assistance (TSA), the largest form of additional assistance was rental assistance eligibility (39.21%; n = 2535) (Table 4.2). Among renters who also received transitional sheltering assistance, personal property replacement was the largest receipt of eligibility assistance (24.21%; n = 1633) (Table 4.2). Among accommodation-requested homeowners without transitional sheltering assistance eligibility, the largest form of assistance was repair assistance eligibility (13.67%; n = 717) (Table 4.2). For renters, it was again assistance for the replacement of personal property (11.25%; n = 1633) (Table 4.2).

Table 4.2 Secondary forms of assistance eligibility by TSA eligibility for those requesting special accommodations.

Type of Service Eligibility	TSA Eligible						Non TSA Eligible					
	Total		*Owners*		*Renters*		*Total*		*Owners*		*Renters*	
	n	%	n	%	n	%	n	%	n	%	n	%
Personal Property	2692	20.36	1059	16.38	1633	**24.21**	1451	**10.13**	431	8.22	1020	**11.25**
Rental Assistance	4118	**31.15**	2535	**39.21**	1583	23.47	939	6.56	486	9.27	453	5
Repair Assistance	1927	14.58	1926	29.79	1	0.01	718	5.01	717	**13.67**	1	0.01
Replacement Assistance	17	0.13	17	0.26			4	0.03	3	0.06	1	0.01

NOTE: TSA eligible applicants requesting special accommodations N = 13, 221. Non-TSA eligible applicants requesting special accommodations N = 14323. TSA – Temporary Sheltering Assistance.

Overall, the number of applicants identified as requiring special accommodations remained low for both the damage and non-damage assessed registrant population, 3.62% or lower (Table 4.3). The percentages of renters eligible for FEMA services varied by damage assessment (25.62% damaged eligible v. 59.92% non-damaged eligible) (Table 4.3). Applicants within the damage population also had a greater percentage of individuals above the median self-reported income and higher SBA disaster home loan eligibility compared to the no-damage assessed applicants (Table 4.3). Lastly, FEMA identified the largest source of Harvey-damage as flood-related (81.45%), with most flood-damaged applicants deemed eligible for assistance (Table 4.3).

Table 4.3 Descriptive statistics of applicant-level variables by assessed damage and FEMA eligibility decision

	No Damage		**Damage**	
	Eligible	*Denied*	*Eligible*	*Denied*
Special Needs Accommodations	**3.62 (8851)**	3.0 (711147)	**3.41 (6570)**	2.45 (976)
Residence Type				
Apartment	31.54 (77064)	30.73 (111564)	13.41 (25817)	4.26 (1698)
House	56.72 (138598)	57.95 (210388)	73.74 (142001)	80.27(31995)
Other	11.74 (28684)	11.32 (41088)	12.85 (24751)	15.47 (6168)
Flood Insurance	8.9 (21743)	7.09 (25742)	21.9 (42163)	19.63 (7826)
Homeowners Insurance	24.33 (59461)	27.19 (98696)	47.35 (91181)	56.39 (22478)
SBA Eligible	1.23 (2994)	1.72 (6243)	13.42 (25839)	7.32 (2917)
Household Composition				
1	44.33 (108307)	45.84 (166427)	20.41 (39305)	19.81 (7896)
2	19.58 (47842)	20.01 (72644)	28.47 (54823)	28.59 (11396)
3- 4	25.43 (62146)	24.04 (87264)	33.75 (65000)	33.86 (13498)
>4	10.66 (26051)	10.11 (36705)	17.37 (33441)	17.74 (7071)
Renters	**59.92 (146410**)	59.69 (216708)	**25.62 (49345)**	12.24 (4879)
Median Income	36.94 (90267)	37.06 (134545)	49.57 (95465)	48.63 (19386)
Inspected	59.87 (146302)	55.28 (200692)	--	--
Habitability Repair Needed	--	--	21.79 (41966)	21.38 (8521)
Destroyed	--	--	0.16 (301)	0.17 (66)
Flood Damage	--	--	**81.45 (156843)**	49.76 (19835)
Roof Damage	--	--	5.02 (9661)	4.87 (1942)
Foundation Damage	--	--	0.87 (1674)	0.81 (324)

NOTE: Damage indicated applicant had at least one of the following: If habitability repairs needed, destroyed, flood damage, roof damage, or foundation damage. All of the applicants under the Damage models were inspected (inspection precedes damage assessment under the verification of loss process by FEMA). Median income is a dichotomous variable coded (1) if applicant self-reported their income greater than $30,000 and coded (0) if self-reported income was listed as $30,000 or less.

Self-identifying as needing special accommodations was a negative predictor of FEMA eligibility denials. Applicants in the FEMA assessed damage pool who identified as needing special accommodations had 57% as high odds of being denied eligibility compared to registrants who did not self-identify, controlling for factors such as flood damage, income, and insurance status. (Table 4.4). Where FEMA did not assess damage, special accommodation registrants' odds of receiving FEMA denials were 67.2% as high as registrants who did not request special accommodations when control for various factors such as completed FEMA home inspection (Table 4.4). Variations in eligibility denials for accommodations seeking registrants did not vary much by renter's status within the FEMA damage models. Among the non-damage assessed models, there was a ten-percentage (10%) point difference in likelihood of eligibility denials by renter's status. Renters with accommodation requests were 29.4% (OR = 0.71) less likely to receive eligibility denials compared to homeowners who are 39.6% (OR = 0.61) less likely to receive denials in eligibility (Table 4.4).

Table 4.4 Logistic regression estimates of FEMA eligibility denials by special accommodations requests per damage-assessed model type

Model Type	Effect	Total: OR Point Estimate	Total: 95% Confidence Limits		Renters: OR Point Estimate	Renters: 95% Confidence Limits		Homeowner: OR Point Estimate	Homeowner: 95% Confidence Limits	
Damage	Accommodation Requested	**0.57**	0.509	0.63	0.55	0.36	0.83	0.57	0.51	0.63
No Damage	Accommodation Requested	**0.67**	0.64	0.70	**0.71**	0.67	0.74	**0.61**	0.56	0.65

Note: Damage model controlled for residence type, flood insurance, homeowner's insurance, SBA eligibility, household size, median income, habitability repairs, flood damage. Total (n = 141600; - 2 log likelihood = 101599.37) Renters (n =33103; - 2 log likelihood = 8178.633) Homeowners (n= 108497; - 2 log likelihood = 92852.866) No Damage model controlled for residence type, flood insurance, homeowners insurance, SBA eligibility, household size, median income, inspection completed. Total (n = 139820; - 2 log likelihood = 462372.77) Renters (n = 207487; - 2 log likelihood = 275229.79) Homeowners (n = 141476; - 2 log likelihood = 185077.52). All of the measures are statistically significant at the $p \leq 0.05$ level.

A bivariate linear regression analysis showed no correlation between the percentage of accommodation registrants within a zip code and the percentage of total disability within the zip code (beta = -0.05, p-value = 0.22) (Appendix H). When I controlled for factors such as race/ethnicity, Harvey-related damage within the community and the percentage of applicants who received FEMA inspections, a slight but statistically significant negative relationship emerged between registrant accommodation requests and disability prevalence within the community (Appendix H). A one percent increase in total disability prevalence in the community decreased the percentage of applicants from the community requesting special accommodations by 0.11 percent (beta = 0.11; p-value =0.027), holding levels of Harvey-damage, FEMA inspections, and race/ethnicity constant (Appendix H). The significant relationship was sensitive to the presence of Latinx in the model, suggesting that the presence of Latinx communities acted as a confounder between the proportion of total disability within and community and the proportion of self-identified registrant accommodations (Appendix H). I was not, unfortunately, able to distinguish the effect by immigration status. The negative relationship indicated that although persons needing special accommodations were less likely to be denied FEMA eligibility, such individuals applying for assistance were less likely to come from communities with higher proportions of pre-Harvey disability.

4.4 Discussion

This chapter evaluated whether individuals who identify as needing special accommodations were more likely to receive eligibility denials in federal assistance. To assess eligibility denials, I used FEMA's dataset on individuals who registered for Hurricane Harvey IHP assistance. The dataset contained information on registrant characteristics, zip code of damaged property, the applicant eligible FEMA service, and type of Harvey-related damage. The dataset also provided information on whether registrants self-identified as needing special accommodations. I separated the sample population based on whether registrants have FEMA-verified damages. I used multivariate logistic regressions to assess the role of special accommodations on FEMA eligibility denials.

Individuals who identified as needing special accommodations were less likely to be denied FEMA eligibility to services. However, the percentage of accommodation requested registrants was far below the disability prevalence within the Harvey impacted region. Moreover, I found that accommodations seeking Harvey registrants were significantly less likely to come from communities with higher disability prevalence, even when controlling for Harvey damage and other socioeconomic factors. This undercounting of persons with disabilities in requests for accommodation needs may be a persistent and structural procedural burden within FEMA application process across different disasters. For example, while the 2017 Census identifies 21.6 percent of the Puerto Rico population as having some form of disability, less than 3 percent of FEMA registrants report needing special accommodations on their 2017 Hurricane Maria assistance application (GAO, 2019). FEMA officials note that "while not all registrants with disability have a related need, the large difference between Census disability data and FEMA's identification of registrants with disability-related needs illustrates the extent of potential under-counting (GAO 2019 p. 41)."

The under-counting of individuals may primarily be due to how registrants self-identify on the FEMA applications. FEMA relies on registrants identifying whether they need special accommodations through one question on the assistance application (GAO, 2019).[8] Stakeholders and officials acknowledge that the question is confusing and easily misinterpreted, resulting in lower requests for accommodations (GAO, 2019). Hurricane Harvey online applications were also non-section 508 compliant under the Rehabilitation Act, further presenting additional informational/knowledge costs for persons with disabilities (GAO, 2019).

In attempting to register, Hurricane Harvey applicants faced long wait times, with 69% of calls going unanswered and daily average wait times close to 1.5 hours long (GAO, 2019)[9] Such delays posed an unequal burden for individuals with disabilities navigating the application process long before decisions on eligibility are made. FEMA also did not identify whether the need for reasonable accommodations related to completing the application itself or disaster assistance claims, resulting in poor targeting of program services with accommodation needs

[8] … section-508 of the Rehabilitation Act generally requires federal agencies to ensure that their electronic and information technology is accessible to individuals with disabilities, including employees and the public. 29 USC § 794d. FEMA completed its self-evaluation report in August 2017 after a six-month assessment to evaluate its facilities, programs, policies, and practices and determine how effectively the agency provides equal physical, program, and effective communication access to people with disabilities (GAO 2019 p. 29).

[9] These administrative interactions were far below the FEMA performance goal of answering helpline calls within 20 seconds, partly due to FEMA having to also respond to Hurricane Irma and Maria at the same time (GAO 2019).

(GAO, 2019). All these procedural burdens most likely resulted in the low percentage of applicants identifying as needing special accommodations.

In the previous chapter, I theorized a distinction between procedural burdens and exclusion burdens. In this chapter, I identified empirically where within the administrative processes these burdens accrued for individuals. In an expansion of administrative burden theory, I found that burdens may not be consistently directional within particular groups. The procedural burdens for receiving special accommodations were high, but exclusion burdens of receiving service eligibility were low. The direction of burdens may differ in other groups, like non-disabled renters (i.e., low procedural burdens but high exclusion burdens).

Can procedural burden be viewed as merely red tape instead of the subtle form of administrative burden which I identify? I contend that it is not just red tape, though rule-constraints may pose some compliance costs. In the case of persons with disabilities, FEMA's budget constraints and policy decisions shifted costs onto the citizens as the bureaucracy coped with providing public services. The burdens emanated from the policy process instead of the internal bureaucratic workings associated with red tape. In some cases, the pass-thru costs imposed through the policy process may be outside of compliance standards, such as violating ADA legal requirements for equal access and reasonable accommodations. This is administrative burden, but with nuanced characteristics based on one's position within the administrative process.

4.4.1 Limitations

I acknowledge several limitations with this study. FEMA applications poorly identified persons needing special accommodations. The results were a subsequent biased estimate of how disability influenced denials of FEMA services and cash assistance. The applicant pool may not have been reflective of the wider disability population impacted by Hurricane Harvey. While the association between community-level disability prevalence and the percentage of registrants seeking accommodations identified the extent of FEMA's misalignment, more work is needed to understand how persons with disabilities navigate federal recovery assistance. Also, I could not assess how specific forms of disability interfaced with individual delays and denials of FEMA services. Government reports identified persons with hearing-related disabilities as having increased difficulties navigating the administrative process due to a lack of American Sign Language interpreters (GAO, 2019). Unfortunately, I could not confirm such findings on the individual level due to limitations in the data.

My study was also limited to the procedural and immediate decision/exclusion outcomes of administrative burden. Persons with disabilities may experience additional costs associated with the receipt of eligibility. For instance, transitional sheltering assistance was the largest type of Harvey eligibility for persons identifying with special accommodation needs. The burden was on the individual to find hotels/motels that met their disability needs, despite accessible options being especially limited during disasters (FEMA, 2017b). In addition, persons with disabilities faced the possibility of placement in congregant care facilities and hospitals during disasters due to shortages in affordable, accessible housing, gaps in response plans, or lack of resources and knowledge by local officials (McDermott et al., 2016; National Council on Disability, 2019). The results of institutionalization include social network disruptions, increased chances of negative health outcomes, and possible civil rights violations (National Council on Disability, 2019). The burden associated with service eligibility and receipt was outside the scope of this work but is very important in the nuanced understanding of administrative burdens in the disaster recovery process.

While I empirically found lower program uptake in special accommodation requests, I did not link the lower requests to specific forms of learning, compliance, or psychological costs. The learning costs were inferred through a review of government assessments and after action reports associated with Hurricane Harvey. Direct assessment of learning, psychological and compliance costs were not possible due to data limitations. The use of experimental studies in information complexity or in-depth interviews around decision-making bias, human capital, and poverty may present a path forward towards directly measuring costs associated with program uptake of special accommodation requests in federal recovery assistance (Bhargava & Manoli, 2012; Chudnovsky & Peeters, 2020).

4.4.2 Future Research

In addition to addressing the limitations above, future studies should focus on the multilayered identities that persons with disabilities utilize in navigating the post-disaster recovery process. Persons with disabilities do not carry their disabilities as their sole identity. Disability exists across age groups, economic status, race/ethnicity, sexuality, and immigration status, as well as the type of disability an individual inhabits. Disability is not a monolith, as persons with disabilities may leverage all forms of social, cultural, legal, and economic capital to reduce their administrative burdens (Masood & Azfar Nisar, 2020). Proposed studies would conceivably utilize qualitative methods and ethnographic studies to elucidate further where disability fits into the citizen's broader identity in their interactions with the state.

Future work should also focus on the psychological costs of administrative burden, not addressed within this research. My underlying assumption in this study is that the government seeks increased utilization of federal assistance for recovery by eligible citizens. However, administrative burden may be an intentional policy tool to advance political agenda and values, such as expanding or limiting government within society (Herd et al., 2013; Moynihan et al., 2016; Wamsley, 2020). Within disaster recovery, administrative burden as a policy tool plays out in shifting policy goals of how government officials define recovery (Mileti, 1999; Tafti & Tomlinson, 2019). For instance, while undocumented individuals cannot receive eligibility for federal assistance during disasters, they may apply for assistance on behalf of their dependents if their dependents are citizens or legal residents (FEMA, 2018c). The application process requires FEMA inspections to verify losses and identify all individuals in the home. Additional psychological costs emerge for mixed-status families as FEMA may share applicant information with other federal agencies, including Customs and Border Protection, Citizenship and Immigration Services, and Immigration and Customs Enforcement (FEMA, 2016, 2018c; Misra, 2018). During Hurricane Harvey, Houston residents received conflicting information on how immigration enforcement would continue during the response and recovery from varying local to federal officials (Lewis et al., 2019; Romero & Jordan, 2017). One proposed way of assessing psychological costs can be through content analysis and sentiment analysis of media and policy document shifts in recovery language. Such methods would clarify and expand the literature on the dynamics of stigma and how the bureaucracy shifts to accommodate burden as a policy tool (Moynihan et al., 2016).

4.4.3 Policy Recommendations and Conclusions

The main policy recommendation from these findings is reduction of the procedural component of administrative burden. One direct policy action is the revision of the identification questions within FEMA's application process. Clearer and more inclusive questions may be designed through specific focus group discussions, which better identify a more grounded and reflective means disability identity instead of the current narrow approach tied narrowly to the specific disasters. The use of multiple questions would also increase the construct validity around the proper identification of special accommodation needs. More work should be done to promote section 508 compliant online federal applications that are compatible with and leverage assistive technologies.

In this chapter, I assessed individual-level experiences of administrative burden in the form of recovery service eligibility denials for persons requesting special accommodations on their federal assistance applications. I found that individuals who requested special accommodations were more likely to receive service eligibility (low exclusion burdens) but were less likely to self-identify as needing special accommodations due to inaccessible application materials (high procedural burdens). I continue to expand on the emerging theme of nuance administrative burdens in the next chapter. In chapter five, I evaluate the different outcomes of administrative burden on disaster recovery one year after Hurricane Harvey as well as perceptions of fairness, equity, and self-identity on the broader society.

CHAPTER 5: ESSAY THREE

5.1 Significance and Justification

When federal assistance designed to offset disaster-induced losses and spur on recovery is limited, there may be adverse cascading effects for short and long-term recovery particularly for vulnerable and marginalized populations. Individuals who are disabled and unable to work are less likely to report a return to normalcy one to three months after a storm (Rivera, 2020). In addition, a greater number of low-income households impacted by a disaster need recovery assistance compared to high-income households several months after a disaster (Fernandez, 2018; Hamel et al., 2018). Long delays in federal assistance compound the recovery gaps, with some disaster-impacted residents no longer seeking assistance, "and suffer[ing] privately, ashamed of their living conditions but unable to move forward with their lives (Barlow et al., 2018)." Research on how administrative burden in federal recovery assistance, which includes perceptions of recovery efforts/investment, may improve equitable recovery. This chapter identifies whether administrative burdens for individuals applying for federal assistance translates to perceptions of inequitable recovery trajectories.

Studies on administrative burden perceptions can be extrapolated from the red tape literature that focuses on compliance costs and rule-constraints. Procedural length and outcome expectations encountered by stakeholders are strong proxy measures for perceived red tape, specifically the perceived fairness of the outcome associated with negative bureaucratic rule-constraining encounters (Kaufmann & Feeney, 2013). Burden et al. (2012) found that perceptions of red tape by election administrators led to more perceptions of flaws in policy objectives, costliness, and bias. Perceiving and experiencing red tape are conceptually fraught with subjective complexity (Bozeman, 1993). Negative emotional responses of stakeholders to red tape occur even if recipients view the rules as meaningful or productive (Hattke et al., 2019). Negative emotions may distort perceptions of dysfunctional rules creating space for subjective red tape experience (i.e., what one person deems as onerous red tape, another may deem a routine acceptable cost) (Hattke et al., 2019). Yet, perceptions of red tape influence bureaucratic support and policy merit attitudes (Burden et al., 2012). Within administrative burden, the stakeholder is explicitly the citizens who must interface with the bureaucracy for needed public services. Negative encounters with the bureaucracy which yield long delays and poor service outcomes drive perceptions around procedural fairness, with significant implications for the broader political economy (Moynihan et al., 2016).

Several studies use simulations among undergraduates, survey questionnaires with public/private administrators, and qualitative methods to assess perceptions of red tape (Feeney & Rainey, 2010; Hattke et al., 2019; Kaufmann & Feeney, 2013; Pandey et al., 2007; Pandey & Kingsley, 2000; Tummers et al., 2016). Another method relies on identifying latent constructs of administrative burden through content analysis of public service applications (Moynihan et al., 2016). Other qualitative methods such as in-depth interviews may also serve as a means to assess citizens' encounters with the bureaucracy and their outcome trajectories from eligible service denials (Heinrich, 2016). I continue in the same path as noted scholars using survey data to assess the experience of bureaucratic encounters. However, unlike the previous scholars who focus on administrator perceptions and their encounters of bureaucratic red tape, I extend the method and focus on the perspective of the citizen stakeholder. Because the central focus rests on the lived experience of the citizen and the onerous administrative process, my perception evaluation is on administrative burden not red tape. I evaluate the broader perceptions of self and society administrative burdens engender over time (Brodkin & Majmundar, 2010; Heinrich, 2016; Moynihan et al., 2016).

I identify two hypotheses related to administrative burden encounters and citizen perceptions.

Hypothesis 3.1: Individuals who report experiencing administrative burdens in federal recovery assistance are less likely to report achieving recovery ten to eleven months after Hurricane Harvey.

Hypothesis 3.2: Individuals who report experiencing administrative burdens in federal recovery assistance are more likely to have negative perceptions of societal recovery investments.

Receiving federal assistance reduces the costs borne by disaster-impacted individuals when recovering. Individuals who must absorb the high disaster costs due to service delays and denials will have fewer resources to achieve recovery. Thus, I expect to see lower long-term recovery for individuals who apply and are excluded from public assistance. Moreover, extending on the research showing the negative emotions associated with red tape, I expect to see administrative burden encounters in federal recovery assistance resulting in negative perceptions of broader societal policy. I expand administrative burden theory by moving past individual outcomes of service exclusion. This study seeks to "extend the quantitative analysis of administrative burden beyond concerns of efficiency of public services to questions of individual and societal impacts (Heinrich, 2016, p. 404)."

5.2 Methods

I utilized the Kaiser Family Foundation/Episcopal Health Foundation (KFF/EHF) *Harvey Anniversary Survey* to assess whether an individual's federal assistance approval status impacted individual recovery perceptions ten to eleven months after Hurricane Harvey. KFF/EHF surveyed adult residents living in twenty-four disaster declared counties in Texas via cellular and landline telephone. The random representative survey sample was collected between June 21st – July 29th, 2018 and conducted in both Spanish and English (Henry J. Kaiser Family Foundation/Episcopal Health Foundation, 2018). The sampling design oversampled specific vulnerable groups – i.e., those most likely to be damaged by the storm, individuals whose incomes were below the federal poverty threshold, African Americans and non-native Latinx residents. The survey also employed a multi-stage weighting design to account for oversampling, initial survey recipient nonresponse, and population parameters in the counties. The *Harvey Anniversary Survey* selected the twenty-four counties sampling frame based on FEMA damage assessment reports to account for the largest share of property damage due to the storm. The survey sample size is N = 1651 respondents. However, my analysis further restricts the sample to individuals who applied for federal assistance (n = 451).

The sampling design relied on random sampling within four county-groups stratification: Harris County, Outside Harris County, Golden Triangle, and South Coast (see Appendix I for specific county inclusion). Weighting parameters were estimated using the 2011 – 2015 American Community Survey (ACS) 5-year estimates for all county groups except Harris County. Sampling weights for Harris County relied on the 2016 ACS. The loss of precision due to the design effects and sampling error was $\pm$3 percentage points. Survey weighting and probability sampling within the stratification design protected against biased survey estimates (Kalton, 1983).

