THE INFLUENCE OF DISASTER LOANS ON LONG-TERM BUSINESS

SURVIVAL IN GALVESTON, TX AFTER HURRICANE IKE

A Dissertation

by

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ABSTRACT

The U.S. Federal Government has taken an increasingly active role in disaster relief efforts, yet program analyses of the efficacy of Federal recovery programs—particularly for businesses—is limited. This dissertation fills the gap by exploring the effects of Federal disaster loans on long-term business post-disaster recovery outcomes. Using the case of the U.S. Small Business Administration (SBA) Disaster Loan Program in Galveston County Texas after 2008 Hurricane Ike, this research examines which businesses benefit from Federal assistance and whether loans improved odds of survival for businesses nine years after Hurricane Ike.

This dissertation contributes to the body of work on disaster assistance programs and business recovery through new methodological and theoretical approaches to these questions. This research is grounded in institutional theory, namely institutional logics and resource dependence, and uses quasi-experimental design to tease out the effect of the loan program from potential confounding factors that affect business survival. This research uses a combination of primary data collected directly from the field and secondary data, such as business information reported by ReferenceUSA, sales tax and franchise tax permit information from the Texas State Comptroller, and data provided by the SBA through Freedom of Information Act requests. Coarsened Exact Matching is used to match businesses that received a loan (treatment sample) to businesses without a loan but otherwise similar in damage and firm characteristics (matched sample). For the matched sample, conditional logistic regression is used to analyze the effect of disaster loans on survival. For the treatment-only sample, linear regression and logistic regression are used to examine determinants of loan amount and which businesses are more likely to utilize the loans.

This research found that businesses that received a loan had higher odds of survival compared to their control, however businesses differed in the amount of money their received and likelihood of accepting the loan based on their damage, their characteristics, and the characteristics of the loan, itself. This research concludes with suggestions of how disaster policy aimed at businesses might be improved, as well as how planners might fill potential gaps in recovery left by the SBA loan program.

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1. INTRODUCTION

The Federal Government's involvement in the disaster recovery process has been steadily increasing since the beginning of the twentieth century. In 1953, the Federal Government provided only one percent of U.S. disaster relief, but by the mid-1970s the federal share had increased to more than 70 percent (Clary, 1985, p. 24). At present, the Stafford Act outlines the process for federal disaster assistance and how the costs will be shared among federal, state and local governments, with the federal share capping at 75 percent (Moss, Schellhamer, & Berman, 2009). This results in several billion dollars of assistance; the 2017 disaster season, for example, resulted in a record high of over $130 billion in federal spending (Lingle, Kousky, & Shabman, 2018).

Although the Federal Government has taken an increasingly active role in disaster relief efforts, program analyses of the effectiveness of these programs are relatively scarce. The literature that does exist is mixed: studies attempting to quantify the role of assistance on business recovery have reported a positive relationship (McDonald, Florax, & Marshal, 2014), a negative relationship (Dahlhamer & Tierney, 1998), and no significant relationship at all (Webb, Tierney, & Dahlhamer, 2002). Although additional capital after a disaster may seem beneficial on its face, the primary source of assistance for businesses in the United States comes in the form of loans rather than grants. Authors have suggested that the additional debt burden put upon an already capital-vulnerable business reduces the effectiveness of this type of assistance (Dahlhamer, 1998). In addition, there's a potential for selection bias where businesses that are the most damaged are the ones receiving assistance, and are therefore less likely to survive regardless of their assistance status (Dahlhamer & Tierney, 1998). The qualitative literature on federal assistance shows dissatisfaction with the process and implementation of the program, indicating a potential mismatch between the needs of the businesses and the structure of the assistance as it exists currently (Furlong & Scheberle, 1998; Runyan, 2006).