In assessing recovery, I relied on four elements based on the available survey questions. The measures addressed disruption, home, financial situation, and overall quality of life for residents affected by the storm who applied for federal assistance (Table 5.1). The use of multiple recovery measures allowed me to assess how administrative burden influenced recovery as a spectrum. The choice of four recovery measures also expanded on previous work which relied on one survey measure (disruption recovery) within survey dataset collected one to two months after Hurricane Harvey (Rivera, 2019). I also expanded the previous recovery time length, assessing recovery perceptions ten to eleven months after the storm.

Table 5.1 Recovery measure survey questions used as dependent variables in the multivariate ordinal logistic regression

Type	Survey Question	Coding
Recovery Measure 1 (Disruption)	*Which of the following best describes your personal situation in terms of recovering from Hurricane Harvey? Would you say that your day-to-day life is largely back to normal, almost back to normal, still somewhat disrupted, or still very disrupted?*	0 = still very disrupted* 1 = still somewhat disrupted, 2 = almost back to normal, 3= largely back to normal, life was not disrupted by Harvey, totally back to normal.
Recovery Measure 2 (Home)	*Has your home been restored to the same condition it was in before Harvey, has it been restored to a livable condition but not the same as before Harvey, or is your home still in an unlivable condition?*	0 = still in an unlivable condition* 1 = been restored to a livable condition but not the same as before Harvey 2 = been restored to the same condition, home is in a better condition now than before Harvey, moved to a new home.
Recovery Measure 3 (Finance)	*Compared to before Hurricane Harvey, is your personal financial situation better, worse, or about the same today?*	0 = worse* 1 = about the same today, or better.
Recovery Measure 4 (Life qual)	*Compared to before Hurricane Harvey, is your overall quality of life better, worse, or about the same today?*	0 = worse* 1 = about the same today, 2 = better.

NOTE: Respondents who reported “Don’t know” or refused were coded as missing. * Reference group. Source: Henry J. Kaiser Family Foundation/Episcopal Health Foundation. Kaiser Family Foundation/Episcopal Health Foundation Poll: Harvey Anniversary Survey, 2018 [Dataset]. Roper #31115647, Version 3. Social Science Research Solutions (SSRS) [producer]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research [distributor]. doi:10.25940/ROPER-31115647

In addition to respondent recovery perceptions, I assessed perceptions of societal recovery investments as my secondary set of dependent variables of interest. I utilized two main survey questions on fairness and equity, with equity containing subcomponents based on class (poor, middle, wealthy), race/ethnicity (White, Black, Latinx), and self-identification (persons like Me) (Table 5.2). I also assessed how survey respondents perceive Harvey recovery efforts for immigrants. Where observations within the various categories were too small to offer variations, I collapsed the categorical variables (see Table 5.2).

Table 5.2 Societal measure survey questions used as dependent variables in the multivariate ordinal logistic regression

Type	Survey Question	Coding
Societal Measure 1 (Fairness)[α]	*How confident are you that the money being spent on Hurricane relief in Texas is benefiting the people who need it most?*	0 = not at all confident* 1 = not too confident 2 = somewhat to very confident
Societal Measure 2 (Equity)	*How much do you think the efforts to rebuild the Texas gulf coast area after Hurricane Harvey have done to help …*	
	Poor People	0 = nothing at all* 1 = not too much 2 =some 3 = a lot.
	Wealthy People	0 = nothing at all* 1 = not too much 2 =some 3 = a lot.
	Middle Class People	0 = nothing at all* 1 = not too much 2 =some 3 = a lot.
	African Americans	0 = nothing at all* 1 = not too much 2 =some 3 = a lot.
	Whites	0 = not too much to nothing at all* 1 =some 2 = a lot.
	Latinx	0 = not too much to nothing at all* 2 =some to a lot.
	People like Me	0 = nothing at all* 1 = not too much 2 =some 3 = a lot.
	Immigrants	0 = nothing at all* 1 = not too much 2 =some to a lot.

NOTE: Respondents who reported "Don't know" or refused were coded as missing. [α] Recoded variables due to small number of observations. 0 = not at all confident (nothing at all), 1 = not too confident (not too much) 2 = Somewhat confident, or very confident (some, a lot). $^{\mu}$ Recoded variables due to small number of observations. 0 = not at all confident, not too confident and 1= somewhat confident, or very confident. * Served as the reference category. Source: Henry J. Kaiser Family Foundation/Episcopal Health Foundation. Kaiser Family Foundation/Episcopal Health Foundation Poll: Harvey Anniversary Survey, 2018 [Dataset]. Roper #31115647, Version 3. Social Science Research Solutions (SSRS) [producer]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research [distributor]. doi:10.25940/ROPER-31115647

I identified measures of administrative burden using program service delays and denials consistent with the literature. Hattke et al (2019) experimented with the length of time study participants received payouts for completed task in assessing administrative delays and emotional responses. Heinrich (2015) assessed how denials in child-welfare cash award program eligibility influenced adolescent participant outcomes later in life. I primarily operationalized administrative burden using following the survey question:

> *What is the status of your [Federal Emergency Management Agency (FEMA) or the Small Business Administration (SBA)] application? Has it been approved, is it still pending, was it denied, or are you not sure of the status?*

I coded survey response 0 = approved, 1 = pending, denied, not sure. Respondents who declined to respond were coded as missing. I was limited in differentiating between delays (i.e., pending reports) and denials in recovery funding assistance as pending and denied assistance were combined due to low numbers of observations in pending reports. “Pending” respondents had yet to receive assistance ten to eleven months after Harvey, whether such assistance would be forthcoming or not. As a result, including them with “denied” respondents should have had minimal effect on burden outcomes given the length of decision delay.

Receiving or not needing assistance has the potential to serve as a mechanism of lowering learning costs for individuals navigating the administrative process (Moynihan et al., 2014). So, I also assessed receiving sufficient assistance in applying for disaster aid. I based disaster aid application assistance on the following survey question:

> *[Applying for disaster assistance*] *Do you need more help, are you getting all the help you need, or is this not an issue for you?*

I coded application assistance = 0, if survey respondents reported needing more help, and application assistance = 1 if respondents reported getting all the help they needed, or it was not an issue. I limited survey response to those who applied for federal assistance.

Consistent with the previous two chapters, I also assessed the role of disability in administrative burdens. Griego et al. (2019) identified disability based only on additional assistance needed to evacuate during Hurricane Harvey. Rivera (2019) tied disability to unemployment, i.e., whether individuals were on disability insurance and could not work. My current definition provided a broader and more inclusive definition of disability. I based the disability measure on the following survey question:

> *Does any disability, handicap, or chronic disease keep you from participating fully in work, school, housework, or other activities?*

I coded survey response 0 = No, 1 = Yes. Participants who declined to respond are coded as missing. Respondents who reported "don't know" were also coded as missing.

I controlled for various factors within the study to reduce bias in my coefficients of interest. Controls included several socioeconomic, damage severity, and additional assistance measures based on the survey data availability. The socioeconomic variables included gender, nativity status, children, renter's status, race/ethnicity (Latinx, African American, White, Other), and political party affiliation (Republican, Democrat/Independent) and schooling. Respondents who fell at or 100% below the federal poverty limit based on self-reported income, I coded poverty = 1, else poverty = 0. *Joint household* measured whether respondents were married or single but living with partners. To ensure that the effects of government bureaucratic encounters on recovery and societal perceptions were isolated, I also controlled for the potential confounders of receiving non-government assistance. I used the survey questions:

> *Since Hurricane Harvey, have you or another family member received help paying for food, housing, or health care, or other financial help from a local or national charity, such as a church or non-profit organization, or not?*

I also included a measure of whether respondents evacuated their home due to the storm, the presence of homeowners/rental insurance and flood insurance, and Harvey damage severity. In measuring the severity of storm damage to home, I coded severity = 0 for no to minor damage and severity = 1 if respondents report major damage or home was destroyed.

5.2.1 Statistical Analysis

I sought to assess the relationship between experiencing administrative burden and perceptions of disaster recovery. Given the categorical nature of the various perception dependent variables, I used multivariate ordinal logistic regression to assess how experiences of administrative burden influenced perceptions of recovery, adjusting for the complex survey design of oversampling through sampling weights. I retained the varying ordered categories within each perception model when there was sufficient data to preserve the meaningful details in describing perception types (Tables 5.1 – 5.2) (Kleinbaum et al., 2014). I chose the categories which denoted the most negative forms of perception (i.e., no confidence, worse today etc.) as the referent category to compare all other forms of recovery perceptions. I used the Chi-square score test to assess the proportional odds assumption, which assumed invariant odds ratios regardless of how the perception categories are dichotomized (Kleinbaum et al., 2014). Where the proportional odds assumption failed, I used a generalized logistic regression model to compare each nonreferent perception category to the referent perception category. All variables were tested for multicollinearity. I present descriptive statistics, as well as odds ratios and 95% Confidence Intervals for the parameter estimates in the next section. I assessed statistical significance at the alpha = 0.05 level.

5.3 Results

Among the survey respondents who applied for federal assistance, 58.6% (n = 440) reported experiencing federal assistance delays or denials in assistance ten to eleven months after Hurricane Harvey (Table 5.3). Within the survey, 32% of the respondents were below the federal poverty limit and 30% identified as having some form of disability. Sixty-seven percent (67%) of individuals sampled reported having to evacuate due to Hurricane Harvey with 58% reporting major Harvey damage or their home was destroyed. However, only 20 percent of the survey respondents reported having flood insurance (Table 5.3).

Table 5.3 Descriptive statistics of Harvey Anniversary Survey respondents who applied to FEMA/SBA for assistance

Variable	Survey Question	N	Mean	Std Dev	Range	N	% Missing
US Native Born	*Were you born in the United States, (on the island of Puerto Rico,) or in another country?*	448	0.84	0.37	0 - Another country 1 - US, Puerto Rico	71 377	0.9
Female	*Respondent's sex*	452	0.58	0.49	0 - Male 1 - Female	192 260	0.0
Republican	*In politics today, do you consider yourself*	452	0.21	0.41	0 - Democrat, Independent, Other 1 - Republican	355 97	0.0
Education	*What is the highest level of school you have completed or the highest degree you have received?*	450	2.99	1.77	0 - Less than high school 1 - High school incomplete (Grades 9-11 or Grade 12 with no diploma) 2 - High school graduate (Grade 12 with diploma or GED certificate) 3 - Some college, no degree (includes some community college) 4 - Two-year associate degree from a college or university 5 - Four-year college or university degree/Bachelor’s degree (e.g., BS, BA, AB) 6 - Some postgraduate or	34 39 134 92 58 57 7	0.4

					professional school, no postgraduate degree		
					7 - Post-graduate or professional degree, including master's, doctorate, medical, or law degree (e.g., MA, MS, PhD, MD, JD)	29	
Poverty	*Calculated Federal Poverty Limit based on self-reported income*	421	0.32	0.47	0 - 100%+	286	6.9
					1 - UNDER 100%	135	
Disability	*Does any disability, handicap, or chronic disease keep you from participating fully in work, school, housework, or other activities?*	450	0.30	0.46	0 – No	316	0.4
					1 - Yes	134	
Joint Household		449	0.48	0.50	0 - Single or widowed	233	0.7
					1 - Single, living with a partner or Married	216	
Kids	*How many children under the age of 19 are living in your household?*	449	1.21	1.49	0 – None	219	0.7
					1 – One	74	
					2 - Two	61	
					3 - Three	54	
					4 - Four	26	
					5 - Five	10	
					6 - Six or more	5	
Rental Status	*Did you own or rent the place where you were living at the time of Hurricane Harvey?*	444	0.38	0.49	0 – Own	276	1.8
					1 – Rent	168	
Evacuation	*Did you evacuate or leave your home for any amount of time*	452	0.67	0.47	0 - No, did not evacuate	148	0.0
					1 - Yes, evacuated	304	

	as a result of Hurricane Harvey, or not?						
Home Insurance	*Did you have homeowners' or renters' insurance at the time Hurricane Harvey hit, or not?*	398	0.49	0.50	0 – No 1 – Yes	204 194	11.9
Flood Insurance	*Did you have flood insurance at the time Hurricane Harvey hit, or not?*	443	0.20	0.40	0 – No 1 – Yes	353 90	2.0
Damage Severity	*Thinking back to last August, was your home or the place you were living damaged as a result of Hurricane Harvey, or not? Was that minor damage that could be repaired within a month, major damage requiring more than a month to repair, or was your home destroyed?*	452	0.58	0.49	0 - minor to no damage 1 - major damage to destroyed	188 264	0.0
Knowledge	*As far as you know, has the federal government provided funding to help Texas with long-term recovery and rebuilding, has the federal government not provided such funding, or do you not know enough to say?*	451	0.20	0.40	0 - Has not provided funding to help Texas, don't know enough to say 1-Provided funding to help Texas	362 89	0.2

Other Help	*Since Hurricane Harvey, have you or another family member received help paying for food, housing, or health care, or other financial help from a local or national charity, such as a church or non-profit organization, or not? (READ IF NECESSARY: Do not include money you received from FEMA or other government sources)*	446	0.35	0.48	0 – No 1 – Yes	291 155	1.3
Delay/Denial	*What is the status of your application? Has it been approved, is it still pending, was it denied, or are you not sure of the status?*	440	0.59	0.49	0 - Application Approved 1 - Application pending, denied, do not know	219 218	2.7
Disaster Application Assistance	*For each of the following areas, please tell me if you need more help than you are getting, you're getting all the help you need, or if this isn't an issue for you? [Applying for disaster assistance]*	437	0.50	0.50	0 - Need more help 1 - Not an issue or getting all the help you need	182 258	3.3
Ethnicity							
Black						128	
Latinx						126	
Other						18	
White						173	
Missing						7	

NOTE: Sample restricted to respondents who answered yes to the following survey question: Have you applied for disaster assistance from either the Federal Emergency Management Agency (FEMA) or the Small Business Administration (SBA)? N = 452.

When controlling for factors such as severity of home damage, poverty, and race/ethnicity, persons with disabilities were not significantly more likely to experience delays or denials in assistance (Table 5.4). Renters were 2.41 times more likely to experience delays and denials in federal assistance than comparable homeowners, even when controlling for factors such as evacuation, flood insurance coverage, and damage severity. Individuals who had evacuated due Harvey, had major storm damage, or received help in applying for disaster assistance were less likely to experience delays and denials in federal assistance. The odds that a person who received sufficient assistance in applying for disaster aid were 27.0% as high in experiencing delays or denials in federal assistance than comparable respondents who did not receive help in applying (Table 5.4). Respondents with major home damage, African Americans, or persons with disabilities were significantly less likely to receive sufficient help in applying for disaster assistance (Table 5.4).

Table 5.4 Logistic Regression estimates of federal assistance decisions and disaster relief application help

Effect	Model 1 (Delays/Denials)			Model 2 (Application Help)		
	Odds Ratio Estimate	**95% Confidence Limits**		**Odds Ratio Estimate**	**95% Confidence Limits**	
Ethnicity (ref=White)						
African American	0.93	0.37	2.32	**0.22***	**0.08**	**0.60**
Latinx	0.65	0.24	1.70	0.47	0.16	1.35
Other	0.76	0.17	3.43	0.30	0.07	1.30
US Native	0.85	0.31	2.35	0.89	0.30	2.60
Female	0.79	0.41	1.54	1.28	0.65	2.52
Republican (ref = (democrats and Independents)	0.74	0.31	1.77	0.64	0.26	1.56
Education	1.11	0.88	1.41	1.14	0.93	1.40
Poverty	1.07	0.48	2.37	0.54	0.23	1.24
Disability	1.85	0.81	4.26	**0.43***	**0.20**	**0.95**
Joint Household	1.41	0.68	2.91	0.49	0.23	1.04
Children	0.95	0.77	1.18	0.83	0.65	1.06
Evacuated	**0.46***	**0.21**	**0.99**	0.69	0.33	1.44
Home Insurance	0.80	0.34	1.86	1.56	0.69	3.53
Flood Insurance	2.41	0.96	6.052	2.04	0.74	5.61
Renters	**2.47***	**1.17**	**5.22**	1.08	0.48	2.42
Home Damage Severity	**0.24***	**0.12**	**0.50**	**0.49***	**0.24**	**0.99**
Application Help	**0.27***	**0.13**	**0.58**	**--**	**--**	**--**
		Model Fit				
-2 Log L	324.80			344.53		
N	334			344		

NOTE: As the dependent variable in model 1, burden measured whether survey respondents who applied for FEMA and/or SBA assistance were denied or application still pending at the time of the survey (ten to eleven months after Harvey). The dependent variable in model 2, application assistance measured whether survey respondent who applied for FEMA and/or SBA assistance received sufficient disaster relief application assistance. Poverty is a dichotomous variable whereby survey respondents below the 100% Federal Poverty Limit was coded 1, and respondents at or above the 100% Federal Poverty Limit was coded as 0. Burden was measured as having survey respondent's FEMA or SBA application pending or denied at the time of the survey.

Across the four dimensions of recovery (disruption, overall life quality, financial and home), there were no statistically significant differences in recovery perceptions and experiencing federal disaster assistance delays or denials (Table 5.5). However, respondents who received all the help they needed in applying for disasters assistance were 8.68 times more likely to report recovery from Harvey – related disruptions, 2.56 times more likely to have financially recovered, and 4.73 times more likely to report home recovery, compared to the reference groups, all else being equal (Appendix table J.1). The significant findings remained in effect during sensitive analyses.

Table 5.5 Generalized logistic regression estimates of recovery outcomes by federal assistance decisions

Recovery Perceptions Models	Delay/Denial Effect	OR Estimates	95% Confidence Limits	
Recovery measure 1 (Disruption):	Still very disrupted (ref)			
	Still somewhat disrupted	0.60	0.19	1.89
	Almost back to normal	1.01	0.29	3.55
	Largely back to normal…	1.07	0.29	3.92
Recovery Measure 3 (Finance):	Worse (ref)			
	About the same today, or Better	1.36	0.66	2.79
Recovery measure 2 (Home):	Still in an unlivable condition (ref)			
	Been restored to a livable condition but not the same as before Harvey	0.45	0.15	1.34
	Been restored to the same condition or better	0.49	0.14	1.65
Recovery Measure 4 (Life qual):	Worse (ref)			
	About the same today	1.02	0.48	2.19
	Better	1.10	0.33	3.72

NOTE: The models control for ethnicity/race, citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, homeowners and flood insurance as well as other factors. The full model is available upon requests. Burden is measured as having your FEMA or SBA application pending or denied at the time of the survey

.

Respondents with disabilities continued to struggle in achieving full recovery close to one year after the hurricane. The significant findings though were not consistent across all recovery perception domains. Disabled individuals were 78.2% less likely to report being largely back to normal compared to being very much still disrupted from Hurricane Harvey, controlling for factors such as damage severity, renter's status, race/ethnicity, and receiving sufficient assistance in applying for disaster aid (Appendix J.2). Such individuals were also 58.7% less likely to report their overall life quality were back to pre-Harvey levels, holding all else constant (Appendix Table J.2). There were no statistically significant relationships between disability and perceptions in home or financial recovery after the storm. These findings too were robust to sensitivity analyses.

I found experiencing federal delays or denials associated with significantly negative perceptions of equity and fairness in societal recovery investments. Such individuals were 68.4% less likely to be confident that rebuilding money spent helped those most in need compared to little to no confidence at all, holding various factors such as recovery level, poverty, and race/ethnicity constant (Table 5.6). Respondents who experienced delays and denials were also 79.2% less likely to be very confident that recovery investments helped the poor compared to no confidence, and 98.6% less likely to be very confident that such investments helped the middle class, holding the same factors constant (Table 5.6). Experiencing delays or denials also resulted in respondents being 78.3% less likely to be very confident that recovery investments helped people like themselves (Table 5.7).

Table 5.6 Generalized logistic regression estimates of societal perception outcomes by federal assistance decisions

Societal Perception Models	**Delay/Denial Effect**	**OR Point Estimate**	**95% Confidence Limits**	
Equity Perception 1 (Fairness):	Not at all confident (ref)			
	Not too confident	0.55	0.22	1.41
	Somewhat confident, or Very confident	**0.32***	**0.13**	**0.78**
Equity Perception 2 (Poor Persons)	Not at all confident (ref)			
	Not too confident	0.85	0.29	2.45
	Somewhat confident	0.58	0.19	1.75
	Very confident	**0.21***	**0.05**	**0.86**
Equity Perception 3 (Wealthy Persons):	Not at all confident (ref)			
	Not too confident	0.59	0.10	3.70
	Somewhat confident	0.47	0.08	2.72
	Very confident	0.76	0.14	4.08
Equity Perceptions 4 (Middle Income Persons)	Not at all confident (ref)			
	Not too confident	**0.11***	**0.02**	**0.54**
	Somewhat confident	**0.10***	**0.02**	**0.41**
	Very confident	**0.02***	**0.00**	**0.108**

NOTE: The models control for ethnicity/race, citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, homeowners and flood insurance as well as other factors. The full model is available upon requests. Burden is measured as having your FEMA or SBA application pending or denied at the time of the survey. * Statistically significant at the $p \leq 0.05$ level.

Table 5.7 Generalized logistic regression estimates of race/ethnicity, immigrant, and self-perception outcomes by federal assistance decisions

Race/ Ethnicity Perception Models	**Delay/Denial Effect**	**OR Point Estimate**	**95% Confidence Interval**	
African- Americans	Nothing at all (ref)			
	Not too much	1.73	0.49	6.09
	Some	0.75	0.22	2.51
	A lot	0.87	0.17	4.36
non-Hispanic Whites	Nothing at all (ref)			
	Not too much	0.56	0.24	1.33
	Some to A lot	0.89	0.31	2.56
Latinx	Not too much to Nothing at all (ref)			
	A lot to Some	0.53	0.25	1.11
Immigrant	Nothing at all (ref)			
	Not too much	0.47	0.15	1.43
	Some to Alot	0.47	0.17	1.28
Persons like Me	Nothing at all (ref)			
	Not too much	0.57	0.20	1.66
	Some	**0.19***	**0.07**	**0.50**
	A lot	**0.22***	**0.05**	**0.89**

NOTE: The models control for ethnicity/race, citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, homeowners and flood insurance as well as other factors. The full model is available upon request. Burden is measured as having your FEMA or SBA application pending or denied at the time of the survey. Statistically significant at the p $\leq$ 0.05 level.

Receiving sufficient help in applying for disaster assistance did have a positive effect on equity and fairness perceptions. Such respondents were almost nine times more likely to be very confident recovery investments helped persons like themselves, 5.84 times more likely to be very confident help was going to the poor, and 7.23 times more likely to be somewhat to very confident help was going to those in greatest need, holding all else constant (Appendix Table K.1). Survey respondents with disabilities had slightly lower varying degrees of confidence that rebuilding efforts were helping the poor and middle class (Appendix Table K.2).

5.4 Discussion

In this chapter, I assessed the role of administrative burden on perceptions of recovery, equity, and fairness. I used the Kaiser Family Foundation/ Episcopal Health Foundation *Harvey Anniversary Survey.* The survey contained a random sample of individuals living in Harvey-impacted counties, collected ten to eleven months after the hurricane, who applied for federal assistance. I measured administrative burden on federal assistance applications at the time of the survey. I also assessed how burden influenced recovery along four dimensions (disruption, home, financial, and overall quality of life) and several perception measures. I evaluated fairness perceptions as confidence measures that money was being spent to help those most in need. Equity perceptions were measured along class lines (poor, middle, wealthy), race/ethnicity (African American, White, Latinx), and immigrant status. I also assessed how experiencing burden influenced self-identification perceptions (i.e., rebuilding efforts were helping "people like me").

In assessing administrative burden on perceptions of recovery and broader societal perceptions, what emerged similar to previous chapters was a nuanced form of burden with distinct outcomes. Receiving sufficient help in applying for disaster may be viewed as lowered procedural burdens. In the previous chapters, I defined procedural burdens as the process (or costs) of applying for services. In receiving application assistance, individuals had additional resources in navigating the bureaucracy and experience lower procedural burdens. The experience and outcomes of procedural burdens were distinct from exclusion burdens, which I identified as receiving delay or denial service decisions.

Survey respondents who encountered delays or denials had no differences in recovery perceptions than those who had received assistance approvals. The insignificant results carried across all four domains of recovery. In addition to delays and denials in federal assistance, I found that receiving assistance from social support networks such as churches and families was also not predictive of recovery. These results were similar to Griego et al. (2020), which found that receiving assistance did not predict more significant household recovery. However, Rivera (2020) found that applying for and receiving federal assistance three months after Harvey was a factor preventing Harvey recovery. Why there were negative effects of federal assistance on recovery in the short run and insignificant effects in the long run was not apparent. There may be an interaction effect occurring in this study. For instance, having home damage and receiving federal assistance may have theoretically offset additional costs and sped up recovery compared to those with home damage and no federal assistance. However, this effect was not directly accounted for in this study.

Encounters with procedural burdens elicited a different recovery outcome response. Individuals who received assistance in applying for disaster relief (lower procedural burdens) were more likely to have positive perceptions of recovery, fairness, equity for the poor, and persons like themselves. The receipt of assistance spoke more towards the process of administrative burden and the resources of overcoming potential costs of delayed and denied services. The theoretical reduced learning and potential compliance costs I surmised were consistent with the administrative burden literature (Brodkin & Majmundar, 2010; Christensen et al., 2020; Herd & Moynihan, 2018; Lipsky, 1984; Moynihan et al., 2016; Wolfe & Scrivner, 2005). For instance, Moreno and Mullins (2017) identified English proficiency as a perceived burden in enrollment of Latinx into the Affordable Care Act. The study confirmed the presence of learning and compliance costs, recommending application assistance in translation services to increase health insurance coverage (Moreno & Mullins, 2017).

My study adds insight into how the subtle shifts in burden may have diverging outcomes. Procedural burden as a process (i.e., the act itself of navigating the bureaucracy) is more influential in recovery than exclusion burden (i.e., delay or denial in receipt of services). In the short term, exclusion burdens influence recovery outcomes (Rivera, 2020). However, in the long term the effects of delays and denials become insignificant on recovery outcomes while procedural burden outcomes remain in effect. Receiving assistance in the administrative process significantly reduced exclusion outcomes and increases positive recovery outcomes ten to eleven months after the event. My results indicated that in leveraging additional resources and support to navigate the bureaucracy, citizens may better achieve desired goals.

African Americans, persons with disabilities, and respondents with major home damage were more likely to experience higher procedural burdens. Only respondents with home damage in the previous group experienced lower exclusion burdens. Such findings were consistent with other studies that indicated FEMA assistance being driven solely by damage, with more social vulnerability considerations needed (Drakes et al., 2021; Emrich et al., 2019). This chapter's findings on procedural burdens and persons with disabilities were also consistent with my findings in chapters three and four. Lower resource allocation for communities with a higher prevalence of disabilities could be empirically explained by the presence of higher procedural burdens for persons with disabilities. If individuals could overcome the procedural burdens, then they would not face differential costs around exclusion burdens.

While exclusion burden was not influential in long-term recovery outcomes, it played an outsized role in broader longer-term equity and fairness perceptions. Persons who encountered exclusion burdens were less likely to be confident that rebuilding money spent helped those most in need, the poor, or the middle class. They were also more likely to experience a sense of alienation in wider recovery efforts. Such negative perceptions were consistent with a study that found frustration, confusion, and anger associated with administrative processes and outcomes (Hattke et al., 2019). The affective nature of lower confidence may lead to the erosion of public servant credibility, lower citizen satisfaction, blame-shifting, and lower rule-following behaviors by citizens (Hattke et al., 2019; Kaufmann & Tummers, 2017; Tummers et al., 2016).

Conversely, lower procedural burdens played a protective factor on perceptions of fairness and equity. Survey respondents were more likely to express greater confidence in rebuilding efforts assisting a larger swath of society. The procedural burden findings were similar to literature that identified citizen satisfaction in electronic participation linked to greater trust and government transparency (Kim & Lee, 2012; Welch et al., 2005). Individuals rely on government sources to receive disaster risk information and assist in the rebuilding efforts. If administrative burdens, through the initial encounters with the administrative process promote isolation and alienation from the wider society, individual and societal recovery efforts are threatened.

5.4.1 Limitations

I faced challenges in the use of the *Harvey Anniversary Survey*. While my choice to limit the sample to individuals who applied to FEMA or SBA for assistance allowed me to assess the role of administrative burden within federal assistance, it reduced my sample size and statistical power. Due to the smaller sample size, I could not differentiate between being denied services versus longer wait times in eligibility decisions. I was also unable to differentiate burden experience by rental status, which most likely influenced recovery and societal perceptions.

More importantly, while I identified the distinct long-term outcomes of procedural and exclusion burdens on recovery and societal perceptions, I could not directly identify which costs mechanisms drove the burdens. I was unable to disentangle where and in what manner survey respondents receive application assistance. I discussed learning and compliance costs as theoretical mechanisms of procedural mechanisms, but they were not validated empirically. Many of the studies measuring compliance costs, measured survey application length or documentation requirements. Learning costs were measured in the complexity of the information provided. Such direct cost measures were outside the scope of this work due to my reliance on secondary survey data. Despite these challenges and limitations, the survey's strength laid in its coverage of Harvey impacted regions and the ability to isolate the effects of administrative burden through process burdens and exclusion burdens.

5.4.2 Future Research

One primary line of inquiry should focus on refining cost measures and their role in burden production. While compliance costs have the greatest ease in operationalization, thanks to the red tape literature, measuring learning costs consistently is still somewhat elusive in the administrative burden literature. Information complexity as a form of learning costs is measured experimentally. One possible way of measuring learning costs may be through qualitative field studies. There is extensive literature within the emergency communications landscape on crafting alerts and warning messages that are actionable and accessible based on such research methods (Davis & Phillips, 2009; LaVigne & Vernon, 2003; Mileti & Peek, 2000; Mileti & Sorenson, 1990; Neuhauser et al., 2013; Sutton et al., 2014). In this area, theories such as emergent norm theory underlie information dissemination in a manner that reduces learning costs and promotes quicker response to emergency directives (Aguirre et al., 1998; Wood et al., 2017).[10] Perhaps the cognitive processes that citizens rely on in seeking assistance after extreme events are different than when individuals seek assistance for other public services such as Medicaid.[9] Linking emergent norm theory with behavioral economics may promote disaster application designs in a way that better aligns needs to resource availability. Work should be done on how well such theories can be adapted to measure and reduce learning costs which promote administrative burden as a whole and procedural burdens specifically.

In tracing the same line of inquiry around costs, future research should understand the role psychological costs play in administrative burden empirically. Previous administrative burden literature rooted within the policy feedback tradition, identified the stress and stigma associated with bureaucratic encounters (Moynihan et al., 2014; Moynihan & Soss, 2014; Soss, 1999). Psychological stress *is* a component of administrative burden that citizens must overcome to utilize program services. Of note, within the disaster research field, there is a growing literature around the mental health trajectories associated with disasters (Aguirre & Pillai, 2013; Bonanno et al., 2007; Galea et al., 2005; Johannesson et al., 2015; Lai et al., 2016, 2018; Nandi

[10] Emergent Norm Theory (ENT) focuses on the behaviors that emerge during uncertainty and the search for information. Individuals search for information through cognitive processes that influence understanding, believing, personalizing, and deciding upon action/inaction around the found information (Turner & Killian, 1987; Wood et al., 2017).

et al., 2009; Raker et al., 2019). These include suicidal ideations, depression, and post-traumatic stress disorders. No work has yet linked administrative burden and mental health trajectories within disasters, though anecdotal reports emerge within the media (Associated Press, 2017b; Chen, 2015; Fernandez et al., 2017; Fernandez, 2018; Lozano, 2020). Here, psychological costs become an *outcome* administrative burden instead of the traditional definition. Such studies may take on a mixed-methods approach using survey design and in-depth/focus group discussion with individuals who traverse the disaster recovery administrative process.

Lastly, exclusionary burden as I defined here takes on a conceptually fuzzy definition. In previous chapters, I identified being denied service eligibility as a possible result of exclusionary burden. Here, I identified being denied (and to a lesser extent delayed) as the exclusionary burden itself. There were clear impacts to being denied services, including a growing sense of alienation and lower perceptions of fairness and equity. This fuzzy definition also reflected that within the literature of administrative burden itself – terminology and definitions around burden and red tape are interchangeable and inconsistent (Brodkin & Majmundar, 2010; Burden et al., 2012; Christensen et al., 2020; Chudnovsky & Peeters, 2020; Moreno & Mullins, 2017; Moynihan, 2012; Tummers et al., 2016). What was consistent within the administrative burden literature wass the focus on citizen experience in the interaction with the state. It was the onerous interactions with the state which were associated with burden (Burden et al., 2012). Eligibility decisions were one significant facet of citizen-state interactions. With that loose theoretical definition, federal recovery assistance delays and denials were onerous to individuals' perceptions of equity and fairness. Future work should focus on testing the constructs of exclusionary burdens as an exercise in administrative burden theory building.

5.4.3 Policy Recommendations and Conclusions

Federal recovery assistance should focus on policies that reduce procedural burdens, similar to recommendations identified in the previous chapters. Such policies include ensuring Section-508 compliant application materials across all application platforms. Online training workshops on navigating the application process for non-profit groups to mobilize information campaigns into communities after disasters quickly may also lower procedural burden encounters. Finally, creating information systems that allow for real-time monitoring and evaluation of the application process from start to decision completion would also allow for the identification and remediation of burdens.

In this chapter, I assessed the long-term outcomes of federal assistance procedural and exclusion burdens on recovery and broader societal perceptions ten to eleven months after Hurricane Harvey. While exclusion burden (delays or denials of FEMA/SBA services) did not influence long-term recovery, individuals who encountered exclusion burdens had more negative views towards the fairness and equity of wider societal recovery efforts. Encounters with procedural burdens (help in applying for assistance) influenced recovery, fairness, and equity perceptions. Individuals who encountered lower procedural burdens were more likely to report positive recovery and greater confidence in fairness and equity of wider societal recovery efforts. In chapter six, I continue to examine the role of administrative burden on long-term outcomes but move away from outcome perceptions to wealth trajectory outcomes.

CHAPTER 6: ESSAY FOUR

6.1 Significance and Justification

In the previous chapters I demonstrated the presence of administrative burden through the observable outcomes of differential resource allocation in federal disaster assistance at the community level. Communities with higher prevalence of disabilities were less likely to receive funds. I then demonstrated that applying to federal assistance programs and receiving eligibility decisions elicited separate types of burdens, with distinct outcomes. The lower resource allocation for persons with disabilities occurred due to high procedural burdens. Such individuals were less likely to be denied if they self-identify, and no more likely to face delays or denials regardless of whether individuals self-identified then others without disabilities. Yet, persons with disabilities faced higher costs in applying for federal assistance. Chapter five demonstrated that both procedural and exclusion burdens influenced subjective recovery experience and broader societal perception around fairness, equity and self-identify. This chapter continues the path of understanding the long-term implications of burden by assessing the impact of administrative burden on long term home values as a measure of wealth generation.

Residential instability, which results in outmigration after disasters, is most significant along the lines of race/ethnicity, rental status, and educational attainment (Elliott & Howell, 2017; Fussell, 2015; Wyczalkowski et al., 2019). Communities with low socioeconomic status before a storm may see greater disaster-related outmigration of minorities, with the same communities experiencing affordability and displacement-issues as a result of storm damages (Wyczalkowski et al., 2019). Moreover, such increases in outmigration have a distinctly gendered disparity, with Latinx and African American women particularly vulnerable (Elliott &

Howell, 2017). Such outmigration is posited as the result of the slower distribution of assistance to restore public housing in addition to larger investment opportunities by the private market (Fucile-Sanchez & Davlasheridze, 2020). As such, homeownership before a disaster and access to post-disaster assistance play a consistent protective factor in returning and rebuilding after disasters (Elliott & Pais, 2006; Fussell & Harris, 2014; Gallagher et al., 2019; Peacock et al., 2014; Zhang & Peacock, 2010). In addition to influencing who experiences displacement, the extent of post-disaster assistance may influence access to health care and public assistance, the maintenance of social support systems, employment, education, and health outcomes (Abramson et al., 2010; Fussell & Harris, 2014; Hori & Schafer, 2010; Peek & Richardson, 2010; Zottarelli, 2008).

Uneven recovery trajectories have implications on future wealth outcomes as well. Such recovery processes may serve to further concentrate marginalized groups into more segregated, lower income, and lower homeownership areas, with greater vulnerability to future disasters (Pais & Elliott, 2008). Wealth inequality may grow as disaster assistance grows (Howell & Elliott, 2018). Increases in FEMA assistance to communities can lead to steep growths in wealth measured in assets and personal finances along the lines of race, homeownership, and education status (Howell & Elliott, 2018). Sharp growth of wealth inequality over time are led by homeownership rates, even when controlling for level of damage (Howell & Elliott, 2018). In addition to the loss of potential wealth, communities may also suffer from a loss of social memory, networks, and identity. The presence of such forms of social capital buffer against pre-disaster vulnerabilities and lead to higher coping skills towards future disasters (Adger et al., 2005; Colten & Sumpter, 2009; Fucile-Sanchez & Davlasheridze, 2020; Tidball et al., 2010).

Further assessments are needed on the role federal assistance plays in exacerbating inequalities on long-term outcomes, particularly through the lens of administration burden theory.

As previous administrative burden scholars note, encounters with administrative burden have distributive consequences on citizen outcomes and wider societal perceptions (Fox et al., 2020; Herd & Moynihan, 2018). As Moynihan and Herd (2010) state,

> *A theory of administrative [burden] has both normative and practical dimensions. On the normative side, such a theory emphasizes the citizen, rather than the administrator or policy, as the central unit of analysis. Such a focus brings attention to how citizens experience the state through the implementation of rules, the capacity of the citizen to respond, and the long-run effects. Such a theory also emphasizes values such as access, responsiveness, and equity (Moynihan and Herd, 2010 p. 13).*

To assess how administrative burden may exacerbate inequity, I examine the role of SBA loan availability and wealth creation through changes in home values.

The Small Business Administration (SBA) Office of Disaster Assistance provides low – interest loans to businesses, non-profits, homeowners, and renters impacted by disasters (GAO, 2020). In addition to separate service and field centers, SBA also works in close partnership with FEMA through shared disaster recovery centers (GAO, 2020). The three forms of low-interest loans provided by SBA include business physical disaster loans, economic injury disaster loans and home disaster loans. Home disaster loans are a form of federal recovery credit assistance used to assist with repairs and replacement costs of primary residences damaged by disasters. The limit on real estate repair/replace assistance is $200,000 and covers the costs for uninsured and underinsured owner occupant homes (SBA, 2017). Homeowners and renters also have access to $40,000 to offset costs of damage to personal property, such as vehicles and clothing (SBA, 2017).

To receive SBA loans, applicants must have an acceptable credit history. In addition to the SBA home loan application, homeowners and renters seeking assistance must submit tax returns. After a completed application is accepted, with a sufficient credit score above the SBA threshold, the SBA verifies losses through inspections to determine loan eligibility amount (SBA, 2017). However, onsite inspections occur when loan amounts are above $25,000, with SBA relying on third party Google Maps, FEMA data and phone interviews for approved applicants requesting funds below that amount (SBA, 2018). Funds are typically received by the applicant within 5 days of loan closing dates.

Those requesting assistance up to $25,000 are subject to new policies meant to speed up disaster assistance processes, whereby applicants are automatically declined if credit scores are below SBA limits (SBA, 2018). Declined applicants are referred to FEMA's Individuals and Households Program unmet needs service for potential cash grants eligibility and other forms of assistance. The policy changes are aimed at addressing issues in timeliness of loan processing and constraints on staffing (SBA, 2018). SBA loans are challenging to acquire for credit-constrained borrowers, with such individuals more likely to sell their homes due to the inability to finance repairs (Billings et al., 2019). Whiter and higher income communities are more likely to receive larger SBA loans (Billings et al., 2019). In addition, minority-majority communities and communities with greater income inequality may see greater SBA home loan denial rates than within the private market (Begley et al., 2020).

During the 2017 hurricane season, SBA rejected fifty-five percent of home loan applications due to poor credit and processed ninety-six percent of applications within forty-five days of the events (GAO, 2020). SBA experienced delays in processing loans and loss verifications due to concurrent hurricanes which impacted the country. Between fifteen to thirty percent of calls to SBA's customer service centers went unanswered during the first two months of Harvey's recovery efforts, with thirty-three to ninety-seven percent of weekly emails remaining unanswered (SBA, 2018). SBA accepted 110,800 applications for Hurricane Harvey disaster relief and approved 43,467 applicants, totaling 3.4 billion dollars in federal recovery loans distributed, twice as much as FEMA's Individuals and Households Program assistance (1.6 billion dollars) (Billings et al., 2019; GAO, 2020). In addition, the agency distributed loan funds within five days of loan closing dates (SBA, 2017; SBA, 2018). Given the administrative processes which fast track federal dollars to individuals with higher credit scores, while automatically excluding individuals with lower credit scores, access to SBA disaster home loans may serve to modify recovery trajectories, specifically in the form of home value recovery in communities impacted by disasters.

The most significant source of wealth in the U.S. occurs through homeownership (Rugh, 2020; Salgado & Ortiz, 2019). For minority communities, particularly African American and Latinx communities, this is especially true (Rugh, 2020; Salgado & Ortiz, 2019). However, minority communities were disproportionately impacted during the Great Recession (December 2007–June 2009) and the concurrent mortgage crises (2007 – 2010) (Duca, 2013; Rich, 2013). While Latino communities recovered for various reasons, African American households were the only group to still lag behind on homeownership rates post housing crises (Rugh, 2020). African American communities experienced steep home price value declines after the housing crises, while White households saw modest declines with a later full recovery in home values (E. Raymond et al., 2016). African American communities face higher rates of negative equity, even when controlling for factors such as high rental vacancies and levels of subprime mortgage lending (Raymond et.al, 2016). Currently, African American homeownership rates are lower than before the 1960s landmark Fair Housing Act, which prevented discrimination in the real estate and mortgage industry (Choi et al., 2019; McCargo et al., 2019; Neal et al., 2020). Even more concerning is the direct link between issues of housing instability and civic participation – leading to impacts on the democratic process (Rugh, 2020). Access to rapid and low burden federal recovery assistance during times of disasters may moderate home price shocks, influencing equity and wealth outcomes in communities.

The purpose of this analysis is to assess the extent to which federal recovery credit assistance (i.e., SBA loan availability) influences future wealth generation through changes in median home values. This research works to expand the understanding of administrative burden to reveal the potential detrimental cascading and exacerbating impacts burden has on long term equity. I propose four hypotheses:

Hypothesis 4.1: Minority communities are more likely to experience administrative burdens in federal recovery credit assistance

Hypothesis 4.2: As the proportion of disability grows within a community, that community will receive less federal recovery credit assistance

Hypothesis 4.3: Communities that receive past federal disaster assistance eligibility are less likely to experience present administrative burdens in federal recovery credit assistance

Hypothesis 4.4: As the availability of federal recovery credit assistance increases within communities, median home values will increase.

I base my first three hypotheses on the literature around administrative burden being consequential and distributive as outlined in my previous chapters. I hypothesize that these findings will demonstrate the extensiveness of administrative burden within already marginalized communities. Hypothesis 4.4 examined the long-term impacts of administrative burden as manifested in wealth accumulation, mainly through the growth of home equity.

6.2 Methods

I defined community at the zip code level. To assess the role of community factors on the extent of federal recovery credit availability, I relied on individual and aggregate SBA data. Individual SBA data was available for all approved Harvey- applicants. The data provided information on zip code of damaged property, loan type (home versus business), application acceptance date, approval date, and original loan approval amount. I aggregated individual applicant data to the zip code level to maintain privacy, as well as to assess community-level implications of administrative burden. Data on SBA declines was provided separately and already aggregated at the zip code levels (Appendix L.1 -L.2). Applicants were declined for various reasons including, determination of the inability to repay the loan, poor credit/debt repayment history, or no disaster-related economic injury/damage (Appendix L.2).

In assessing the extent of federal recovery credit assistance by demographic profiles (Hypotheses 4.1 – 4.3) within zip codes, I created several dichotomous dependent variables. The variables measured the extent of availability of the SBA disaster home loans, conditional upon demographic factors within the community. These variables included:

- SBA Loans: Eligible zip codes received at least one loan I coded as one, eligible communities which received no loans, I coded as zero.
- SBA Approval Rates: I classified SBA approval rates as eligible zip codes having a percent decline below the median (61.9 %) as one, eligible zip codes with percentage

decline above the median, I coded as zero. I measured percentage of declines as total number of declines per total SBA applicants at the zip code level.

- SBA Low Approval Delays: I coded zip codes as one if their median approval times were below 24.5 days, the median for the study area. If zip codes had median approval times greater than 24.5 days, I coded SBA low approval delays as zero. I measured approval times as application acceptance date minus loan approval date for each individually approved applicant, then I identified the median approval time within the zip code and the study area.
- FEMA and SBA Assistance Mix. Eligible zip codes which received above the median in both total FEMA assistance and total SBA loans were code one (1). Zip codes which received a mixture of total FEMA and SBA funding below the median, I coded as zero (0).

The demographic profile variables of interest included the percentage of total disabled, the percentage of African Americans, and the percentage of Latinx within zip codes. I also assessed the role of prior recovery eligibility, meaning prior disaster assistance eligibility for the 2015 Memorial Day Floods, the 2016 Tax Day Floods, or the June 2016 Floods. I controlled for population density, homeownership rates, and poverty using the 2016 ACS – 5 year estimates. I also controlled for disaster damage within the zip code using the USGS High Watermarks data. In addition, I controlled for median housing values one month prior to Hurricane Harvey using private market data discussed in the next section.