This research, therefore, contributes to our understanding of the influence of federal assistance on the recovery of businesses by looking more deeply at several of these issues and breaking them into separate research questions. Specifically, this dissertation will examine the outcome success of federal assistance to businesses by looking at the largest federal assistance program available to businesses, the U.S. Small Business Administration (SBA) Disaster Loan Program, and its implementation in Galveston, TX after Hurricane Ike. This dissertation will use this case to explore several research questions related to the effectiveness of loans on long-term survival. Following the work of Furlong and Scheberle (1998), I propose a holistic approach to the study of loan effectiveness, taking the perspective of both the loan provider and the receivers of the assistance to understand not only the outcome of interest, but also why that outcome occurs, and how the program may be realistically improved.

First, it's necessary to understand the participation in the program and who is most likely to be approved for and ultimately take disaster loans. These issues can be approached from the side of the SBA as well as the business, namely that the SBA selects the businesses that are approved, and business self-select by choosing to participate in the program once they are approved. This has consequences for the study in that these businesses may be more likely to survive or fail at the onset (Dahlhamer & Tierney, 1998). Therefore, the first set of research questions relate to program participation:

Research Question 1. Which businesses benefit from the SBA loan program?

Research Question 1.1. What determines loan amount?

Research Question 1.2. Which businesses are more likely to use SBA loans in recovery?

Secondly, empirical research is mixed on the influence of federal assistance, including SBA loans, on business recovery. This research will provide additional evidence to research question:

Research Question 2. Do SBA loans improve survival probabilities in the long term?

The benefits of conducting this research are two-fold. First, the annual expenditures on disaster recovery for businesses naturally lead to a question of their effectiveness from a government accountability perspective—how best can this money be used so that it has its intended outcome (i.e. help businesses recover)? Secondly, research has shown the importance of businesses are important in overall community recovery. Businesses contribute to psychological well-being of residents after a disaster (Liu, Black, Lawrence, & Garrison, 2012) and influence household return (Xiao & Van Zandt, 2012). Understanding how to best encourage business recovery, particularly small businesses, has both social and economic consequences.

To answer the proposed research questions, I will utilize a research design and methodology more akin to program or policy analysis to isolate the effect of the loan program from potential confounding variables. I will also incorporate institutional theory (namely institutional logics and resource dependence) as well as the empirical business and disaster research to understand the intersection of organizational behavior, environmental pressure, and business characteristics on long-term survival.

This dissertation is organized as follows: Section 2 begins with a literature review of the factors influencing business performance after disasters, a review of recovery assistance in the disaster literature, and theoretical perspectives relevant to this research. Section 3 combines the literature into a conceptual framework for this research and justifies the hypotheses to be tested. Section, then, 4 discusses the research design, including the research context, data sources, analytical method, and reliability and validity of the study. Section 5 presents the results of this research and, lastly, Chapter 6 provides discussion on the support for the various hypotheses; implications for planning, policy, and theory; limitations of the study; and considerations for future research.

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2. LITERATURE REVIEW

As previously introduced, this research will take a holistic approach to understanding the effectiveness of loan as a recovery tool by examining whether the assistance is effective, why, and how it might be improved. Therefore, I will review the historical context of federal assistance and its evaluation in the literature in addition to the factors influencing business performance after disasters. I will also review two theoretical perspectives—institutional logics, and resource dependence—to provide additional perspective on the motivations of organizations in the recovery context, the role of resources (in general) in organizational strategy, and how organizations react to and are affected by the external environment.

2.1. Business Disaster Assistance: History, Current Programs, and Empirical Evidence of Effectiveness

Although the amount of federal spending on disasters has gotten recent attention (Lingle et al., 2018; Trusts, 2018), the practice of federal involvement in disaster recovery has been around for over a century. The first federal disaster relief grants or loans to individuals occurred in 1915 but was not embraced as the standard for disaster relief: up until 1950, there were 128 disaster relief acts adopted by Congress (Barnett, 1999). A majority of these acts did not provide individual assistance but instead provided medical personnel, supplies and other services (Barnett, 1999).