I then evaluated changes in median home values by the extent of federal recovery credit assistance (Hypotheses 4.4) within zip codes. My dependent variable of interest was monthly median Zillow single-family home value estimates at the zip code level. Zillow is a private marketplace that provides pricing information on homes, real estate, and mortgages (Corcoran & Liu, 2014). Pricing information is provided by both consumers (sellers and real estate agents) as well as publicly available data (Corcoran & Liu, 2014). Zillow Home Value Index (ZHVI) incorporates seasonally adjusted price records of homes sold and not sold for median estimates by zip code (Hryniw, 2019). The strength of the ZHVI is that through reweighting, it limits the bias associated with repeat sales which may artificially drive home price increases and not represent the housing stock (Fleming & Humphries, 2013; Hryniw, 2019; Raymond et al., 2016; Raymond, 2016). I assessed four separate independent variables of interest as recovery credit assistance treatment variables; receipt of at least one SBA loan, high SBA loan approval rates, low SBA approval delays, and high SBA and FEMA dollar allocations. I discussed the creation of the treatment variables in the previous sections.

6.2.1 Statistical Analysis

In assessing the role of community characteristics on the extent of federal recovery credit assistance, I used multivariate logistic regressions given the dichotomous nature of the dependent variables. Separately, I used a difference-in-difference (DiD) fixed-effect regression design to assess whether communities which received federal recovery credit assistance (treatment) had a statistically significant change in median home values compared to communities which did not receive the varying levels of credit assistance (non-treatment) after Hurricane Harvey. The DiD fixed effects regression design allowed me to control for fixed omitted variable bias when controlling for time invariant fixed effects within zip codes (Allison, 2005; Angrist & Pischke, 2008). Differences within home values were assessed within zip codes, with the differences averaged across the study sample of communities eligible to receive federal disaster recovery assistance (Allison, 2005). Fixed-effects models have higher sampling variability because the models discard between group variability to limit omitted variable bias from within groups. However, controlling for unmeasured time-invariant covariates which may cause omitted bias allowed me to represent the data realistically in a less restrictive means (Allison, 2005).

$$y_{zt} = \beta\ (Treatment_z^k\, x\ Post_t) +\ \alpha_z +\ \delta_t\ +\ \varepsilon_{zt}$$

For the study, the dependent variable y_{zt} was the log of monthly home values for zip code (z) during the month – year (t). Home values were seasonally adjusted using the Consumer Price Index - for All Urban Consumer provided by the U.S. Bureau of Labor and Statistics before the log transformation. I assessed (k = 4) *Treatment* variables: 1. SBA Loans, 2. SBA Approval Rates, 3. SBA Low Delays, 4. FEMA and SBA Assistance Mix. The control group were zip codes which received no or low recovery credit assistance, depending on the treatment variable I assessed. I created a binary time measure (*Post)* whereby monthly median home values before August 31, 2017 were coded zero, and monthly home values afterwards, coded one. I controlled for the zip code fixed effect (α_z) and month – year (δ_t) fixed effects to capture the within community and within time variations, respectively. The coefficient (β) on the interaction term $(\ Treatment_z^k\, x\ Post_t)$ served as my coefficient of interest, allowing me to compare whether there was a statistically significant difference in median housing values between zip codes which received various forms of federal recovery credit assistance and zip codes which did not, pre- and post-Hurricane Harvey.

The study period was from December 31st, 2014 to August 31, 2019. A total of n = 470 zip codes had home value data for each month within the study period, which I used to create a balanced panel dataset. I presented a propensity score (average treatment effect) weighted regressions, the weights being the condition probability that the specific zip codes would receive recovery credit assistance conditional upon several observed covariates including disaster damage, population density and the percentage of minorities (Warton & Parker, 2018). The weighted regression served to minimize differences between treatment and control groups by accounting for sampling variability due to unaddressed variations between zip code (Austin, 2011; Warton, 2020). To account for the within zip code serial correlation bias which would occur due to the monthly panel dataset on median home values, I clustered the standard errors around the zip code fixed effects (Bertrand et al., 2004). I present descriptive statistics, odds ratios with 95% confidence intervals, and beta coefficient estimates in the next section. I assessed statistical significance at the p-value = 0.05 level.

6.3 Results

Within the study area, zip codes received on average 6.5 million dollars in SBA loans (n = 448) (Table 6.1). Communities which received SBA loans had higher percentages of African American and Latinx populations present relative to communities which did not receive loans. However, those communities also had lower proportions of disabled present (Table 6.2). With regards to SBA approval rates, communities with lower approval rates (i.e., denial rates greater than 61.9%) had greater proportions of minority and disabled populations present (Table 6.2). Separately, communities which also received shorter loan approval times of 24.5 days or less had a slightly higher Latinx population percentage than communities with longer loan approval delays. In contrast, communities with higher proportions of African Americans and the disabled had longer approval delays (greater than 24.5 days) (Table 6.3). Despite these delays, communities which received above the median in total SBA recovery credit and above the median in total FEMA grant assistance, had larger proportions of African Americans (17.2% vs. 9.46%) and Latinx (34.1% vs. 31.7%) communities, compared to other communities which received a mixture of high and low FEMA/SBA total assistance (Table 6.2).

Table 6.1 Descriptive statistics on federal recovery assistance within the study area at the zip code level

	N	*Mean*	*Std Deviations*	*Median*
Median SBA Approval Time (days)	380	25.46	14.05	24.25
IHP total Amounts	448	3612858.14	7418472.62	832568
Fed Total Assistance	448	10164683.40	22597509.80	2199695
SBA Total Loan Amounts	448	6551825.22	15850525	1180700
PCT SBA Loan Decline	424	62.48	20.17	61.91

NOTE: IHP = FEMA's Individual Household Program grant assistance. SBA = Small Business Administration home loans. Fed Total Assistance = total FEMA grant amount + SBA loan total amounts.

Table 6.2 Descriptive statistics of demographic profile within the study area by the extent of federal credit recovery assistance

	SBA Loans		*High SBA Approval Rate*		*SBA Low Approval Delay*		*SBA/FEMA Mix*	
	No	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
African American (%)	9.61	13.62	16.99	9.39	14.73	12.50	9.46	17.20
Latinx (%)	23.59	33.03	34.99	28.95	32.16	33.90	31.73	34.13
Disability (%)	17.97	13.78	14.88	13.73	15.13	12.42	15.71	12.13
N	68	380	212	212	190	190	174	205

NOTE: SBA Loans 1 = communities received at least one loan, 0 = communities which received no loans. SBA Approval Rates: 1= community has a percent decline rate below the median (61.9 %), 0 = eligible communities with decline rate above the median. SBA Low Approval Delays: 1= median approval times were below 24.5 days, 0= median approval times greater than 24.5 days. FEMA and SBA Assistance Mix: communities received above the median in both total FEMA assistance and total SBA loans (code = 1) compared to all other communities (code = 0). Indicates the share of social group within each federal assistance category by zip code. Ex. The average percentage of African Americans within zip codes which received at least one (1) SBA Loan is 13.62%. The average percentage of African Americans within zip codes which received no SBA loans is 9.61%.

African American communities were slightly more likely to have lower SBA approval rates, even when controlling for factors such as level of damage at the community level, population density, and median home values before the storm. Conversely, such communities were statistically more likely to be above the median in high FEMA and SBA total assistance than comparable communities (Table 6.3). Such results most likely captured the nature of intensive damage and higher property values within the Houston Metroplex even when controlling for population density in my models. Latinx communities also had a similar effect on mixture of high FEMA and SBA recovery assistance (OR 1.02; 95% CI 1.00 –1.03) (Table 5.3). Consistent with my previous chapter findings, communities with higher proportions of the disabled present were 6.4 percent less likely to be above the median in high FEMA and SBA recovery funding, all else being equal (Table 6.3). Prior recovery eligibility had no statistically significant effect across all four extent measures of federal recovery credit assistance (Table 6.3).

Table 6.3 Logistic regression estimates of the extent of SBA credit availability by community-level characteristics

Effects	*SBA Loans*	*SBA Approval Rate*	*SBA Low Approval Delay*	*SBA/FEMA Mix*
*African American **(%)***	1.00 (0.97 – 1.02)	**0.98* (0.96 –1.00)**	1.01 (0.99 –1.02)	**1.03* (1.01 –1.04)**
*LatinX **(%)***	**1.0*2 (1.00 – 1.04)**	1.00 (0.99 –1.01)	1.01 (1.00 –1.02)	**1.02* (1.00 –1.03)**
*Disability **(%)***	0.97 (0.93 – 1.01)	0.98 (0.94 –1.02)	0.98 (0.94 –1.02)	**0.94* (0.89 –0.98)**
Prior recovery eligibility	0.78 (0.40 – 1.50)	0.64 (0.38 – 1.09)	0.92 (0.53 –1.59)	0.99 (0.55 –1.79)
AIC	311.084	550.082	516.925	455.481
SC	352.199	590.627	556.379	494.909
-2 Log L	291.084	530.082	496.925	435.481
N	451	426	382	381

NOTE: Model 1- dependent variable – SBA Loans (1 – received at least one loan, 0 – received no loans). Model 2: dependent variable – SBA Approval Rate (1 – decline rate below the median (61.9%), 0 -decline rate above the median). Model 3: SBA Low Approval Delay (1 – approval time below the median (24.5 days), 0 – approval time above the median). Model 4: High SBA +High FEMA mix (1 – community above the median in total SBA assistance and total FEMA assistance, 0 – all other eligible communities which received FEMA and SBA recovery assistance. Each model controls for the median monthly housing value one month before Hurricane Harvey (July 31st, 2017), population density, poverty (%), homeownership (%), and level of disaster related damage (zip code centroid distance from high water mark). * statistical significant at p-value < = 0.05.

Prior recovery eligibility was a binary variable which measured whether a community was eligible for recovery assistance from either the 2015 Memorial Day Floods, the 2016 Tax Day Floods, or the June 2016 Floods. I assessed whether the two largest pre-Harvey events (Memorial Day Floods and the Tax Day Floods) had a more significant effect on the extent of federal recovery credit assistance as a robustness check. Eligibility to one of the events alone did not significantly affect federal recovery credit assistance across any measures. Yet, communities eligible for prior assistance to both events did have a significant effect across some measures of federal recovery credit assistance. Communities eligible to receive federal assistance for both the 2015 Memorial Day Floods and 2016 Tax Day Floods were 3.11 (95% CI: 1.097 - 8.827) times more likely to receive at least one Hurricane Harvey SBA loan, holding factors such as disaster damage and pre-Harvey home values constant. These communities were also 55.6% less likely to be above the median in approval rates, controlling for all else (Appendix Tables M.1 – M.4). These results were most likely due to the structure of federal recovery assistance. Many individuals who applied to FEMA were referred to SBA to apply for assistance (FEMA, 2020b). If the individual was approved by SBA, they were not obligated to accept the loans, but may have been limited in FEMA grant assistance (FEMA, 2020b). If SBA declined the applicant, the applicant was then referred back to FEMA for grant assistance, explaining why there were no significant differences in African American communities being more likely to receive at least one loan but having statistically significant lower approval rates.

When assessing the treatment effects of federal recovery credit assistance on monthly median home values, communities which received various forms of the treatment had on average higher home values pre-Hurricane Harvey than communities which received no or low forms of recovery credit assistance, with a common underlying trend of increasing home values over time (Figure 6). The largest pre-post Hurricane Harvey home value gap occurred among the groups of zip codes which received below the median SBA approval wait times (treatment) and zip codes above the median wait times (controls) (Figure 6C). In assessing the effects of recovery credit assistance on monthly median home values, communities which received at least one SBA loan saw a statistically significant 6.4% faster increase in home values over control communities which received no SBA loans, post Harvey (Table 6.4). Communities which had above median approval rates and high total FEMA- SBA assistance experienced slower increases in their monthly home values compared to the control group, post Harvey (- 0.036 and -0.035 respectively) (Table 6.4).

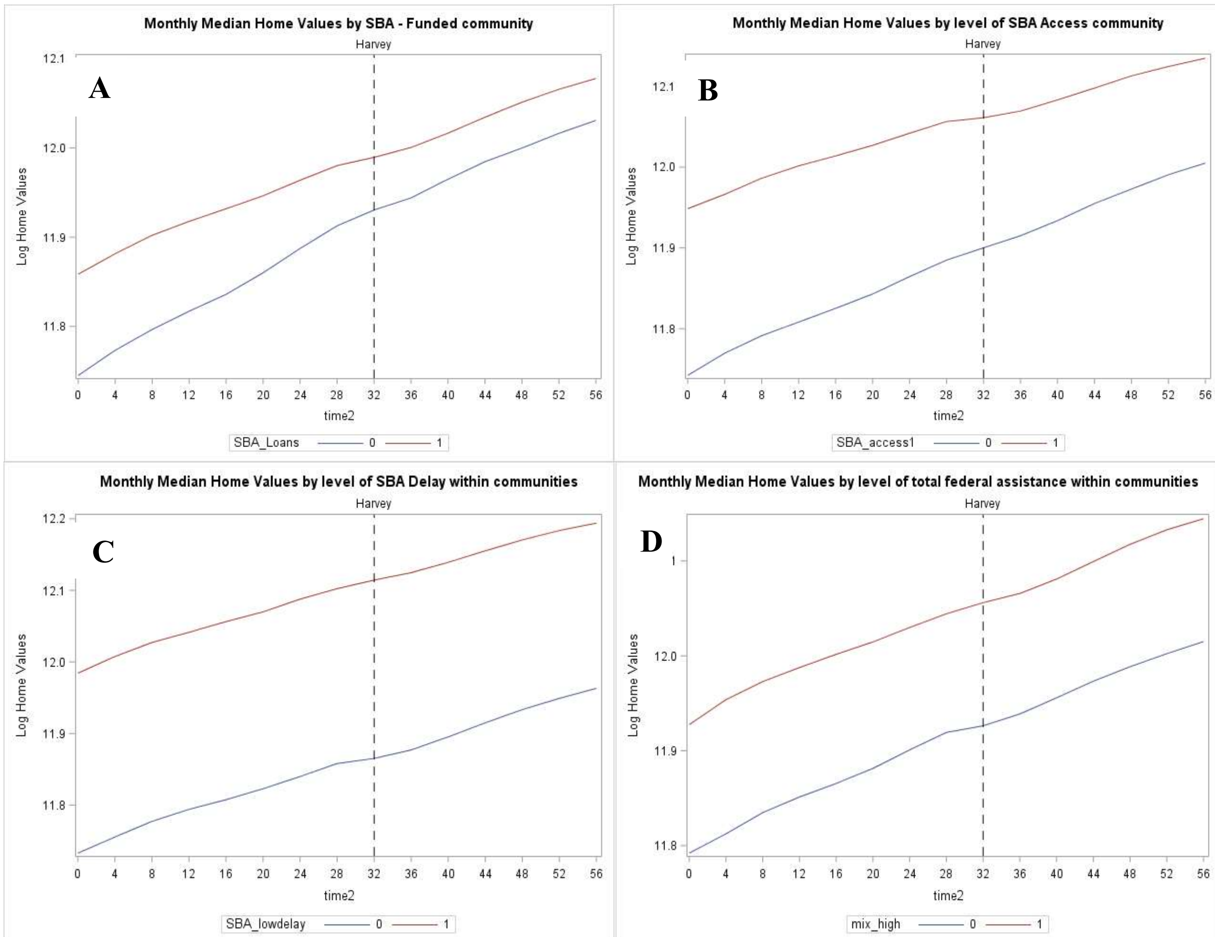


Figure 6 Monthly median home prices by extent of federal recovery credit availability.
NOTE: Panel A: SBA Loans (1 – received at least one loan, 0 – received no loans). Panel B: dependent variable – SBA Approval Rate (1 – decline rate below the median (61.9%), 0 -decline rate above the median). Panel C: SBA Low Approval Delay (1 – approval time below the median (24.5 days), 0 – approval time above the median). Panel D: High SBA +High FEMA mix (1 – community above the median in total SBA assistance and total FEMA assistance, 0 – all other eligible communities which received FEMA and SBA recovery assistance. The study period was December 31st, 2014 to August 31, 2019, n = 57 month-year observations and n = 470 zip codes with complete housing data for a balanced panel dataset for a total of n = 57 x 470 = 26790 observations.

Table 6.4 Difference-in-Difference fixed effect regression estimates by the extent of federal credit recovery assistance

MODEL	***DiD Estimate***	***Standard Error***	***p-value***
SBA Loans	0.06	0.00127	<0.01
SBA Approval Rate	-0.04	0.00135	<0.01
SBA Low Approval Delay	0.00	0.00143	0.02
SBA/FEMA Mix	-0.03	0.00156	<.0001

NOTE: Dependent variable – (log) monthly housing values. Independent variable Post and extent of SBA credit availability. There were four separate measures of SBA credit availability as a Treatment variable. Model 1: SBA Loans AIC: -57738.7 n = 25704. Model 2: SBA Approval Rate AIC: -68922.9 n= 24280 Model 3: SBA Low Approval Delay AIC -62442.2 n = 21772 Model 4: SBA/FEMA mix -56128.1 n = 21715. The regression was weighted using propensity score matching of the Average Treatment Effect. All DiD estimates were statistically significant at the p-value ≤ 0.05 level.

When introducing a one-month and two-month lag post-Hurricane Harvey, the statistically significant relationships persisted across the time periods, apart from SBA approval times (Appendix N.1 – O.4). The statistically significant higher rise in home values for communities with shorter approval times compared to the control group disappeared, post-Harvey (Appendix O.3). SBA approval rates as a treatment intervention was also subject to sensitivity in approval percentages (Appendix P.1 – P.2). For instance, while communities which received average approval ratings of 38% or higher experienced slower increases in monthly median home values compared to their control groups post-Harvey, communities with SBA approval rates above 60% experienced slightly faster increases in their monthly median home values compared to their control groups post-Harvey (Appendix P.2). Similarly, the positive effect of shorter SBA approval time on monthly median home values post-Harvey strengthened when treatment groups decrease median wait times for loan approvals (Appendix Q.1 – Q.2). In assessing the effects of recovery credit assistance on monthly median home values, communities which had a median loan approval time of two weeks or less had a statistically significant 2.0% faster increase in home values over control communities which received greater than two-week SBA approval times (Appendix Q.1).

6.4 Discussion

This chapter focused on administrative burden within federal credit recovery assistance. I built upon my previous chapters, which found administrative burdens in federal recovery grant assistance by disability prevalence. The previous chapters also found that experiencing administrative burdens engendered negative perceptions of societal fairness and equity. In this chapter, I used the SBA disaster home loan dataset to create several federal recovery credit assistance measures. The preceding chapters identified procedural and exclusion burdens as separate forms of administrative burden. In this chapter, I again expanded on the role exclusion burden had on outcomes of recovery. I also identified another form of administrative burden, delivery burden. Delivery burden refers to how public services/resources are dispensed to citizens after the point of eligibility decisions.

My two-part study relied first on multivariate logistic regression. I used multivariate logistic regressions to identify how zip code level characteristics influenced the extent of federal credit recovery assistance. I linked SBA administrative data to demographic information from the 2016 ACS 5 – year estimates to measure the extent of federal credit recovery assistance by demographic profile. I then used a difference-in-difference (DiD) regression with propensity score matching to estimate the effect of federal credit recovery assistance on median home values over time. I used seasonally adjusted monthly median housing data from Zillow's Home

Value Index to measure home price changes in response to federal recovery credit assistance. I assessed four treatment variables: receipt of SBA loans, loan approval rate, loan processing delays, and a mixture of SBA loan and FEMA grant assistance.

I found that Latinx communities were more likely to receive at least one SBA loan, whereas largely African American communities were less likely to receive higher approval rates. Both communities were more likely to be above the median in total federal assistance (SBA and FEMA). When assessing home values and the extent of federal credit assistance, all zip codes within the study area saw steady increases in home equity post-Hurricane Harvey. Communities that received at least one SBA loan experienced faster growth in home equity than control communities that received no loans. Communities that received higher approval rates also experienced faster increases in home equity post-Harvey than control communities with lower approval rates. These findings were consistent with the previous chapters showing lower administrative burden serving as a protective factor to recovery.

Similar to chapter five, I identified exclusion burden as being denied or deemed ineligible for services. Facing lower exclusion burdens had implications on future home values. Communities saw faster growth in home equity with lower exclusion burdens compared to communities with higher burdens. African American communities faced a higher exclusion burden to SBA assistance, consistent with the literature (Begley et al., 2020; Billings et al., 2019). It is important to note that minorities did not face exclusion burden equally; Latinx communities had lower exclusion burdens compared to African Americans. The increase in access to SBA loans for Latinx communities may have been one explanation as to why recent studies on Hurricane Harvey found the greatest recovery among Latinx communities (Griego et al., 2020; Rivera, 2020). The more significant effect of recovery for Latinx communities may also have been due to Texas's unique nature and the economic/political, and social connectedness of the Latinx population (Collins et al., 2013; Griego et al., 2020; Liu, 2020).

The SBA disaster home loan program is primarily an assistance program targeting homeowners with higher property values. Recent studies show that Latinx communities have in large part recovered from the housing crises, while African American homeowners face the lowest homeownership rates since the 1960s with lower home values (Choi et al., 2019; Raymond et al., 2016; Rugh, 2020). Importantly, homeownership rates and Latinx communities may vary by immigration status (Rugh, 2020). Within my analysis, although I identified Latinx communities as facing lower exclusion burden to federal recovery credit assistance, I could not disaggregate the impact of immigration status and exclusion burdens within these communities.

I identified another form of administrative burden is evaluating SBA disaster home loan program, distinct from exclusion and procedural burden. Delivery burden is the processing time of services from eligibility notification to receipt of resources. Within SBA, the program allocated assistance with a relatively lower delivery burden compared to FEMA. It provided a shorter processing time and faster disbursement of larger fund amounts. Conversely, the average FEMA payout was often far below repair costs, with wait times stretching into months, indicating a high delivery burden for FEMA resources (Vinik, 2018).

The SBA loan program was much more likely to exclude lower-income individuals by design. Poor credit history and repayment ability were the most frequent list of SBA denial reasons within the Houston area, indicating an assistance program that skewed towards pre-existing disaster wealth (Billings et al., 2019; Childers, 1999; Fothergill & Peek, 2004; Peacock et al., 2014; Tafti & Tomlinson, 2019). Individuals who were credit-constrained before Harvey would be automatically denied SBA services and were more likely to have worse financial outcomes after the storm (Billings et al., 2019).

As such, delivery burdens and exclusion burdens were two potential mechanisms by which administrative burden may have exacerbated wealth inequity in federal recovery systems. A provocative question stems from whether the rapid growth in home equity fueled by federal credit recovery assistance was made possible by the shift in exclusion burden to the poor? More administrative and financial resources were allocated to a smaller portion of disaster-impacted individuals by automatically excluding the poor. Were poor communities subsidizing the growth and recovery in wealthier, and often Whiter communities, through both their exclusion and slower delivery of services with less financial payouts? While I could not answer this question based on my data, such findings would have implications for wider political, civic, and social rights (Moynihan & Herd, 2010). My previous chapter points to how disparate experiences of burden may lead to such negative perceptions.