The current U.S. policy of individual loans began in 1949 with the establishment of the US Department of Agriculture's (USDA) Farm Service Agency (FSA) emergency disaster loan program (Barnett, 1999). Through this program, farmers and ranchers that had been affected by a natural disaster could apply for low-interest loans (Barnett, 1999). Loans to businesses post-disaster began in 1953 after the establishment of the U.S. Small Business Administration (Barnett, 1999). The same year, public law 1953 allowed individuals impacted to receive surplus federal supplies (the 1950 act only gave aid to state and local governments) (Clary, 1985). Loans to businesses surprisingly came before loans to individual households—the Disaster Relief Act of 1974 was the first to create a loan program to households (Lindsay & Murray, 2010).

In general, there has been a "steady expansion of federal aid" and government involvement since the disaster relief act of 1950, which was the first legislative act to create a comprehensive national relief system (Clary, 1985; Lindsay & Murray, 2010). The major legislation that currently dictates government involvement after natural disasters is the Stafford Act. Passed in 1988 and most recently amended in 2016, the Stafford Act outlines the process for federal disaster assistance including how the costs will be shared among federal state and local governments (75 percent federal, 25 percent state and local) (Moss et al., 2009). Although there is an annual Disaster Relief Fund, there are often supplemental appropriations that are passed through Congress to go beyond the scope of the Stafford Act (Moss et al., 2009). Clary (1985) notes that in 1953 the federal government provided only 1.0 percent of US disaster relief. By the mid-1970s the federal share had increased to more than 70 percent (p. 24). This amounted to an average of close to $2 billion in Stafford Act related assistance each year around the time of Hurricane Ike (Moss et al., 2009). The recent 2017 disaster season in the United States incurred an estimated $300 billion worth of damages to which the U.S. Federal Government spent a record $130 billion in response (Lingle, Kousky, & Shabman, 2018).

Most of the current funding is used primarily for public assistance, for example rebuilding infrastructure, debris removal, and emergency life safety measures. To illustrate, the largest amount of disaster supplemental appropriations between 2017 and 2018 were given to the Department of Homeland Security (programs managed by the Federal Emergency Management Agency). These appropriations totaled approximately $50.7 billion, with 47 percent of those funds historically going to the public assistance program (Lingle et al., 2018). For an individual, non-agricultural businesses, the largest source of post-disaster governmental assistance is the U.S. Small Business Administration where homeowners and businesses can apply for low-interest loans. According to the Federal Emergency Management Agency (FEMA) “U.S. Small Business Administration disaster loans are the primary source of federal long-term disaster-recovery funds for loss and damage not fully covered by insurance or other compensation” (FEMA, 2018). In 2008, the SBA Disaster Loan Program had $959,000,000 in obligations; in 2017 its obligations were estimated at $1,600,000,000 (U.S. General Services Administration, 2008, 2017).

When it comes to academic research on the effectiveness of these programs, only a few studies have looked at the role of federal assistance in businesses recovery after disasters. Internationally, Fischer-Smith (2013) examined the Earthquake Support Subsidy that was provided to businesses after the February 2011 Christchurch Earthquake. The subsidy gave financial support for businesses to retain staff for six weeks (later extended). Business that were interviewed generally had a positive view of the program. The program was implemented very quickly (one week after the earthquake). It supports the idea of iteration proposed by Olshansky, Hopkins, and Johnson (2012) by allowing businesses to retain and take care of employees while freeing-up time and capacity for the business to deal with other post-disaster issues. Businesses were able to make more sound decisions without having to worry about their cash flow (Fischer-Smith, 2013, p. 45 & 47).

The Earthquake Support Subsidy is unique because it took the form of a grant. Government aid to businesses in the U.S., however, generally takes the form of loans. There is also a historical pattern of dissatisfaction with government intervention after disasters due to the bureaucratic nature of the process. Furlong and Scheberle (1998), for example, looked at the gaps in perceptions of small business owners and government officials about federal assistance after the Northridge earthquake, noting that "those not happy with either FEMA or SBA pointed toward the belief that there was too much paperwork and that the process for applying for assistance was too time-consuming" (p. 374). Additionally, the SBA Disaster Loan Program and private loans require paperwork such as financial statements and tax returns. These records can be lost due to the disaster, which happened to several businesses after Hurricane Katrina (Runyan, 2006). There is a mismatch of expectations between businesses and the federal agencies proving the assistance, as described by Furlong and Scheberle (1998):

> "…only about a third of small business owners interviewed believed that either the SBA or FEMA understood their concerns, provided assistance that was useful to them, or acted promptly to meet their needs...On the other hand, most of the SBA and FEMA staff believe that individuals have unreasonable expectations for what government should (or can) do to assist them in recovering from a disaster. For example, an unprofitable business should not expect to receive an SBA loan any more than an individual should expect a FEMA grant if they are able to qualify for an SBA loan instead" (p. 383).

The SBA bases repayment ability on the businesses' profitability before the disaster, and it's true that most businesses in Galveston were denied an SBA loan due to lack of repayment ability (of the 1,042 denial codes provided by the SBA, 997 were lack of repayment ability or poor credit). Qualitative literature is therefore useful in understanding the perceptions of government aid and whether the program functions the same in theory and in practice. However, there is evidence from the quantitative literature that indicated there are other factors that determine which businesses receive an SBA loan. Josephson and Marshall (2016) looked at factors influencing whether businesses applied for a loan, and found that "female owners, those on the coast, those with a greater percent of their income coming from the business, those with more perceived and actual damage, those with higher stress, and those making less than $50,000 per year were more likely to apply, while those operating from home, those with insurance, and those with high success before Katrina were less likely to apply" (p. 12). In terms of approval, "female business owners, those on the coast, those with more employees, those with a paid insurance claim, and several of the revenue tiers are more likely to be approved, while non-white owners, those who went to college, older businesses, and those with cash flow problems are less likely to be approved" (p.12). Lastly, the authors found that "married business owners, those with more experience, those with previous cash flow problems, and those with a paid insurance claim on their residence were more likely to receive a larger loan, while female owners, copreneurial owners, businesses on the coast, those with a paid insurance claim on their business, and several revenue tiers were less likely to receive a large loan" (p. 14).

The results of this research were somewhat contradictory. The results suggest that businesses that were more likely to apply when they needed the money were more likely to be approved (e.g. businesses on the coast). However, repayment ability was a less clear predictor. Older businesses and businesses with cash flow problems were less likely to be approved, larger businesses were more likely to be approved, and businesses with cash flow problems received larger loans. Dahlhamer (1994) also looked at businesses that were more or less likely to receive a loan and found that older businesses, businesses that own their property, and businesses with credit availability elsewhere (i.e. businesses with better repayment ability) were more likely to receive loans.

Many more quantitative studies, however, include government aid after a disaster as a predictor in their more general recovery models. Table 1 is a summary of studies that include financial assistance in their analyses:

Table 1 Summary of Empirical Research on Federal Disaster Assistance.

Source	Independent (Aid) Variable	Dependent Variable	Significant (Y/N)	Direction of Relationship	Time Post-Event
Asgary, Anjum, and Azimi (2012)	Government help and support	Disaster Recovery Time	N	-	6 months
Coelli and Manasse (2014)	Business located within a municipality that received aid	Value added growth (post-disaster)	N	-	1-2 years
Cole, Elliott, Toshihiro, and Strobl (2015)	Government Aid	Post-disaster Sales	N	-	6 months
Dahlhamer and Tierney (1998)	**Postdisaster Aid**	**Recovery**	**Y**	**Negative**	**18 months**
Dietch and Corey (2011)	**Lack of federal assistance (perception)**	**Amount of gain/ loss in post-disaster business volume**	**Y**	**Negative**	**4 years**
Khan and Sayem (2013)	Received a loan	Recovery	Y	Negative	varies
McDonald et al. (2014)	**SBA loan (thousands)**	**Open (vs. closed)**	**Y**	**Positive**	**8 years**
Resosudarmo, Sugiyanto, and Kuncoro (2012)	Received grant in time	Rate of recovery	Y	Positive	6-12 months
Stafford, Danes, and Haynes (2013)	**Business federal disaster assistance receipt**	**Business survival**	**Y**	**Positive**	**10 years**
Webb et al. (2002)	**Number of aid sources used**	**Long-term recovery**	**N**	**-**	**6-8 years**