These findings extend the literature on administrative burden by identifying how lower delivery burden in receiving services impact long-term inequality, specifically wealth accumulation. Societal norms and values of deservedness are symbolically communicated to citizens through policy design (Ingram & Schneider, 1993; Mettler & Soss, 2004; Moynihan & Soss, 2014; Soss, 1999). Where wealthier communities experience lower delays and receive larger assistance amounts, lower income and predominantly African American communities receive long wait times, and lower funding amounts. The higher delivery burden is often accompanied by explicit language that government will not meet their full recovery needs (Fernandez, 2018; Rice, 2020). The value-laden nature and "deservedness" of administrative burden come into play. As Tafti and Tomlinson (2019) note,

> *Justice in assistance distribution for housing recovery is intrinsically linked to the question of 'recovery to what' and who gets to decide how to address this question. The answers to these questions are a reflection of political struggles, cultural norms and perceptions of how disaster recovery should be situated in broader development processes, and the importance of the role of the affected areas in these broader processes* (Tafti and Tomlinson 2019 p. 16).

The landscape of federal recovery assistance and the weight of its administrative burden shapes resource allocation and perceptions of fairness/equity while widening wealth inequity.

6.4.1 Limitations

My study had several limitations. First, I assessed the impact of federal credit assistance on home values alone while not accounting for the impact of wealth among other groups such as renters. SBA disaster loans, as an assistance mechanism, target homeowners with limited options for renters (Bolin & Stanford, 1998; Peacock et al., 2014; Tafti & Tomlinson, 2019; Zhang & Peacock, 2010). Renters can receive assistance from the SBA to repair and replace personal property at a lower loan amount of $40,000 max (SBA, 2017). Prior recovery eligibility by homeowners conceivably cannot be transferred to renters, particularly as rebuilding affordable rental properties often do not receive sufficient resource allocation to be quickly put onto the market (Peacock et al., 2007; Tafti & Tomlinson, 2019; Zhang & Peacock, 2010). Other ways to account for wealth changes inclusive of renters may be through the use of yearly federal income tax income data similar to studies on income inequality (Chetty et al., 2014).

I found that the timing and approval rate of SBA loan treatments influenced home value trajectories after Hurricane Harvey. Through my DiD study design, I could not assess when the effects of the treatment degraded over time. DiD relies on appropriate treatment and control groups to isolate the effect of the treatment (Angrist & Pischke, 2008). I constructed a control group based on similar population density, level of disaster damage, and the percentage of minorities to the treatment group using propensity score matching. I assessed the conditional probability of zip codes receiving the treatment based on the above covariates, using the estimated average treatment effects as weights (Austin, 2011). My goal was to limit threats to validity within the DiD by balancing zip code characteristics between the treatment and control groups (Warton & Parker, 2018; Zeng et al., 2010). With the propensity score weighted DiD, I isolated the effects of the treatment as I balanced the controls based on the observable characteristics. If I did not weight the DiD, I could not tease out the effects of the treatment over the damage of the storm. Weighting the DiD, however, prevented me from identifying how the effect of the treatment degrades over time, as it constrained my models. As a result, my findings were dependent on the proper selection of controls and limited in an understanding of when the treatment effect began to disappear.

Another challenge was that I did not assess other forms of federal assistance, such as the U.S. Housing and Urban Development Community Development Block Grant (CDBG) programs. This study also did not account for the federal assistance appeals process due to limitations in the data. Successful appeals require additional time, effort, and knowledge of the process, all of which are linked to social connectedness and economic resources, less likely for poorer disaster impacted households and communities (Finch et al., 2010; Fothergill et al., 1999; Muñoz & Tate, 2016; Peacock et al., 2014; Vinik, 2018). Individuals may have also had access to personal finances and other forms of assistance (Bolin & Stanford, 1998). Such additional forms of assistance may have increased the speed of wealth recovery in specific communities. However, interaction with separate government assistance programs requires large amounts of paperwork, with different eligibility criteria, wait times, and processes which disaster impacted households must traverse (Fazio, 2014; Muñoz & Tate, 2016; Vinik, 2018). Currently, the CDBG program in Texas is being sued for discriminatory practices, with the suit alleging that recovery funds are disproportionally favoring wealthier white homeowners while excluding lower-income renters who are predominantly persons of color (Fernandez, 2019; Novack, 2019; Wharton et.al, v. HUD et.al, 2019).

Finally, I did not present a measure of burden either within exclusion or delivery tied directly to learning, psychological, or compliance costs. The exclusion and delivery burdens I presented were still in fact onerous interactions with the state. However, it extended from administrative decisions as the outcome of higher learning, psychological, or compliance costs, to the administrative decisions as onerous exposure. The exposure to administrative burdens I found had tangible outcomes on wealth generation, exacerbating pre-disaster inequities. As I called for in previous chapters, more work on firming up the constructs of the onerous experience of burden is needed but beyond the scope of this work.

6.4.2 Future Research and Policy Recommendations

In addition to addressing the above limitations, future studies should expand the study area and disaster events to increase the study findings' generalizability. Other measures in wealth accumulation, such as changes in income, should also be assessed, particularly those inclusive of renters. Separately, SBA instituted the automatic decline of low credit borrowers' policy after Hurricane Sandy. Additional studies should assess how the policy shift impacted low-income communities. Did the benefits of faster processing time outweigh the costs of exclusion of otherwise eligible individuals? Alternative means of extending credit assistance to low-income borrowers should be studied. For instance, can loans be provided at slightly higher interest rates to individuals with less credit history? What are the default rates among low credit disaster-impacted individuals? Considering how the exclusion from federal recovery services promotes unequal recovery, ways in which programs may extend wider access to services should be explored.

Further development of my delivery burden concept is also needed. I empirically assess delivery burden within SBA. An empirical assessment of onerous experiences within FEMA and the impacts on wealth trajectories is needed. For Hurricane Harvey recovery efforts, FEMA transferred partial federal disaster recovery administration (the short-term housing program) to the state of Texas (DHS, 2017). Future research may address whether this FEMA policy shift of federal administration to the states impacted onerous experiences of recovery services. Media reports attest to the Texas General Land Office's lack of procedures, slow provision of housing, and deficient/substandard repairs by pre-selected contractors (Formby, 2018; Morris, 2018). More research should assess how the delivery of services is onerous and how such interactions influence recovery outcomes.

6.4.3 Conclusions

In this chapter, I assessed the role administrative burden played in future wealth generation. Using SBA disaster home loan data, I found that the extent of federal recovery credit assistance influenced future home prices. The extent of credit assistance demonstrated the role exclusion and delivery burdens played on citizen outcomes. My final chapter discusses the overall study findings, linking the administrative burden's presence through disparities in resource allocations to the implications of burden experiences on recovery, fairness, equity, and wealth trajectories.

CHAPTER 7: DISCUSSION AND CONCLUSIONS

7.1 What disasters have to say about moving administrative burden theory forward

I demonstrated that communities with a higher prevalence of disabilities faced lower federal recovery dollar allocations, pointing to the potential presence of administrative burdens. I then identified that although disabled individuals who self-identified on federal disaster assistance applications were more likely to receive eligibility for assistance, persons with disabilities were less likely to self-identify. Thus, administrative burden became nuanced. I identified higher procedural burdens but lower exclusion burdens which individuals with disabilities navigated and contended with as citizens. I later identified administrative burdens associated with how assistance was delivered, with citizens who experienced lower delivery burdens having more rapid recovery trajectories. The outcomes of such forms of burdens (procedural, exclusion, and delivery) included lower federal resources allocated for disaster recovery and slower wealth-generation at the community-level. Administrative burden experiences in federal recovery assistance were also associated with negative perceptions on fairness, equity, a sense of alienation, and lower recovery.

Administrative burden is the citizen side of red tape theory. Red tape is internally or externally generated program rules, regulations, and procedures that negatively constrain organizational efficiency, or rule-constraints (Baldwin, 1990; Bozeman, 1993; Bozeman & Feeney, 2013; DeHart-Davis & Pandey, 2009; Heinrich, 2016; Pandey & Scott, 2002). When the concern of organizational efficiency translates to delays and denials of needed services for citizens, red tape becomes administrative burden (Herd & Moynihan, 2018; Pandey et al., 2007). Both red tape and administrative burden involve compliance costs for the citizen. Compliance costs include documentation needed to meet and maintain citizen eligibility requirements for program services.

Administrative burden notably expands from the compliance costs citizens must engage when interacting with the bureaucracy to include learning and psychological costs. Learning costs occur through the additional knowledge and information citizens must accrue to navigate public programs successfully. Psychological costs occur in the form of stress and social stigma associated with the program, either through participation or applying for the services (Herd & Moynihan, 2018; Moynihan et al., 2014; Peeters, 2019). Learning, psychological, and compliance costs are constructed intentionally or unintentionally through the political process and impact public services delivery (Bozeman & Feeney, 2013; Herd & Moynihan, 2018; Moynihan et al., 2014). The outcome of administrative burden encounters results in delays and denials of service, with potential implications on broader citizenship participation, particularly among the already socially marginalized (Chudnovsky & Peeters, 2020; Heinrich, 2016; Herd & Moynihan, 2018; Moynihan et al., 2014).

Federal disaster assistance programs are designed to address the recovery needs of households and communities impacted by disasters when local and state jurisdictions become overwhelmed (FEMA, 2017a; GAO, 2017, 2018, 2020). Within the bureaucratic recovery processes, administrative burden occurs through the distribution of assistance along the lines of race, gender, socioeconomic status, and age (Bullard, 2008; Bullard & Wright, 2012; Cole & Foster, 2001; Domingue & Emrich, 2019; Harrison, 2014; Herd & Moynihan, 2018; Mohai et al., 2009; Morello-Frosch, 2002; Muller et al., 2018; Pellow, 2017; Pulido, 2015; Schlosberg, 1999, 2009; Shrader-Frechette, 2002; Thomas et al., 2013). The presence of burden along the recovery process for individuals has implications on how quickly and to what extent individuals can recover from disaster impacts, with implications for larger community-wide and societal recovery.

7.1.1 Hurricane Harvey and the parsing out of burden

Hurricane Harvey made landfall in Texas as a Category 4 storm on August 25, 2017. The storm was one of the costliest hurricanes on record, resulting in an estimated 125 billion dollars in damages and massive flooding due to record rainfall (Blake & Zelinsky, 2018; Walters, 2018). To assist in the extensive rebuilding efforts, the federal government provided disaster recovery assistance through the Federal Emergency Management Agency (FEMA) and the Small Business Administration (SBA). FEMA provided cash grants through the Individuals and Households Program (IHP), while the SBA provided low-interest loans to homeowners through their disaster home loan program. In chapters three through six, I evaluated the above federal programs to untangle the impact of administrative burden.

In chapter three, I assessed the role disability plays in federal recovery funding allocation. Of the marginalized groups traditionally assessed as facing slower recovery trajectories, persons with disabilities are the only ones accorded specific rights which are to be protected under the Americans with Disabilities Act (Americans With Disabilities Act of 1990., 1990; Kailes & Enders, 2007; National Council on Disability, 2019). I assessed variations in the percentile distribution of disaster assistance conditional upon zip code level total disability through cross-sectional quantile regression analysis. I relied on FEMA IHP data to assess recovery dollars invested at the zip code level. Total disability, which included vision, ambulatory, cognitive, hearing, independent living, and self-care impairments, was assessed using the U.S. Census American Community Survey (ACS). I found that communities with higher disability prevalence experienced disparities in receipt of FEMA recovery dollars. Moreover, the gap in federal dollars by disability widened as FEMA distributed more money to communities. I attributed such disparities in resource allocation to the presence of administrative burden for persons with disabilities navigating the federal recovery process.

In chapter four, I began to uncover the mechanism by which administrative burdens emerged. Using multivariate logistic regression on individual application data from FEMA, I found that individuals who identified as needing special accommodations were more likely to receive FEMA eligibility, facing lower exclusion burdens. Communities with higher disability prevalence received less FEMA dollars in part because individuals who needed special accommodations were less likely to self-identify on FEMA applications, specifically when controlling for the presence of Latinx. The disconnect occurred primarily due to the FEMA special accommodations request question and overall application process, which were easily misunderstood, promote confusion, and are not accessible (GAO, 2019). I classified the application process as a unique impediment (procedural burden) for individuals separate from eligibility decisions (exclusion burden), given the disparate results persons with disabilities faced when encountering the different points within the recovery bureaucracy.

In chapter five, I further expanded on procedural and exclusion burdens by linking administrative burdens to recovery outcomes and societal perceptions of equity, fairness, and self-identity. I analyzed individual responses from the Kaiser Family Foundation/ Episcopal Health Foundation *Harvey Anniversary Survey* using generalized logistic regression. The complex weighted survey contained a random sample of individuals living in Harvey-impacted counties, collected ten to eleven months after the storm. I found that when individuals received help in applying for disaster assistance (lower procedural burdens), they were less likely to face delays and/or denials in federal assistance eligibility (lower exclusion burdens). Experiencing high procedural burdens (receiving no help in applying for assistance) resulted in a greater sense of alienation, lower disruption, home, and finance - related recovery, and negative perceptions of societal fairness and equity. Individuals who faced exclusion burdens in the form of delays and/or denials in federal assistance were more likely to perceive broader recovery efforts as being less fair to those who needed it the most and inequitable for the poor, middle class, and people like themselves.

Chapter six employed a weighted difference-in-difference study design to assess how varying degrees of federal assistance influenced long-term home values (as a form of wealth accumulation) at the zip code level. I relied on the SBA disaster home loan dataset for Hurricane Harvey. I linked the SBA dataset to ACS demographic data and used seasonally adjusted monthly median housing data from Zillow's Home Value Index. Communities that received at least one SBA loan and had lower SBA denial rates, two measures of exclusion burden, saw faster increases in monthly home values after Hurricane Harvey. In addition, communities that experienced shorter approval times of loan disbursements or lower delivery burdens also saw greater home values rise after the storm. Despite the benefits of low exclusion and delivery burdens, I found that communities with a higher percentage of African Americans and disabled present were less likely to experience lower forms of these administrative burdens.

7.1.2 Expanding administrative burden theory into more expansive spaces

Administrative burden works to create inequitable recovery for individuals and communities through the bureaucratic environment of program implementation, the political landscape, and pre-existing social vulnerability. The bureaucratic environment speaks to the types of red tape present in public organizations in rules, procedures, and regulations, or rule-constraints. Whether these rule-constraints have legitimacy or not occurs within the context of the public organization's institutional tasks and perceptions of the administering bureaucrats (Bozeman, 1993; Pandey & Scott, 2002). Here, the federal agencies of FEMA and the SBA serve as the bureaucracies in administering recovery aid. FEMA’s internal workings hinder the administration of recovery services, such as the lack of Section-508 compliant information, subjective inspection processes, and long delays in services (Fernandez, 2018; Fernandez et al., 2017; GAO, 2019). Comparatively, the SBA provides shorter processing times and larger funding amounts for individuals who meet credit requirements (SBA, 2018). Such rapid administration of services comes through the automatic exclusion of individuals with poor credit (Lindsay & Webster, 2019; SBA, 2018). Individuals denied eligibility for SBA loans are then referred to FEMA, which often results in additional bureaucratic paperwork and slowdowns (U.S. Small Business Administration, 2017). Yet how does the assessed disaster recovery policy environment inform the broader discussion on administrative burden theory?

Unlike other administrative services where the socioeconomic population is fixed through needs-based eligibility requirements, federal recovery assistance provides almost a two-tiered service system. Individuals impacted by storms who are homeowners with greater pre-storm wealth have broader assistance options in the form of greater access to subsidized capital as well as shorter wait times in the delivery of public resources. Individuals who are renters, or have poor credit, are diverted to a federal recovery system that is riddled with delays, strained budgets, and lower funding amounts, which prolong their recovery process. Added to the weaknesses of administrative processes, agencies are now entering into a period of cyclical and cascading disasters under a changing climate, stretching their bureaucratic capacity further. Hurricane Harvey occurred shortly after the 2017 California Wildfires and within weeks of Hurricane Irma and Maria.

The availability and timing of resources to reduce disaster damage varies, particularly in already marginalized communities. Resource allocation also belies the historical preference for single-family homes, which has marked the presence of U.S. housing policy since the Herbert Hoover administration (Hays, 2012; Rothstein, 2017). Coupled with the fact that African American homeownership saw disproportionate impacts due to the 2007 foreclosure crises and now the COVID-19 pandemic, such disaster recovery processes will structurally exclude certain groups due to implicit policy design while maintaining the air of non-exclusionary administrative processes (Choi et al., 2019; Johnson & Martin, 2020; Neal et al., 2020; Raymond et al., 2016). With present homeownership rate disparities as well as disaster-related vulnerabilities, administrative burden within federal disaster assistance programs take on a racialized and ableist component in its distribution of resources, with corresponding implications for citizen outcomes (Elliott et al., 2009; Elliott & Howell, 2017; Elliott & Pais, 2006; Stough, 2017; Stough & Kelman, 2018).

It is precisely through the multilayered identification of procedural, exclusion, and delivery burdens that I move beyond a transaction costs-based model of red tape to citizen outcome, to a more nuanced landscape of compounding and unequally weighted administrative burdens as onerous experiences (Moynihan & Herd, 2010). In my conceptual framework, I identify the nuanced forms of burden that emanate from the political process, bind the administration of services as onerous exposures, and influence citizens' negative outcomes (Figure 7.1).

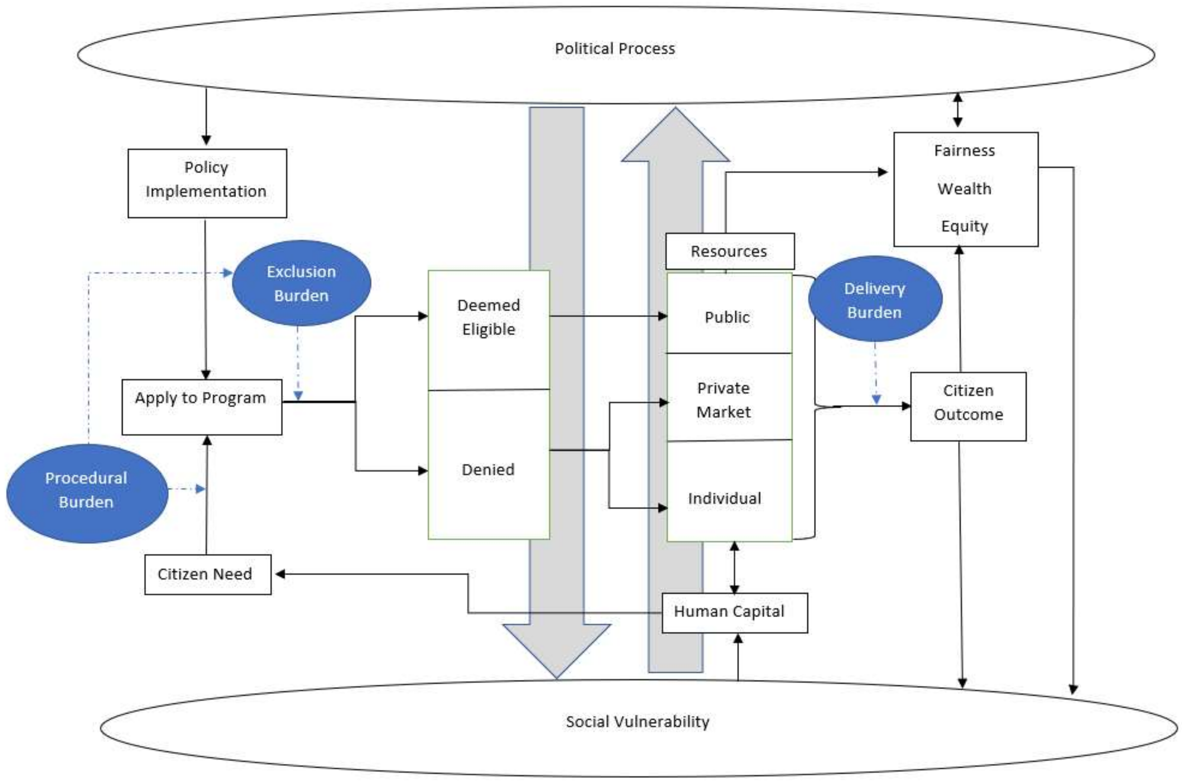


Figure 7.1 Conceptual framework of the nuanced forms of burden within the administrative process

Where individuals experience burden along the administrative process may weaken or enhance citizen outcomes and have long-term implications on fairness, equity, and wealth (Figure 7.1). Administrative burdens exist within the interchange of social vulnerability and the political process. The iterative feedback present between social vulnerability and the political process is known within the policy feedback tradition and links how program design/implementation impacts the citizen-state interaction (Burden et al., 2012; Soss, 1999). Within the policy feedback literature, societal values on standing, worthiness, the expectation of fair treatment, and power are often symbolically communicated, reflecting, and constructing social vulnerability (Keiser & Miller, 2020; Mettler & Soss, 2004). The placement of administrative burden within the policy process – social vulnerability milieu results in differential burdens with distributive consequences for citizens on resource allocation (Brodkin & Majmundar, 2010; Fox et al., 2020; Moreno & Mullins, 2017; Moynihan et al., 2014; Peeters, 2019).

With federal recovery assistance, the focus only on disaster damage will ultimately bias assistance towards those with higher property values. Individuals are not born inherently vulnerable; they are situated within politically constructed spaces that limits or promotes the level of human capital individuals must avail themselves to in moving through society (Figure 7.1). The socio-political construct occurs through political agendas or world views, which burdens individuals receiving services, such as increased documentation requirements, limiting administrative capacity through budgetary constraints, or preferencing recovery dollars based on property valuation.

Procedural burdens are the onerous experiences that individuals must overcome to fully engage with the program (Figure 7.1). For persons with disabilities traversing the recovery assistance landscape, procedural burdens arise when they encounter inaccessible application materials, long wait times at call centers, and the inability to request reasonable accommodation. Similarly, when considering other examples, procedural burdens arise through intentionally flawed application procedures, further deteriorating the individual's effort in applying for services. The recovery policy process which leads to increased procedural burden for persons with disabilities is most likely the unintentional results of the underfunding of disability integration initiatives, though still rooted in the policy making process (GAO, 2019). Despite the unintentionality of the evidenced results, the presence of procedural burdens for persons with disabilities is still a violation of the ADA and requires specific attention (National Council on Disability, 2019).

Exclusion burden refers to the experience associated with administrative eligibility decisions (Figure 7.1). This is most traditionally assessed within the administrative burden literature through delays and denials of services. Within the disaster policy arena, exclusion criteria are heavily reliant on subjective home inspections, which may promote fraud, undervalue property damage, fail to provide reasonable accommodations such as needed interpreters, and exclude lower-income homes (GAO, 2019; Martín & Teles, 2018; Massarra, 2012; Rice, 2020; "The Storm after the Storm," 2017). SBA disaster home loans have another form of exclusion burden, whereby applications are automatically denied for individuals with poor credit (SBA, 2018). Individuals who are automatically denied must either appeal the SBA's decision or engage with FEMA for assistance, compounding the individual's experience of administrative burden with a much slower and less responsive bureaucracy.