*bold indicates U.S. research context

As can be seen in Table 1, results are mixed on the effectiveness of aid in recovery. Some of the variability may stem from the differences between aid programs.

Different government have different aid programs and the studies in this selection span a variety of countries. However, those studies that focus on U.S. programs (in bold), the result is still mixed. Dietch and Corey (2011) found that the perceived lack of federal assistance was associated with loss of business volume, but this does not establish a causal relationship between the two since the business owners could be wrongly attributing their difficulties to their lack of assistance. The other studies, however, have more directly tied federal assistance receipt to business outcomes. McDonald et al. (2014) and Stafford et al. (2013) found federal disaster receipt to be positively associated with recovery in the long term. Stafford et al. (2013) took a sample of family businesses across the U.S. and looked specifically at family business survival, finding that businesses that received federal disaster assistance were more likely to remain open after ten years. However, the damage control variable is at the county level. McDonald et al. (2014) were able to control for damage at the individual business level, and found that small businesses that received an SBA loan were more likely to remain open seven years after Hurricane Katrina.

By contrast, Dahlhamer (1998) and Webb et al. (2002) found disaster assistance to be negatively associated with recovery and insignificant, respectively. Dahlhamer (1998) offer three possible reasons for this finding. The first is that aid could simply be insufficient or other factors were driving their demise. The second and third reasons are related. Aid to businesses is often in the form of loans, meaning that businesses could be reluctant to incur debt in an already unstable business environment. Therefore, aid receipt could be an indicator of severe damage. This also may explain why amount of aid sources used was insignificant in Webb et al. (2002). More aid sources may mean more severe damage as well as more debt.

To summarize, addressing the role of assistance in business recovery is complex and the existing literature has not found consensus on whether it is effective in promoting recovery or survival. To answer the research questions posed by this dissertation, therefore, I extend the review beyond the empirical evidence of disaster assistance and business recovery to a broader understanding of the factors influencing business performance after natural disasters. I also review relevant theoretical literature. Together, this literature can provide a better understanding of business characteristics that affect post-disaster performance, the role and importance of the environment in business selection processes and resource attainment, and strategies and foundations of organizational behavior that affect their ability to adapt. Ultimately this research can help us understand how a disaster affects a business, how a business might respond to the disaster, and how assistance complements or hinders this process

2.2. Empirical Factors Influencing Business Recovery

The empirical literature on businesses and disasters identifies a variety of factors that influence a business's performance after a disaster that will need to be considered when examining the research questions. These factors range from the availability and nature of critical business inputs, the management and operational processes of the businesses, and external factors related the disaster and community as a whole. I discuss the implications each has on post-disaster business performance.

2.2.1. Critical Inputs

To begin, there are a few key inputs that businesses require in order to function; broadly, all businesses require capital, suppliers, labor, and customers in order to provide a good or service. In a disaster situation, however, the availability and fashion in which the business utilizes these components can also make a business more or less vulnerable (Zhang, Lindell, & Prater, 2009). Consider capital and labor. Amount of capital and labor is important after a disaster because more resources directed at solving an issue seem intuitively better than fewer. Business size and age are often used as indicators of business performance due to the amount of capital resources a business is likely to have—the larger and older the business, the more resources it probably has to dedicate to recovery (Brunton, 2012; Runyan, 2006; Webb, Tierney, & Dahlhamer, 2000; Zhang et al., 2009). Larger, older, businesses are more likely to have multiple locations, which enables them to move to an alternative storefront if one location is damaged (Alesch, Holly, Mittler, & Nagy, 2001; Brunton, 2013; Hatton, 2015; Zhang et al., 2009). Similarly, franchises and chains have a wide range of locations and a larger pool of resources to draw from (Ergun, Heier Stamm, Keskinocak, & Swann, 2010).

However, it's not simply the amount of resources but the nature of the resources that make capital and labor more or less effective after a disaster. A business's capital, for example, consists of both the business's physical assets as well as its liquid assets (such as cash or accounts receivable). A business requires physical capital in order to produce goods, operate out of a storefront, and assist in transactions. However, a business's physical assets are vulnerable to damage and more difficult to liquidate—and even more so if the physical assets are rented as opposed to owned—whereas cash assets are more flexible and can be drawn upon as needed during recovery (Zhang et al., 2009). Similarly, with labor, franchises benefit from a large pool of labor not only because they have so many employees, but because they are all similarly trained across locations and can be substituted from other locations if need be. Zhang et al. (2009) refer to this as employee replaceability; businesses that rely on subcontractors, for example, have more flexibility (Wedawatta, Ingirige, & Jones, 2010).

The same can then be said for customers. Having a higher number of customers leads to more profit, however the spatial location and demand of those customers matters. After a disaster, households are also damaged, which will mean changing markets and labor pools for a business (Alesch et al., 2001; Graham, 2007; Runyan, 2006). In general, there are three population forces a business might contend with after a disaster: changing demand in the resident population, new population influx from recovery workers, and more permanent population changes due to in-migrants bringing different markets and population loss due to dislocation and displacement. Changing demand in the resident population can stem from household damage, where residents have less purchasing power and their priorities are focused on the rebuilding and repair of their homes and property (Alesch et al., 2001). This can have a disproportionate impact on business sectors, where retail and sectors catering to discretionary spending see less business and construction or manufacturing business might see a boom in residents needing services, tools, and raw materials during recovery (Alesch et al., 2001; Brunton, 2014; Scanlon, 1988; Webb et al., 2000).

Change in demand can also come from temporary relief and recovery workers, where accommodation businesses may be able to take advantage of the need for temporary housing and restaurants that are able to open quickly will be able to serve relief workers and residents who are unable to cook their own meals (Runyan, 2006). However, relief workers will eventually leave and the resident population may or may not be able to provide the same level of support to these businesses, particularly tourism economies that are more likely to be negatively affected by the perception of the disaster and recovery in the media once temporary workers have gone (Wilson, 2016). As alluded to here, there can be long-term or even permanent population changes that might occur in a community after a disaster and businesses may struggle to adapt and cope with these effects (Alesch et al., 2001; Graham, 2007).

Customers and supplier relate in their effect on businesses because they can both be located within or outside the disaster impact area (Zhang et al., 2009). Most businesses rely on suppliers for some piece of their business, and therefore may still experience interruption after a disaster through supplier damage even if their own premise was unaffected (Haraguchi & Lall, 2015; Zhang et al., 2009). Utilities are a particularly important input for a business (Al-Badi, Ashrafi, Al-Majeeni, & Mayhew, 2009; Orhan, 2014; Piotrowski & Armstrong, 1997; K. J. Tierney & Nigg, 1995), with some research suggesting that loss of utilities may be similarly if not more consequential than the physical impacts of a disaster in terms of interrupting operations (K. J. Tierney & Nigg, 1995). Utility loss can result in additional damage to inventory, particularly those that rely on refrigeration (Alesch et al., 2001). Restaurants, grocers, and other food retailers that stock frozen food may lose almost all of their contents due to lack of refrigeration caused by power loss. Although having more suppliers helps disperse risk, the nature of the supplier relationship is also important. Companies with strong supplier relationships may engage in collaborative recoveries where the supplier and receiver share resources (Brüning, Hartono, & Bendul, 2015).