Lastly, I identify forms of delivery burden, i.e., how long one must wait to receive approved services. Individuals who have access to public, private market/non-profit, and personal resources have greater flexibility in overcoming disaster-induced losses to achieve positive citizen outcomes compared to those who must rely on limited and delayed resources. Delivery burdens may include long wait times, varying quality of services, the flexibility within services (i.e., being able to select one's own contractor or having to rely on a list of approved vendors), and the amount of resources available. FEMA limits awards to $30,000 for disaster recovery, with months-long wait times (see Figure 7.2) (Fernandez et al., 2017). Conversely, individuals who utilize SBA loans have award limits of $200,000 with estimated 5-day processing of funds from the loan date close. One year after Hurricane Harvey, reports from residents in low-income neighborhoods continued to show slow recovery signs, with denials in assistance and undervalued damage assessments from FEMA (Fernandez, 2018).

Figure 7.2 Woman and child waiting two months after Harvey for FEMA relief
NOTE: Rachel Roberts with her sons, Troy and Harrison, at their home in Houston. After Hurricanes Harvey and Irma, long delays for assistance from the Federal Emergency Management Agency have frustrated residents. Credit...Scott Dalton for The New York Times Source: https://www.nytimes.com/2017/10/22/us/fema-texas-florida-delays-.html

While I use administrative burden as my theory in practice for identifying why unequal disaster recovery trajectories occur, I departed from the literature in my conceptualization of burdens. In identifying procedural, exclusion, and delivery burdens, I did not directly assess the onerous transaction costs typically associated with the administrative burden literature. Instead, I viewed the burdens themselves not as an outcome but as an exposure metric. The experience of dealing with bureaucracy itself and its administrative decisions led to adverse citizen outcomes. I did not dismiss the role of learning, psychological, and compliance costs in administrative burden, but viewed them more as upstream causes, leading to the branching forms of burden that I identified in my conceptual framework (Figure 7.1). Due to the limitations in the data, I did not assess the upstream causes of burden, but rather focused on how and where nuanced forms of burden presented themselves within administrative process and the effects such burdens had on citizen outcomes.

7.2 Limitations

One overall limitation of this study was the generalizability of my study findings. I relied on one natural disaster at a specific time and place. There were most likely forms of vulnerability unique to Texas. The study was also biased by the political culture that pervades recovery processes at the time of a disaster. I strengthened my study findings by relying on multiple data sources and statistical regression models at the individual and zip code levels. I also corroborated my significant findings by reviewing government assessments, policy guidance documents, and after-action reports of the federal response to Hurricane Harvey. It was through this thorough analysis of the administrative processes and outcomes that I developed my conceptual framework.

Another limitation arose in my conceptualization of burdens. While I identified the various burden forms within the administrative landscape, I did not consistently measure how learning, psychological and compliance costs manifested within these distinct forms of burden. I measured or inferred the presence of procedural, exclusion, and delivery burdens. I did measure some aspects of learning costs through proxy indicators, but they were not always statistically significant. In measuring prior recovery experience as a form of knowledge learning costs, I found weak associations in explaining federal resource allocations. In measuring help in applying for disaster assistance, another form of knowledge learning costs, I found a strong association with cascading exclusion burden and recovery outcomes. How well learning costs could be measured directly poses an interesting methodological question. Assessing who is learning, the quality of the information, the supply of information, and the ability to apply the information in navigating the bureaucracy are outside the scope of my work. In addition, compliance costs that may be measured in time to complete applications and meet documentation requirements were not addressed in my study, nor were the psychological costs of navigating various points in the administrative system.

7.3 Future research

In identifying future research directions, I suggest expanding the generalizability of the research findings. Expansion may include adding additional natural disasters to examine further the points of burden within the recovery administration landscape. Quantitative studies may assess how SBA disaster home loans influenced wealth trajectories during Hurricane Sandy, making landfall in the northeast United States in 2012. Such analyses would be of interest because much of the streamlined processes that characterize present-day SBA disaster home loans occurred due to Hurricane Sandy (SBA, 2018). Thus, Hurricane Sandy's inclusion would allow one to see potential shifts and changes to exclusion and delivery burden. The review of FEMA and SBA policy documents across presidential administrations and federal recovery agencies may also shed light on burdens' politically constructed nature. The potential study could occur through case study reviews and content analyses of government policy documents, Presidential statements, and media coverage. Generalizability may also be expanded by assessing my conceptual framework across other policy arenas, such as unemployment benefits programs and the outcome of such burdens on pandemic recovery.

Another future line of inquiry is on the role information plays in administrative burden. Can information gathered at the individual level be aggregated to the community and reflect learning? If so, does this learning at the community level reflect changes to the procedural and exclusion burdens communities experience? Individual learning through information gathering may be assessed through a qualitative research design, such as in-depth interviews and focus group discussions. At the community level, potential studies which link Google keyword search data and administrative data on application completion and denial rates may illuminate how well community learning moderates procedural and exclusion burdens.

In addition, more work should be done on the psychological costs of administrative burden. The psychological costs of burden may well vary, similar to learning costs, depending on the burden's typology (procedural, exclusion, and delivery). For instance, within Hurricane Harvey's events, Texas was set to enforce Senate Bill (S.B.) 4. The bill requires local law enforcement (many of whom are also traditional disaster first responders) to comply with Immigration Customs and Enforcement (ICE) on detaining undocumented persons in Texas (Walsh, 2017). While undocumented persons are not eligible to receive federal disaster assistance, they may file on behalf of their underage children if the children are U.S. citizens. Texas Governor Greg Abbot signed the law on May 7, 2017. Hurricane Harvey made landfall in Texas on August 25, 2017. S.B. 4 was set to be enforced on September 1, 2017. The law was challenged and successfully blocked 24-hours before it was set to be enforced on the grounds that it was unconstitutional, that it would harm the economic recovery of the state, and promote discrimination (*City of El Cenizo, et. al. v. State of Texas, et. Al.*, 2017). The well-publicized rhetoric and attempted enforcement of S.B. 4 may have posed an added psychological cost to individuals who would otherwise apply and be eligible to receive recovery resources for their households (Aguilar, 2017; Associated Press, 2017a; Lind, 2017).

Psychological costs may also manifest differently for delivery burdens when compared to procedural burdens as individuals who receive approval of recovery assistance wait months to years for assistance (Fernandez, 2018; Fernandez et al., 2017). Within the disaster literature, there is a growing body of work that focuses on the mental health trajectories of individuals impacted by disasters (Aguirre & Pillai, 2013; Bonanno et al., 2007; Galea et al., 2005; Johannesson et al., 2015; Lai et al., 2016, 2018; Nandi et al., 2009; Raker et al., 2019). Do psychological costs associated with the administrative recovery process serve to moderate the mental health trajectories of individuals? Such work would have wide ranging implications on how federal resources are distributed but also around the growing research of how psychological first aid during disasters is understood.

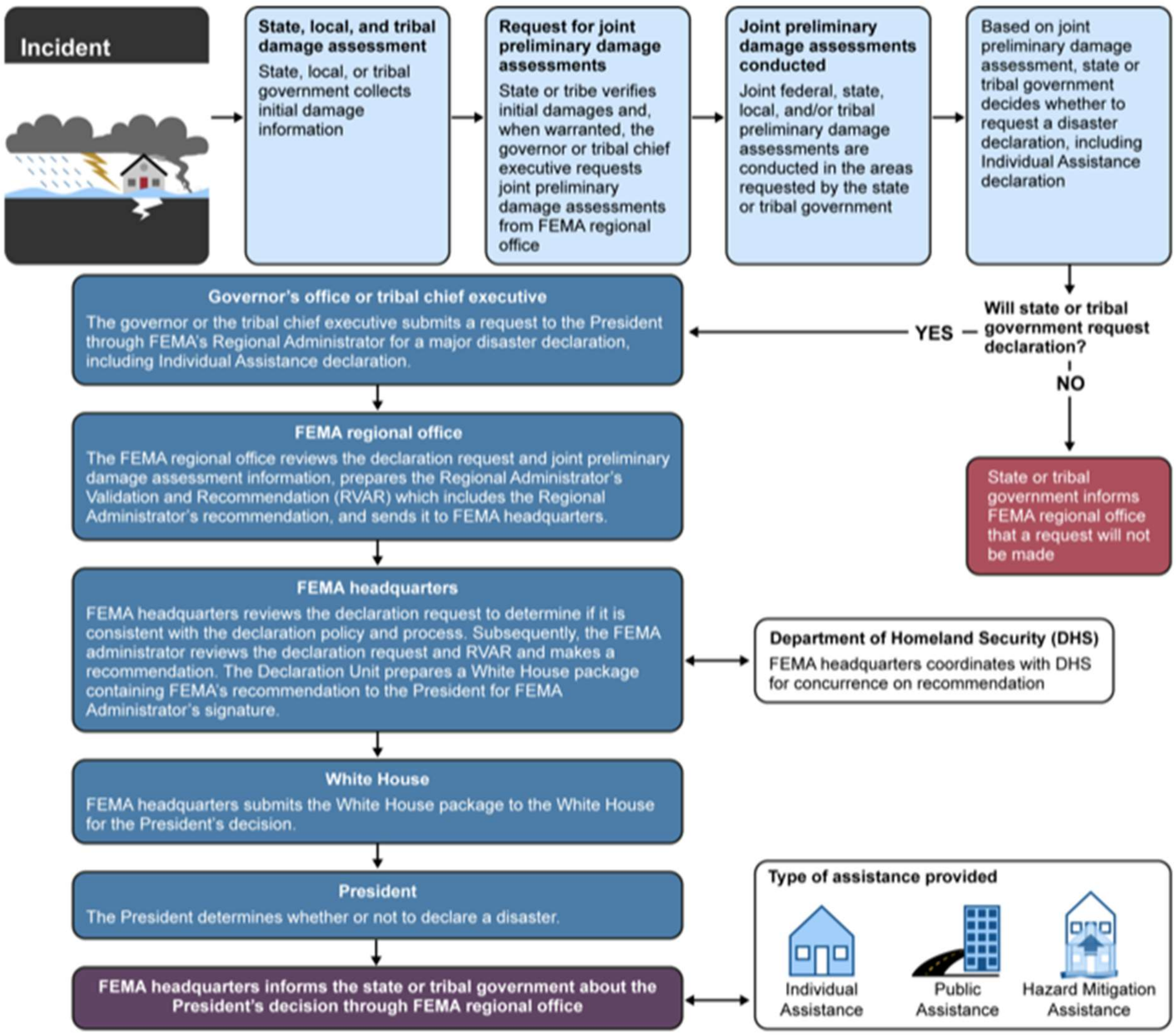
7.4 Policy Recommendations and Conclusion

Administrative burden arises from the interactions of social vulnerability and the political landscape as citizens interact with the state through the bureaucratic (red tape) environment of policy implementation. These forces converge to impose distinct burden costs throughout the administration of services. These include procedural, exclusion, and delivery burdens which vary in influence and compound along the administrative service pipeline to influence citizen outcomes, perceptions of fairness, equity, and wealth generation. By providing additional resources such as application assistance, language translators and interpreters, and streamlined appeals processes, burdens may be moderated as citizens have the opportunity to utilize the needed services in a time-sensitive manner.

In assessing racial disparities in homeownership rates, the Urban Institute puts forth an idea of transitioning to other forms of creditworthiness assessments, such as consistent rental payment history (McCargo et al., 2019). This should be explored within the SBA disaster home loan program as well. Much more difficult are the bureaucratic and policy design requirements needed to shift the focus of damage-only models to explicitly include segments of the citizenry that are not homeowners and do not control greater resources. Currently, FEMA's processes are too slow and ill-funded. However, the SBA is not designed to facilitate recovery for credit-insecure individuals. Other federal programs such as the Housing and Urban Development Community Development Block Grant and state and local assistance programs focus on long-term recovery. More work should be done around creating a recovery assistance ecosystem that provides disaster-impacted communities with a streamlined means of interacting with bureaucracies in receiving the appropriate services to facilitate recovery. The federal government can create an inclusive ecosystem by providing the framework in which the different entities meet and operate to lower the learning costs of state and local governments, community advocates, and citizens in utilizing needed services.

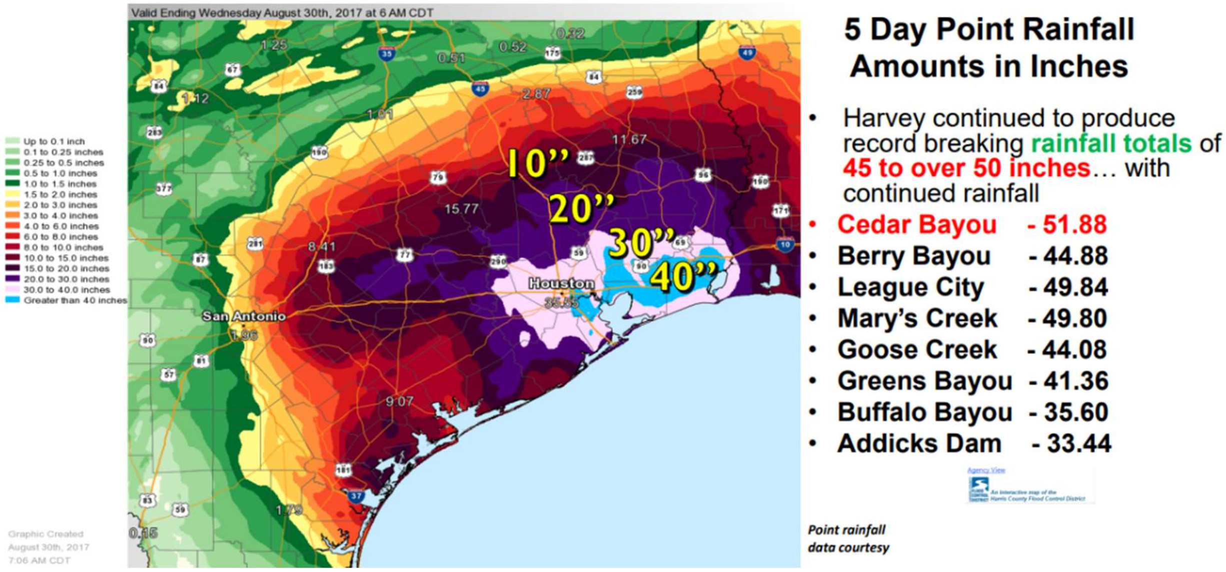
APPENDICES

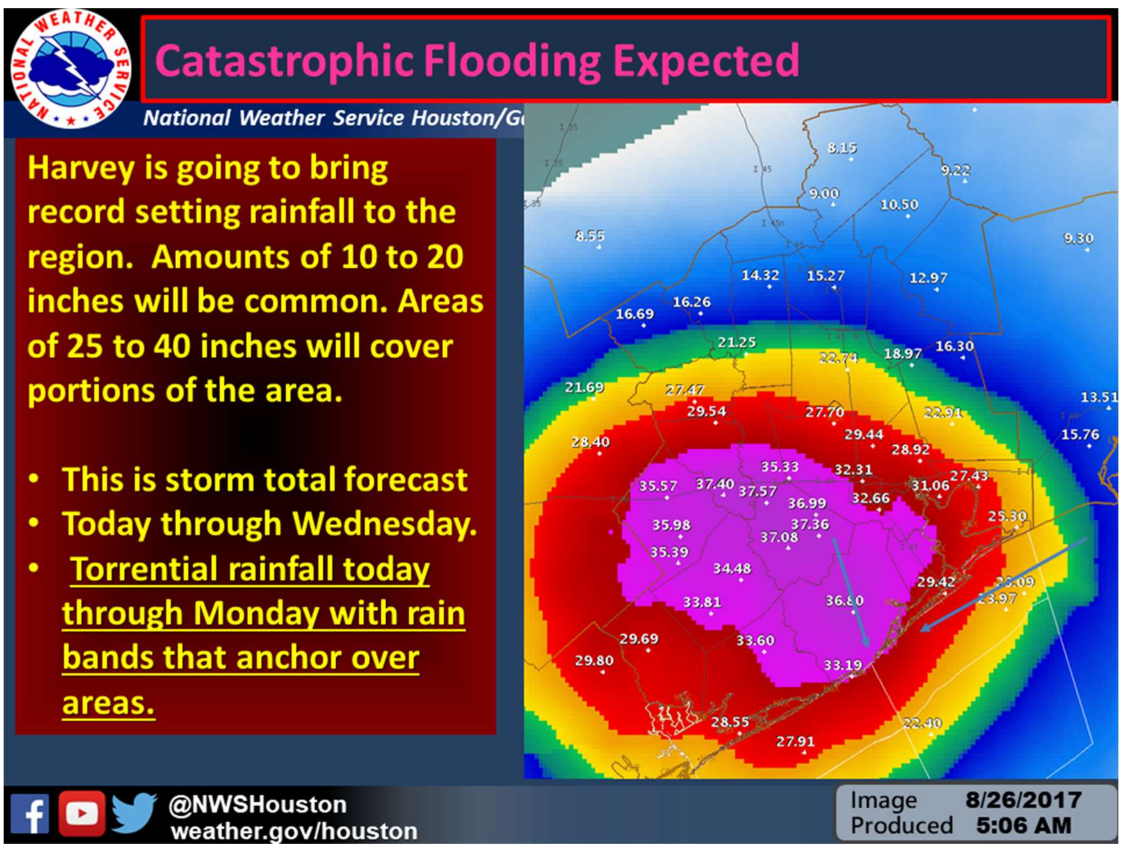
APPENDIX A: Federal Emergency Management Agency's (FEMA) Major Disaster Declaration Process



Source: U.S. GAO. (2018). Federal Disaster Assistance Requests Often Granted, But FEMA Could Better Document Factors Considered. U.S. Government Accountability Office [Report Number GAO – 18-366]. Accessed 05/04/2020. Available at: https://www.gao.gov/products/GAO-18-366

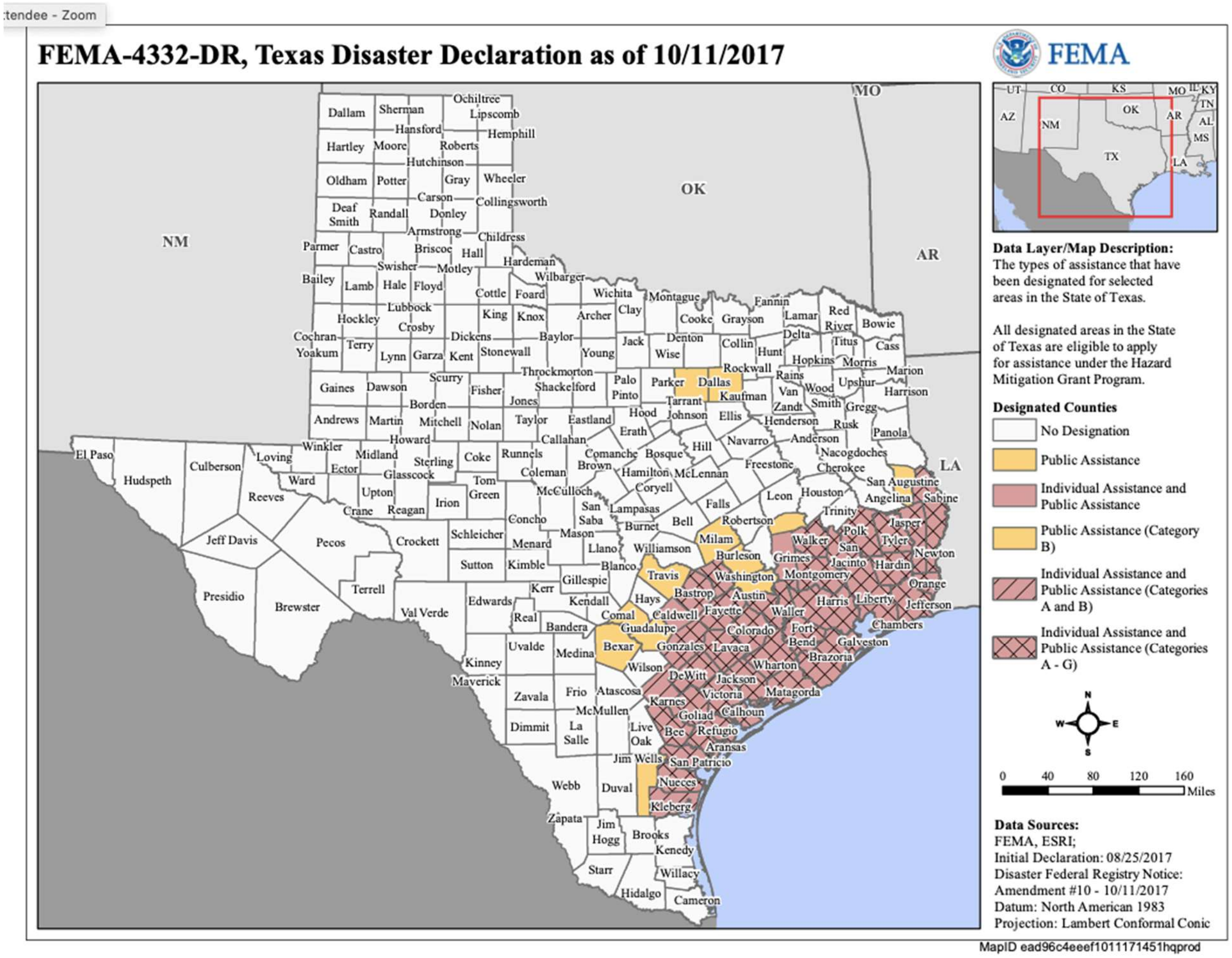
APPENDIX B: NWS Radar estimates of Hurricane Harvey 5 Day Rainfall Totals





Source: National Weather Service (NWS). N.d. Hurricane Harvey & Its Impacts on Southeast Texas. (August 25-29, 2017). National Weather Service. Accessed 04/02/2020. Available at: https://www.weather.gov/hgx/hurricaneharvey

APPENDIX C: Counties receiving disaster declaration for Hurricane Harvey



Incident Period: August 23, 2017 - September 15, 2017
Major Disaster Declaration declared on August 25, 2017

Individual Assistance Applications Approved: 373,150

Total Individual & Households Program Dollars Approved: $1,656,894,979.68

Designated Counties (Individual Assistance): Aransas, Austin, Bastrop, Bee, Brazoria, Caldwell, Calhoun, Chambers, Colorado, DeWitt, Fayette, Fort Bend, Galveston, Goliad, Gonzales, Grimes, Hardin, Harris, Jackson, Jasper, Jefferson, Karnes, Kleberg, Lavaca, Lee, Liberty, Matagorda, Montgomery, Newton, Nueces, Orange, Polk, Refugio, Sabine, San Jacinto, San Patricio, Tyler, Victoria, Walker, Waller, Wharton

Source: FEMA. (2017). Texas Hurricane Harvey (DR -4332). Federal Emergency Management Agency. Accessed 04/02/2020. Available at: https://www.fema.gov/disaster/4332

APPENDIX D: FEMA Aggregate Individual and Household Program Data Codebook

Field	Description
Disaster Number	Unique number of declared disaster
State	Two-letter state abbreviation for disaster state
County	The name of a U.S. county, parish, borough, independent city or other political subdivision of a U.S. state or territory.
City	City
Zip	Zip code
Registration Intake (RI) Information	This section outlines the breakdown of how FEMA received its registrations.
Total Valid Registrations	The total number of valid registrations.
Valid Call Center Registrations	The total number of valid registrations submitted through the call center.
Valid Web Registrations	The total number of valid registrations submitted through the website.
Valid Mobile Registrations	The total number of valid registrations submitted through a mobile device.
Individuals and Households Program (IHP) Information	This section outlines the breakdown of FEMA's Individuals and Households Program (IHP). http://www.fema.gov/public-assistance-local-state-tribal-and-non-profit/recovery-directorate/assistance-individuals-and
IHP Referrals	Cumulative number of applicants referred to the IHP Program
IHP Eligible	The total number of valid registrations eligible for IHP assistance.
IHP Amount	Total IHP Amount awarded for Housing Assistance (HA) and Other Needs Assistance (ONA) among eligible applicants for designated incident.

Instructions for Use of this Dataset
This submission contains aggregated, non-PII data from Housing Assistance Program reporting authority within FEMA’s Recovery Directorate to share data on registrations and Individuals and Households Program (IHP) for declarations starting from disaster declaration number 4116, segmented by city where registration is valid. Additional core data elements include: valid call center registrations, valid web registrations, valid mobile registrations, IHP eligible, IHP amount, HA eligible, HA amount, ONA eligible, and ONA amount.
Please Note: IHP is intended to help with critical expenses that cannot be covered in other ways. The IHP is not intended to return all homes or belongings to their pre-disaster condition. In some cases, IHP may only provide enough money, up to the program limits, for you to return an item to service. Secondary or vacation residencies do not qualify. Visit for more information about the program **http://www.fema.gov/public-assistance-local-state-tribal-and-non-profit/recovery-directorate/assistance-individuals-and**.
This is raw, unedited data from FEMA's National Emergency Management Information System (NEMIS) and as such is subject to a small percentage of human error.
The financial information is derived from NEMIS and not FEMA's official financial systems. Due to differences in reporting periods, status of obligations and how business rules are applied, this financial information may differ slightly from official publication on public websites such as usaspending.gov; this dataset is not intended to be used for any official federal financial reporting.
This dataset is not intended to be an official federal report, and should not be considered an official federal report.
Citation: Federal Emergency Management Agency (FEMA), 2020. Registration Intake and Individuals and Households (RI-IHP) Program Data.. FEMA. Accessed 05/03/2020. Available at: https://www.fema.gov/media-library/assets/documents/34752 FEMA and the Federal Government cannot vouch for the data or analyses derived from these data after the data have been retrieved from the Agency's website(s) and/or Data.gov.

APPENDIX E: Sensitivity Analyses of Disability Estimates

Table E.1 Sensitivity Analysis (I) of Disability Estimates within the cross-sectional IHP grants quantile regression.

FEMA CASH ASSISTANCE QUANTILE LEVEL	DISABILITY ESTIMATE	STANDARD ERROR	95% CONFIDENCE LIMITS		T VALUE	P-VALUE
10TH	0.01	0.03	-0.05	0.06	0.28	0.78
50TH	-0.05*‡	0.03	-0.10	0.01	-1.63	0.10
60TH	-0.06*‡	0.03	-0.12	-0.00	-2.05	0.04
70TH	-0.07*‡	0.03	-0.12	-0.02	-2.79	0.00
60TH	-0.08*‡	0.03	-0.14	-0.01	-2.44	0.01
90TH	-0.07*‡	0.03	-0.14	-0.00	-2.05	0.04

NOTE: The dependent variable is (log) IHP grants per zip code. ** Indicates statistical significance Likelihood ratio test at p-value ≤ 0.05. Median Income is reported for total households. Population Density is measured in total population estimates/ zip code square miles. ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. Each quantile-level controls for income, disaster damage, homeownership, race/ethnicity (Latinx), limited English speakers, poverty, unemployment, population density and recovery experience at the zip code level. ***Race/ethnicity (African American) was removed in the sensitivity analysis.***
N = 434

E.2 Sensitivity Analysis (II) of Disability Estimates within the cross-sectional IHP grants quantile regression.

FEMA CASH ASSISTANCE QUANTILE LEVEL	DISABILITY ESTIMATE	STANDARD ERROR	95% CONFIDENCE LIMITS		T VALUE	P-VALUE
10TH	-0.04	0.03	-0.10	0.03	-1.15	0.25
50TH	-0.06*‡	0.03	-0.12	-0.00	-2.04	0.04
60TH	-0.07*‡	0.03	-0.12	-0.02	-2.77	0.01
70TH	-0.10*‡	0.02	-0.14	-0.05	-4.35	<0.01
60TH	-0.09*‡	0.02	-0.14	-0.04	-3.82	<0.01
90TH	-0.10*‡	0.02	-0.15	-0.06	-4.27	<0.01

NOTE: The dependent variable is (log) IHP grants per zip code. ** Indicates statistical significance Likelihood ratio test at p-value ≤ 0.05. Median Income is reported for total households. Population Density is measured in total population estimates/ zip code square miles. ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. Each quantile-level controls for income, disaster damage, homeownership, race/ethnicity (Latinx, African-American), limited English speakers, poverty, unemployment, population density and recovery experience at the zip code level. ***Income was removed in the sensitivity analysis.*** N = 453

Table E.3 Sensitivity Analysis (III) of Disability Estimates within the cross-sectional IHP grants quantile regression.

FEMA CASH ASSISTANCE QUANTILE LEVEL	DISABILITY ESTIMATE	STANDARD ERROR	95% CONFIDENCE LIMITS		T VALUE	P-VALUE
10TH	-0.03	0.03	-0.09	0.03	-1.05	0.29
50TH	-0.06*‡	0.02	-0.10	-0.01	-2.26	0.02
60TH	-0.06*‡	0.03	-0.11	-0.01	-2.24	0.03
70TH	-0.07*‡	0.02	-0.12	-0.02	-2.68	0.01
60TH	-0.08*‡	0.03	-0.13	-0.02	-2.85	0.00
90TH	-0.09*‡	0.03	-0.15	-0.02	-2.55	0.01

NOTE: The dependent variable is (log) IHP grants per zip code. ** Indicates statistical significance Likelihood ratio test at p-value $\leq$ 0.05. Median Income is reported for total households. Population Density is measured in total population estimates/ zip code square miles. ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. Each quantile-level controls for income, disaster damage, homeownership, race/ethnicity (African American), limited English speakers, poverty, unemployment, population density and recovery experience at the zip code level. ***Race/ethnicity (Latinx) was removed in the sensitivity analysis.*** N = 434

APPENDIX F: Sensitivity Analysis of Prior Recover Experience Estimates

PARAMETER		ESTIMATE	STANDARD ERROR	95% CONFIDENCE LIMITS		T VALUE	P-VALUE
INTERCEPT		10.35	1.15	8.09	12.61	9.01	<0.01
MEDIAN INCOME		0.00	0.00	-0.00	0.00	1.59	0.11
HWM DISTANCE		-2.35	1.11	-4.54	-0.16	-2.11	0.03
BLACK		0.01	0.01	-0.00	0.032	1.73	0.08
HOMEOWNERS		-0.01	0.01	-0.03	0.01	-0.85	0.40
LATINX		0.03	0.01	0.01	0.04	3.66	<0.01
LIMITED ENGLISH PROFICIENCY		-0.03	0.03	-0.08	0.03	-1.00	0.32
POVERTY		0.04	0.02	-0.00	0.08	1.74	0.08
DISABILITY		-0.01	0.02	-0.05	0.02	-0.84	0.40
UNEMPLOYED		0.17	0.06	0.06	0.28	3.09	<0.01
POPULATION DENSITY		-0.00	0.00	-0.00	0.00	-0.06	0.95
MEMORIAL/TAX DAY FLOODS	0	-2.34*‡	0.39	-3.10	-1.57	-5.98	<0.01
MEMORIAL/TAX DAY FLOODS	1	-3.01*‡	0.66	-4.31	-1.71	-4.56	<0.01
MEMORIAL/TAX DAY FLOODS	2	Ref				.	.

NOTE: Where Memorial/Tax Day Floods = 0, the zip code was not eligible to receive assistance for either the 2015 Memorial Floods or the 2016 Tax Day Flood. Where Memorial/Tax Day Floods = 1, the community was eligible to receive assistance for either of the declared disasters. Memorial/Tax Day Floods = 2 served as the reference. Communities were eligible to receive assistance for both events. ‡ statistically significant Wald test. * Statistically significant Likelihood Ratio test. Each quantile-level controls for income, disaster damage, homeownership, race/ethnicity (African American, LatinX), limited English speakers, poverty, unemployment, population density and recovery experience at the zip code level.

APPENDIX G: FEMA Individual Assistance Housing Registrants Large Disasters Codebook

Title	Description
ID	Unique ID assigned to the record
Disaster Number	Sequentially assigned number used to designate an event or incident declared as a disaster. For more information on the disaster process, https://www.fema.gov
Damaged City	Damaged Dwelling City
Damaged State Abbreviation	Damaged Dwelling State Abbreviation
Damaged Zip Code	Damaged Dwelling Zip Code
Household Composition	Number of individuals living in household at time of damage
Gross Income	Self-reported Gross Income
Special Needs Indicator	Applicant requires special accommodations to use FEMA assistance
Owner or Renter	Applicant is Owner or Renter of Dwelling
Residence Type	Damaged Dwelling Residence Type
Home Owners Insurance	Does the applicant have Home Owner's Insurance
Flood Insurance Indicator	Does the applicant have flood insurance
Inspected Indicator	Has the applicant been inspected by FEMA
RPFVL	Real property damage amount observed by FEMA
Habitability Repairs Required	Are repairs required to make the dwelling habitable
Destroyed	Is structure permanently uninhabitable
Water Level	Total depth of water in damaged dwelling
Flood Damage Indicator	Was damage caused by flooding
Foundation Damage Indicator	Has the damaged dwelling's foundation been damaged
Foundation Damage Amount	Foundation damage amount observed by FEMA
Roof Damage Indicator	Has the damage dwelling's roof been damaged
Roof Damage Amount	Roof damage amount observed by FEMA

Temporary Sheltering Assistance Eligible	Is applicant eligible for Temporary Sheltering Assistance
TSA Checked In	Has applicant checked in to FEMA provided Temporary Sheltering Assistance facility
Rental Assistance Eligible	Is applicant eligible for FEMA rental assistance
Rental Assistance Amount	Amount of Rental Assistance in dollars
Repair Assistance Eligible	Is applicant eligible for FEMA assistance to repair the damaged dwelling
Repair Amount	Amount of Repair Assistance in dollars
Replacement Assistance Eligible	Is applicant eligible for FEMA assistance to replace the damaged dwelling
Replacement Amount	Amount of Replacement Assistance in dollars
Small Business Association Eligible	Is applicant eligible for a Small Business Association loan
Renter Damage Level	Level of Damage: Moderate, Major, Destroyed
Rental Assistance End Date	Final Month applicant received Rental Assistance
Rental Resource City	Rental Resource City
Rental Resource State Abbreviation	Rental Resource State Abbreviation
Rental Resource Zip Code	Rental Resource Zip Code
Primary Residence	Is the applicant's damaged dwelling his/her primary residence
Personal Property Eligible	Is the applicant eligible for FEMA's Other Needs Assistance (ONA) to cover damaged personal property
Personal Property Verified Loss	FEMA Verified Loss captured during inspection of personal property
Census Block ID	Address-based 15-character code that is the concatenation of fields consisting of the 2-character state FIPS code, the 3-character county FIPS code, the 6-character census tract code, and the 4-character tabulation block code. Please see: https://www.census.gov/geo/maps-data/data/baf_description.html CENSUS BLOCK ID MAY HAVE TO BE RE-FORMATTED IN EXCEL TO SEE THE ID CORRECTLY. CREATE A CUSTOM DATA TYPE WITH FIFTEEN HASH SYMBOLS: ###############
Census Year	Census period used to obtain Census Block ID

Source: Federal Emergency Management Agency (FEMA) OpenFEMA Dataset: Individual Assistance Housing Registrants Large Disasters - V1. FEMA. Accessed 05/03/2020. Available at: https://www.fema.gov/openfema-dataset-individual-assistance-housing-registrants-large-disasters-v1

APPENDIX H: Sensitivity Analyses of community disability prevalence and the percentage of individuals seeking special accommodations using linear regression

	MODELS – BETAS (P-VALUE)			
	1	*2*	*3*	*4*
DISABILITY	-0.05 (0.22)	-0.11 (0.03)*	-0.10 (0.06)	
BLACK	----	0.00(0.90)	0.01 (0.69)	-0.00 (0.90)
LATINX	----	-0.03 (0.02)*	---	-0.03(0.04)*
ROOT MSE	7.25	7.21	7.24	7.24
ADJUSTED R-SQUARE	0.00	0.01	0.00	0.00

NOTE: OLS Full model Dependent variable is the percentage of applicants who were identified as needing special accommodations at the zip code level from the FEMA Individual Assistance large dataset (See Appendix G). N =467. Models 2 – 4 control for disaster damage, population density and percentage of applicants who received FEMA inspections at the zip code level. * statistically significant p-value.

APPENDIX I: *Harvey Anniversary Survey* county inclusion and coverage by region stratification

Thinking back to last August, which county were you living in at the time Hurricane Harvey hit Texas?

	Total	Harris	Outside Harris	Golden Triangle	Coastal
Aransas	1	-	-	-	9
Austin	*	-	1	-	-
Brazoria	5	-	16	-	-
Calhoun	*	-	-	-	4
Chambers	1	-	4	-	-
Colorado	1	-	2	-	-
Fort Bend	8	-	27	-	-
Galveston	5	-	18	-	-
Hardin	1	-	-	12	-
Harris	57	100	-	-	-
Jackson	*	-	-	-	1
Jefferson	3	-	-	55	-
Lavaca	*	-	-	-	2
Liberty	1	-	5	-	-
Matagorda	*	-	2	-	-
Montgomery	5	-	18	-	-
Nueces	4	-	-	-	46
Orange	2	-	-	33	-
Refugio	*	-	-	-	3
San Patricio	1	-	-	-	14
Victoria	2	-	-	-	21
Walker	1	-	2	-	-
Waller	1	-	2	-	-
Wharton	1	-	2	-	-
Other	-	-	-	-	-
Don't know/Refused	-	-	-	-	-

NOTE: Names of the twenty-four counties included in the Kaiser Family Foundation/ Episcopal Health Foundation Harvey Anniversary Survey. Henry J. Kaiser Family Foundation/Episcopal Health Foundation. Kaiser Family Foundation/Episcopal Health Foundation Poll: Harvey Anniversary Survey, 2018 [Dataset]. Roper #31115647, Version 3. Social Science Research Solutions (SSRS) [producer]. Cornell University, Ithaca, NY: Roper Center for Public Opinion Research [distributor]. doi:10.25940/ROPER-31115647

APPENDIX J: Predicted Models of Recovery

Table J.1 Predicted Models of recovery by receiving sufficient help in applying for disaster assistance using generalized ordered logistic regression.

RECOVERY MODELS	APPLICATION HELP EFFECT	OR POINT ESTIMATE	95% CONFIDENCE LIMITS	
OVERALL	0 = worse(ref)			
	1 = about the same today	2.29	0.97	5.42
	2 = better.	3.22	0.93	11.09
HOME	0 = still in an unlivable condition(ref)			
	1 = been restored to a livable condition but not the same as before Harvey	0.65	0.20	2.06
	2 = been restored to the same condition, home is in a better condition now than before Harvey, moved to a new home.	4.73*	1.30	17.23
DISRUPTION	0 = still very disrupted(ref)			
	1 = still somewhat disrupted	0.85	0.21	3.44
	2 = almost back to normal,	1.89	0.48	7.37
	3= largely back to normal, life was not disrupted by Harvey, totally back to normal.	8.68*	2.03	37.16
FINANCIAL	0 = worse(ref)			
	1 = about the same today, or better	2.56*	1.18	5.55

NOTE: The dependent variables are the four dimensions of recovery (disruption, finance, home, overall). (ref) indicates the reference category. The models all controlled for control for ethnicity/race (African American, Latinx, Other vs. White), citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, renter status, poverty, home insurance, flood insurance, joint household status, other forms of assistance outside of the federal government, federal disaster assistance application decision as well as other factors. The full regression outputs are available upon request. * Statistically significant at p-value $\leq$ 0.05.

Table J.2 Predicted Models of recovery by disability status using generalized ordered logistic regression.

RECOVERY MODELS	DISABILITY EFFECT	OR POINT ESTIMATE	95% CONFIDENCE LIMITS	
OVERALL	0 = worse (ref)			
	1 = about the same today	0.41	0.17	0.99
	2 = better.	0.91	0.31	2.71
HOME	0 = still in an unlivable condition (ref)			
	1 = been restored to a livable condition but not the same as before Harvey	1.18	0.43	3.23
	2 = been restored to the same condition, home is in a better condition now than before Harvey, moved to a new home.	0.64	0.20	2.07
DISRUPTION	0 = still very disrupted (ref)			
	1 = still somewhat disrupted	0.62	0.22	1.79
	2 = almost back to normal,	0.21*	0.05	0.86
	3= largely back to normal, life was not disrupted by Harvey, totally back to normal.	0.22*	0.05	0.95
FINANCIAL	0 = worse (ref)			
	1 = about the same today, or better	0.68	0.31	1.48

NOTE: The dependent variables are the four dimensions of recovery. Ref= indicates the reference category. The models all controlled for control for ethnicity/race (African American, Latinx, Other vs. White), citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, renter status, poverty, home insurance, flood insurance, joint household status, other forms of assistance outside of the federal government, federal disaster assistance application decision as well as other factors. * Statistically significant at p-value ≤ 0.05.

APPENDIX K: Predicted Models of Perceptions

Table K.1 Predicted Models of perceptions by receiving sufficient help in applying for disaster assistance using generalized ordered logistic regression.

PERCEPTION MODEL	APPLICATION HELP EFFECT	OR POINT ESTIMATE	95% CONFIDENCE LIMITS	
PERSONS LIKE ME	Nothing at all (ref)			
	Not too much	2.36	0.67	8.37
	Some	5.72*	1.60	20.51
	a lot	8.99*	1.61	50.25
LATINX	Not too much to Nothing at all (ref)			
	a lot to Some	0.93	0.43	2.03
WHITE	Nothing at all (ref)			
	Not too much	1.90	0.65	5.52
	Some to a lot	1.81	0.55	5.99
BLACK	Nothing at all (ref)			
	Not too much	0.78	0.13	4.78
	Some	1.49	0.26	8.36
	A lot	1.46	0.19	11.42
MIDDLE CLASS	Not at all confident (ref)			
	Not too confident	0.29	0.06	1.32
	Somewhat confident	1.30	0.32	5.21
	Very confident	3.10	0.52	18.47
WEALTHY	Not at all confident (ref)			
	Not too confident	0.47	0.06	3.55
	Somewhat confident	0.57	0.08	3.85
	Very confident	1.36	0.21	8.84
POOR	Not at all confident (ref)			
	Not too confident	0.84	0.24	3.03
	Somewhat confident	1.21	0.30	4.82
	Very confident	5.84*	1.27	26.92
MONEY SPENT	Not at all confident (ref)			
	Not too confident	2.33	0.84	6.42
	Somewhat confident, or Very confident	7.23*	2.59	20.21
IMMIGRANT	Nothing at all (ref)			
	Not too much	1.72	0.55	5.39
	Some to a lot	2.41	0.82	7.05

NOTE: Ref= indicates the reference category. The models all controlled for control for ethnicity/race (African American, Latinx, Other vs. White), citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, renter status, poverty, home insurance, flood insurance, joint household status, other forms of assistance outside of the federal government, federal disaster assistance application decision, disruption related recovery as well as other factors. *statistically significant p-value ≤ 0.05.

Table K.2 Predicted Models of perceptions by disability status using generalized ordered logistic regression.

PERCEPTION MODEL	DISABILITY EFFECT	OR POINT ESTIMATE	95% CONFIDENCE LIMITS	
PERSONS LIKE ME	Nothing at all (ref)			
	Not too much	0.62	0.21	1.87
	Some	0.54	0.16	1.84
	A lot	0.21	0.04	1.15
LATINX	Not too much to Nothing at all (ref)			
	A lot to Some	2.13	0.91	4.99
WHITE	Nothing at all (ref)			
	Not too much	0.64	0.22	1.86
	Some to Alot	0.76	0.25	2.33
BLACK	Nothing at all (ref)			
	Not too much	0.69	0.13	3.71
	Some	0.80	0.17	3.72
	A lot	1.51	0.20	11.11
MIDDLE CLASS	Not at all confident (ref)			
	Not too confident	0.17	0.04	0.76
	Somewhat confident	0.40	0.11	1.39
	Very confident	2.78	0.37	20.63
WEALTHY	Not at all confident (ref)			
	Not too confident	0.52	0.09	3.02
	Somewhat confident	0.52	0.12	2.18
	Very confident	0.76	0.22	2.69
POOR	Not at all confident (ref)			
	Not too confident	0.33	0.11	0.97
	Somewhat confident	0.76	0.23	2.50
	Very confident	1.12	0.25	5.07
MONEY SPENT	Not at all confident (ref)			
	Not too confident	0.38	0.14	1.02
	Somewhat confident, or Very confident	0.49	0.18	1.31
IMMIGRANT	Nothing at all (ref)			
	Not too much	0.85	0.26	2.77
	Some to Alot	1.81	0.64	5.15

NOTE: Ref= indicates the reference category. The models all controlled for control for ethnicity/race (African American, Latinx, Other vs. White), citizenship, gender, political affiliation, schooling, number of children present in the home, damage severity to the home, renter status, poverty, home insurance, flood insurance, joint household status, other forms of assistance outside of the federal government, federal disaster assistance application decision, disruption related recovery as well as other factors.

APPENDIX L: Small Business Administration Disaster Home loan coding

Table L.1 Small Business Administration Disaster Home loan code specification and description of application declines

CODE	DESCRIPTION
20	Lack of repayment ability - Applicant's income below minimum income level for the family size
21	Lack of repayment ability
22	Lack of ability to repay a loan within a maximum seven year term
23	Inadequate cash flow to repay disaster loan and meet other obligations
24	Excessive amount of debt relative to net worth
25	Inadequate working capital even if SBA could approve a loan
26	Unsatisfactory history on an existing or previous SBA loan
27	Unsatisfactory history on a Federal obligation
28	Unsatisfactory credit history
29	Unsatisfactory debt payment history
30	No disaster-related damage
31A	Economic injury is not substantiated - No Needs
31B	Economic injury is not substantiated - Disaster Gross Margin Exceeds Normal
31C	Economic injury is not substantiated - Custom Text
32	Business activity is not eligible
33	Not eligible because the applicant is not a small business
34	Credit is available elsewhere
35A	Not located in the declared disaster area – Physical
35B	Not located in the declared disaster area
36	Ineligible real property
37	Ineligible personal property
38	Not eligible due to recoveries from other sources
39A	Not eligible due to failure to maintain flood insurance coverage on an existing SBA loan
39C	Not eligible due to failure to maintain required flood insurance as directed by the Federal Emergency Management Agency (FEMA)
40A	Not a qualified business – Business
40B	Not a qualified business – Rental
41	Refusal to pledge available collateral
42	Not eligible due to delinquent child support payments
43	Not eligible due to character reasons
44I	Lack of repayment ability - Below minimum income level for the family size based upon the applicant's income alone
44R	Lack of ability to repay a disaster loan based upon the applicant's income alone
45	Not eligible due to an outstanding judgment lien for a Federal debt
46B	Members of a fishing crew do not qualify as an eligible small business concern
46C	Not eligible due to property being located in a Coastal Barrier Resource Area
46D	Other
47A	Not eligible due to policy (NOT a qualified alien, Minor applicant)
47B	Not eligible due to policy (NOT a qualified alien, adult applicant using minor?s SSN)

47C	Not eligible due to policy (non-citizen, NOT a qualified alien)
60D	Character Eligibility Determination – Decline

Table L.2: Variables available for Small Business Administration Disaster Home loan (accepted) applicants

Disaster Number
Declaration Number
EIDL Number
FEMA Number
Borrower Name
Damaged Property Address
Damaged Property City
Damaged Property State
Damaged Property Zip
Damaged Property County
Current Mailing Address of Borrower
Current Mailing City
Current Mailing State
Current Mailing Zip Code
Loan Type (Home Vs. Business)
Application Accepted Date
Approval Date
Original Loan Amount Approved
Interest Rate

NOTE: The SBA data was first obtained through a Freedom of Information Act (FOIA) request. It shows approved disaster assistance loans for those impacted by Hurricane Harvey in Texas. The data was first used in the following study: Billings, S. B., Gallagher, E., & Ricketts, L. (2019). Let the rich be flooded: The unequal impact of Hurricane Harvey on household debt. Available at SSRN 3396611.

APPENDIX M. SBA Sensitivity analyses of prior recovery experience

Table M.1. Sensitivity analysis of prior recovery experience and receiving SBA loans using logistic regression

EFFECT	OR POINT ESTIMATE	95% Wald Confidence Limits	
(LOG) JULY -31ST, 2017 MEDIAN HOME VALUE	0.49	0.20	1.20
POPULATION DENSITY	1.00	1.00	1.00
AFRICAN AMERICAN (%)	0.99	0.97	1.01
HOMEOWNERS (%)	1.00	0.97	1.02
LATINX (%)	1.02**	1.00	1.04
POVERTY (%)	1.02	0.98	1.06
DISTANCE TO DAMAGE	0.01**	0.00	0.06
DISABILITY (%)	0.97	0.93	1.01
2015 MEMORIAL DAY FLOOD OR 2016 TAX DAY FLOOD*	0.56	0.27	1.15
2015 MEMORIAL DAY FLOOD AND 2016 TAX DAY FLOOD*	3.11**	1.10	8.83
MODEL FIT STATISTICS			
CRITERION	Intercept Only	Intercept and Covariates	
AIC	387.93	301.44	
SC	392.05	346.67	
-2 LOG L	385.93	279.44	
N	451		

NOTE: **Statistical significant assigned at the p-value < = 0.05 * reference category are zip codes which were not eligible for either the 2015 Memorial Day flood or the 2016 Tax Day Flood federal recovery assistance

Table M.2. Sensitivity analysis of prior recovery experience and median SBA approval rates using logistic regression

EFFECT	OR POINT ESTIMATE	95% Wald Confidence Limits	
(LOG) JULY -31ST, 2017 MEDIAN HOME VALUE	1.30	0.66	2.55
POPULATION DENSITY	1.00	1.00	1.00
AFRICAN AMERICAN (%)	0.98**	0.97	1.00
HOMEOWNERS (%)	1.01	0.99	1.03
LATINX (%)	1.00	0.99	1.01
POVERTY (%)	0.95**	0.92	0.98
DISTANCE TO DAMAGE	0.05**	0.01	0.29
DISABILITY (%)	0.98	0.94	1.02
2015 MEMORIAL DAY FLOOD OR 2016 TAX DAY FLOOD*	1.03	0.55	1.94
2015 MEMORIAL DAY FLOOD AND 2016 TAX DAY FLOOD*	0.44**	0.24	0.83
MODEL FIT STATISTICS			
CRITERION	Intercept Only	Intercept and Covariates	
AIC	592.55	545.94	
SC	596.61	590.54	
-2 LOG L	590.552	523.94	
N	426		

NOTE: **Statistical significant assigned at the p-value < = 0.05 * reference category are zip codes which were not eligible for either the 2015 Memorial Day flood or the 2016 Tax Day Flood federal recovery assistance

Table M.3. Sensitivity analysis of prior recovery experience and median SBA approval delay using logistic regression

EFFECT	OR POINT ESTIMATE	95% Wald Confidence Limits	
(LOG) JULY -31ST, 2017 MEDIAN HOME VALUE	3.40**	1.60	7.23
POPULATION DENSITY	1.00	1.00	1.00
AFRICAN AMERICAN (%)	1.01	0.99	1.02
HOMEOWNERS (%)	0.99	0.98	1.01
LATINX (%)	1.01	1.00	1.03
POVERTY (%)	0.98	0.95	1.02
DISTANCE TO DAMAGE	2.30	0.34	15.63
DISABILITY (%)	0.98	0.93	1.02
2015 MEMORIAL DAY FLOOD OR 2016 TAX DAY FLOOD*	0.84	0.43	1.63
2015 MEMORIAL DAY FLOOD AND 2016 TAX DAY FLOOD*	0.83	0.43	1.58
MODEL FIT STATISTICS			
CRITERION	Intercept Only	Intercept and Covariates	
AIC	531.56	518.61	
SC	535.51	562.01	
-2 LOG L	529.56	496.61	
N	382		

**Statistical significant assigned at the p-value < = 0.05 * reference category are zip codes which were not eligible for either the 2015 Memorial Day flood or the 2016 Tax Day Flood federal recovery assistance.

Table M.4. Sensitivity analysis of prior recovery experience and high SBA and FEMA assistance using logistic regression

EFFECT	OR POINT ESTIMATE	95% Wald Confidence Limits	
(LOG) JULY -31ST, 2017 MEDIAN HOME VALUE	0.81	0.39	1.69
POPULATION DENSITY	1.00	1.00	1.00
AFRICAN AMERICAN (%)	1.02	1.00	1.04
HOMEOWNERS (%)	1.00	0.98	1.02
LATINX (%)	1.01	1.00	1.03
POVERTY (%)	0.98	0.94	1.01
DISTANCE TO DAMAGE	<0.01**	<0.01	0.01
DISABILITY (%)	0.94**	0.90	0.99
2015 MEMORIAL DAY FLOOD OR 2016 TAX DAY FLOOD*	1.04	0.49	2.17
2015 MEMORIAL DAY FLOOD AND 2016 TAX DAY FLOOD*	1.59	0.82	3.09
MODEL FIT STATISTICS			
CRITERION	Intercept Only	Intercept and Covariates	
AIC	527.97	455.15	
SC	531.91	498.52	
-2 LOG L	525.97	433.15	
N	381		

NOTE: **Statistical significant assigned at the p-value < = 0.05 * reference category are zip codes which were not eligible for either the 2015 Memorial Day flood or the 2016 Tax Day Flood federal recovery assistance

APPENDIX N: Difference-in-Difference estimates sensitivity analyses – lag 1-month

Table N.1 Difference-in-Difference estimates of zip codes which received at least one SBA disaster home loan with a one- month post-event lag

SOLUTION FOR FIXED EFFECTS							
EFFECT	Post (lag 1)	SBA Loans	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.88	0.06	449	197.85	<0.01
POST (LAG 1)	1		0.04	0.00	#######	63.78	<0.01
POST (LAG 1)	0		0	.	.	.	.
SBA LOANS		1	0.05	0.06	#######	0.71	0.48
SBA LOANS		0	0	.	.	.	.
POST (LAG 1) × SBA LOANS	1	1	0.07	0.00	#######	51.13	<0.01
N	25704						
FIT STATISTICS							
-2 RES LOG LIKELIHOOD	-57336.1						
AIC (SMALLER IS BETTER)	-57332						
AICC (SMALLER IS BETTER)	-57332						
BIC (SMALLER IS BETTER)	-57324						
NULL MODEL LIKELIHOOD RATIO TEST							
DF	Chi-Square	Pr > ChiSq					
1	124978	<0.01					

Table N.2 Difference-in-Difference estimates of zip codes being above the median in SBA approval rates with a one- month post-event lag

SOLUTION FOR FIXED EFFECTS

EFFECT	Post (lag 1)	SBA_ Approval Rate	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.83	0.03	424	352.15	<0.01
POST (LAG 1)	1		0.13	0.00	#######	129.17	<0.01
POST (LAG 1)	0		0	.	.	.	.
SBA APPROVAL RATE		1	0.18	0.05	#######	3.9	<0.01
SBA APPROVAL RATE		0	0	.	.	.	.
POST (LAG 1) × SBA APPROVAL RATE	1	1	-0.03	0.00	#######	-26.12	<0.01
N	24280						

FIT STATISTICS

-2 RES LOG LIKELIHOOD	-68571.0
AIC (SMALLER IS BETTER)	-68567
AICC (SMALLER IS BETTER)	-68567
BIC (SMALLER IS BETTER)	-68559

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	104837	<0.01

Table N.3 Difference-in-Difference estimates of zip codes being above the median in SBA short approval delays with a one- month post-event lag

SOLUTION FOR FIXED EFFECTS							
EFFECT	Post (lag 1)	SBA Low Delay	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.81	0.03	380	332.47	<0.01
POST (LAG 1)	1		0.10	0.00	#######	103.05	<0.01
POST (LAG 1)	0		0	.	.	.	.
LOW SBA APPROVAL DELAY		1	0.24	0.05	#######	4.83	<0.01
LOW SBA APPROVAL DELAY		0	0	.	.	.	.
POST (LAG 1) × LOW SBA APPROVAL DELAY	1	1	0.00	0.00	#######	2.07	0.04
N	21772						
FIT STATISTICS							
-2 RES LOG LIKELIHOOD	-62177.2						
AIC (SMALLER IS BETTER)	-62173						
AICC (SMALLER IS BETTER)	-62173						
BIC (SMALLER IS BETTER)	-62165						
NULL MODEL LIKELIHOOD RATIO TEST							
DF	Chi-Square	Pr > ChiSq					
1	94752.1	<0.01					

Table N.4 Difference-in-Difference estimates of zip codes being above the median in SBA total loan amount AND FEMA total grant amount (SBA/FEMA mix) with a one- month post-event lag.

SOLUTION FOR FIXED EFFECTS

EFFECT	Post (lag 1)	SBA/FEMA Mix	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.87	0.04	379	312.78	<0.01
POST (LAG 1)	1		0.11	0.00	#######	97.46	<0.01
POST (LAG 1)	0		0	.	.	.	.
SBA/FEMA MIX		1	0.12	0.05	#######	2.35	0.01
SBA/FEMA MIX		0	0	.	.	.	.
POST (LAG 1) × SBA/FEMA MIX	1	1	-0.03	0.00	#######	-22.19	<0.01
N	21715						

FIT STATISTICS	
-2 RES LOG LIKELIHOOD	-55953.0
AIC (SMALLER IS BETTER)	-55949
AICC (SMALLER IS BETTER)	-55949
BIC (SMALLER IS BETTER)	-55941

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	91568.3	<0.01

APPENDIX O: Difference-in-Difference estimates sensitivity analyses – lag 2-month

Table O.1 Difference-in-Difference estimates of zip codes which received at least one SBA disaster home loan with a two- month post-event lag

SOLUTION FOR FIXED EFFECTS							
EFFECT	Post (lag 2)	SBA Loans	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.88	0.06	449	197.87	<0.01
POST (LAG 2)	1		0.04	0.00	#######	60.78	<0.01
POST (LAG 2)	0		0	.	.	.	.
SBA LOANS		1	0.05	0.06	#######	0.72	0.47
SBA LOANS		0	0	.	.	.	.
POST (LAG 1) × SBA LOANS	1	1	0.07	0.00	#######	51.44	<0.01
	25704						
FIT STATISTICS							
-2 RES LOG LIKELIHOOD	-56907.7						
AIC (SMALLER IS BETTER)	-56904						
AICC (SMALLER IS BETTER)	-56904						
BIC (SMALLER IS BETTER)	-56895						
NULL MODEL LIKELIHOOD RATIO TEST							
DF	Chi-Square	Pr > ChiSq					
1	124552	<0.01					

Table O. 2 Difference-in-Difference estimates of zip codes being above the median in SBA approval rates with a two- month post-event lag

SOLUTION FOR FIXED EFFECTS							
EFFECT	Post (lag 2)	SBA Approval Rate	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.83	0.03	424	352.22	<0.01
POST (LAG 2)	1		0.13	0.00	#######	127.26	<0.01
POST (LAG 2)	0		0	.	.	.	.
SBA APPROVAL RATE		1	0.18	0.05	#######	3.88	<0.01
SBA APPROVAL RATE		0	0	.	.	.	.
POST (LAG 1) × SBA APPROVAL RATE	1	1	-0.04	0.00	#######	-25.8	<0.01
	24280						
FIT STATISTICS							
-2 RES LOG LIKELIHOOD	-68197.3						
AIC (SMALLER IS BETTER)	-68193						
AICC (SMALLER IS BETTER)	-68193						
BIC (SMALLER IS BETTER)	-68185						
NULL MODEL LIKELIHOOD RATIO TEST							
DF	Chi-Square	Pr > ChiSq					
1	104467	<0.01					

Table O. 3 Difference-in-Difference estimates of zip codes being above the median in SBA short approval delays with a two- month post-event lag

SOLUTION FOR FIXED EFFECTS

EFFECT	Post (lag 2)	SBA Low Delay	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.81	0.03	380	332.51	<0.01
POST (LAG 2)	1		0.11	0.00	#######	101.83	<0.01
POST (LAG 2)	0		0	.	.	.	.
SBA LOW APPROVAL DELAY		1	0.24	0.05	#######	4.83	<0.01
SBA LOW APPROVAL DELAY		0	0	.	.	.	.
POST (LAG 1) × SBA LOW APPROVAL DELAY	1	1	0.00	0.00	#######	1.87	0.06
	21772						

FIT STATISTICS

-2 RES LOG LIKELIHOOD	-61894.3
AIC (SMALLER IS BETTER)	-61890
AICC (SMALLER IS BETTER)	-61890
BIC (SMALLER IS BETTER)	-61882

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	94472.4	<0.01

Table O. 4 Difference-in-Difference estimates of zip codes being above the median in SBA total loan amount AND FEMA total grant amount (SBA/FEMA mix) with a two- month post-event lag.

SOLUTION FOR FIXED EFFECTS

EFFECT	Post (lag 2)	SBA/FEMA mix	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.87	0.04	379	313.07	<0.01
POST (LAG 2)	1		0.11	0.00	#######	96.39	<0.01
POST (LAG 2)	0		0	.	.	.	.
SBA /FEMA MIX		1	0.12	0.05	#######	2.34	0.02
SBA/FEMA MIX		0	0	.	.	.	.
POST (LAG 1) × SBA FEMA MIX	1	1	-0.05	0.00	#######	-21.92	<0.01
N	21715						

FIT STATISTICS

-2 RES LOG LIKELIHOOD	- 55766.5
AIC (SMALLER IS BETTER)	-55763
AICC (SMALLER IS BETTER)	-55763
BIC (SMALLER IS BETTER)	-55755

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	91384.2	<0.01

APPENDIX P: Difference-in-Difference estimates sensitivity analyses – approval rates

Table P.1 Difference-in-Difference estimates of zip codes having greater than 50% SBA approval rates

SOLUTION FOR FIXED EFFECTS							
EFFECT	POST	SBA Approval Rates (2)	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.85	0.03	424	443.72	<0.01
POST	1		0.11	0.00	#######	111.11	<0.01
POST	0		0	.	.	.	.
SBA APPROVAL RATES (2)		1	0.29	0.05	#######	5.22	<0.01
SBA APPROVAL RATES (2)		0	0	.	.	.	.
POST × SBA APPROVAL RATES (2)	1	1	-0.00	0.00	#######	-2.77	<0.01
	24280						
FIT STATISTICS							
-2 RES LOG LIKELIHOOD	-60906.5						
AIC (SMALLER IS BETTER)	-60903						
AICC (SMALLER IS BETTER)	-60903						
BIC (SMALLER IS BETTER)	-60894						
NULL MODEL LIKELIHOOD RATIO TEST							
DF	Chi-Square	Pr > ChiSq					
1	101331	<0.01					

Table P.2 Difference-in-Difference estimates of zip codes having greater than 60% SBA approval rates

SOLUTION FOR FIXED EFFECTS							
EFFECT	POST	SBA Approval Rates (3)	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.88	0.02	424	476.46	<0.01
POST	1		0.11	0.00	#######	105.98	<0.01
POST	0		0	.	.	.	.
SBA APPROVAL RATES (3)		1	0.33	0.07	#######	4.34	<0.01
SBA APPROVAL RATES (3)		0	0	.	.	.	.
POST × SBA APPROVAL RATES (3)	1	1	0.003	0.00	#######	2.3	0.02
	24280						

FIT STATISTICS	
-2 RES LOG LIKELIHOOD	-56095.2
AIC (SMALLER IS BETTER)	-56091
AICC (SMALLER IS BETTER)	-56091
BIC (SMALLER IS BETTER)	-56083

NULL MODEL LIKELIHOOD RATIO TEST		
DF	Chi-Square	Pr > ChiSq
1	100996	<0.01

APPENDIX Q: Difference-in-Difference estimates sensitivity analyses – approval delays

Table Q.1 Difference-in-Difference estimates of zip codes being having an SBA approval delays of two weeks or less

SOLUTION FOR FIXED EFFECTS

EFFECT	POST	Low SBA Approval Delays (2)	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.94	0.03	380	439.97	<0.01
POST	1		0.10	0.00	#######	99.82	<0.01
POST	0		0	.	.	.	.
LOW SBA APPROVAL DELAYS (2)		1	-0.14	0.09	#######	-1.54	0.12
LOW SBA APPROVAL DELAYS (2)		0	0	.	.	.	.
POST × LOW SBA APPROVAL DELAYS (2)	1	1	0.02	0.00	#######	13.74	<0.01
	21772						

FIT STATISTICS	
-2 RES LOG LIKELIHOOD	-52980.5
AIC (SMALLER IS BETTER)	-52977
AICC (SMALLER IS BETTER)	-52977
BIC (SMALLER IS BETTER)	-52969

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	95074.6	<0.01

Table Q.2 Difference-in-Difference estimates of zip codes being having an SBA approval delays of three weeks or less

SOLUTION FOR FIXED EFFECTS

EFFECT	POST	Low SBA Approval Delays (3)	Estimate	Standard Error	DF	t Value	Pr > |t|
INTERCEPT			11.90	0.03	380	393.82	<0.01
POST	1		0.10	0.00	#######	102.64	<0.01
POST	0		0	.	.	.	.
LOW SBA APPROVAL DELAYS (3)		1	0.10	0.06	#######	1.82	0.07
LOW SBA APPROVAL DELAYS (3)		0	0	.	.	.	.
POST × LOW SBA APPROVAL DELAYS (3)	1	1	0.01	0.00	#######	5.86	<0.01
	21772						

FIT STATISTICS

-2 RES LOG LIKELIHOOD	-60046.8
AIC (SMALLER IS BETTER)	-60043
AICC (SMALLER IS BETTER)	-60043
BIC (SMALLER IS BETTER)	-60035

NULL MODEL LIKELIHOOD RATIO TEST

DF	Chi-Square	Pr > ChiSq
1	95321.3	<0.01

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EXPERIENCE

CENTERS FOR DISEASE CONTROL AND PREVENTION (CDC)
Atlanta, GA
Health Scientist/Epidemiologist
October 2008 – November 2015

- Evaluated 62 grantees on preparedness standards and practices.
- Conducted 8 site visits with grantees to monitor the execution of projects and identified promising practices to inform the wider grantee community.
- Managed presentations and briefs on grantee progress to senior leadership.
- Provided technical assistance to 18 grantees and partners.
- Designed work plans, recruitment strategies and deliverables for work study students.
- Designed policy briefs, technical reports, research agendas, congressional testimony, and memorandums for agency directors, and other federal/non-federal partners.
- Provided technical assistance in the creation of a customizable educational campaign for city health departments.
- Oversaw $7 million + in programmatic and funding request budgets.

EMORY UNIVERSITY, RELIGION AND HEALTH COLLABORATIVE
Atlanta, GA
Geographic Information System (GIS) Mapping Specialist
October 2007 – October 2008

- Developed a GIS mini-lab for participatory mapping among specific populations in metro-Atlanta, Zambia, Lesotho, Kenya and South Africa.
- Designed a GIS-based curriculum for use by over 50 participants.
- Created a database linking religious entities that provide specific health services in Zambia, Lesotho, Kenya, and South Africa.

SKILLS & TRAININGS

Computer Skills: Microsoft Office · Outlook · SAS· SPSS· STATA· ArcGIS ·MAXQDA· ATLAS.ti

Trainings: US State Department Foreign Affairs Counter Threat (FACT), FEMA Environmental Health Training in Emergency Response (EHTER), IS-100.b, Introduction to the Incident Command System, IS-700.b, National Incident Management System (NIMS), An Introduction

SELECTED PRESENTATIONS & PUBLICATIONS

- **Malmin N.** The Weight of Administrative Burden: The Distributive Consequences of Federal Disaster Assistance on Recovery after Hurricane Harvey. Oral Presentation at the annual Natural Hazards Research and Applications Workshop, Broomfield, CO; July 2020.
- **Malmin N.** Historical Disaster Exposure and Household Preparedness across the US. Disaster Medicine and Public Health Preparedness. Disaster Med Public Health Prep. 2020 Jan 13;1-7. doi: 10.1017/dmp.2019.123
- Esnard A-M, Lai BS, Wyczalkowski C, **Malmin N**, Shah HJ. School vulnerability to disaster: examination of school closure, demographic, and exposure factors in Hurricane Ike's wind swath. Natural Hazards. 2017. https://link.springer.com/article/10.1007/s11069-017-3057-2
- Stehling-Ariza T, Fisher E, Vagi S, Fechter-Leggett E, **Prudent N**, Dott M, Daley R, Avchen RN. Monitoring of Persons with Risk for Exposure to Ebola Virus Disease - United States, November 3, 2014-March 8, 2015. MMWR Morb Mortal Wkly Rep. 2015 Jul 3;64(25):685-9.
- **Prudent N.** Community acceptance and annual maintenance fee contracts for sustaining improved drinking water sources: an evaluation of the faith-based shallow well program Northern Region, Malawi 2007. Master's Thesis from Emory University: Rollins School of Public Health. 2008.