To summarize, availability of these components in addition to their attributes are important in business recovery. This research, for example, focuses specifically on capital as a critical input to a business. There is little question that the existence of additional capital will benefit a business because it will buffer the impact of a disaster, however it's also true that the nature of the capital matters. For SBA loans then, an important question becomes whether the nature of the capital (e.g. term, interest, and timing) affects business survival.

2.2.2. Management and Business Operation

The next category of variables relates to the internal processes of the business or how the business is run. Park, Seager, Rao, Convertino, and Linkov (2013) conceptualize resilience as "an emergent property of what an engineering system does, rather than a static property the system has. Therefore, resilience cannot be measured at the systems scale solely from examination of component parts" (p.1). For businesses, then, it is worthwhile to look not only at the attributes of the business (such as size discussed above), but the capacity the business has for action, adaptivity, and problem solving. McManus (2008) identified four useful indicators for resilient decision-making:

situational awareness, adaptive capacity, keystone vulnerabilities—renamed as disaster planning and preparation for the purpose of this research—and network connectivity. Situational awareness includes recognizing roles of both the staff and the organization at large as well as understanding potential hazards, their consequences, and the level of the organization's exposure; this knowledge can assist in knowing what to prioritize and when after a disaster (McManus, 2008). Adaptive capacity is a resilience principle that has been used to explain resilience in both human and ecological systems (Holling & Gunderson, 2002). Improving adaptive capacity might include minimizing silo mentalities, improving communication and knowledge transfer within the organization, and flexibility and creativity in the leadership of the organization (Sheffi & Rice Jr, 2005). Planning and preparation can be defined as creating a business continuity or recovery plan or taking actions prior to the disaster in order to minimize the physical impact, disruption of operation, and/or recovery time (Xiao & Peacock, 2014). Lastly, building and maintaining relationships with suppliers, other businesses, banks, or other organizations that may be able to provide post-disaster assistance can also be beneficial (Zhang et al., 2009). This type of social capital can help in securing additional resources or making it easier to find needed resources after an event (Hatton, 2015).

Consider the discussion of critical inputs in the previous section, particularly the discussion on customers. After a disaster, there are several ways a community (and a business's customer base) can change after a disaster due to demand changes and population migration. Even a business with no damage can be at risk of failure if the surrounding community changes in such a way that the demand for the business's product or service is permanently altered. To survive, a business needs situational awareness to recognize that such a change might be happening. In the face of this information, adaptive capacity would then be the business's willingness and ability to move or change its operation to accommodate these changes. Planning and preparation and network connectivity can facilitate both situational awareness and adaptive capacity. If a business had previously conducted a continuity or disaster recovery plan, it may have already identified suitable alternative locations which would make the decision to make much easier. Moving quickly can give a business an advantage, in that they have the first choice of available locations and may even be able to capitalize on reduced competition early on in the recovery process (Runyan, 2006). Additionally, strong network connectivity may facilitate collaborative recoveries, where businesses share locations, resources, and information (Hatton, 2015).

Although customer issues were used as an initial example, business management and operational decisions can address many of the issues related to disruption of essential inputs. Business assets are physically vulnerable to disaster impacts, but through planning and preparation these contents can be elevated, secured or moved prior to the event (Gissing & Blong, 2004). Adaptive capacity in the face of labor disruption may mean that employees are given modified hours, able to work in an alternative location, or able to work remotely. Network connectivity in supply chains may lead to businesses collaborating to help a shared supplier recover (Brüning et al., 2015). In sum, these four terms represent a business's ability to recognize a potential issue (situational awareness) and react to it (adaptive capacity) in a timely manner (planning and preparation and network connectivity).

2.2.3. External Factors

A business can also be impacted by external factors, including the nature of the disaster and the recovery and resources of the community as a whole. For example, the damage and severity of a hurricane can damage the business directly, but may also cause transportation issues through road closures or detours debris from standing water or debris. Additionally, an earthquake may cause entire blocks of buildings to be deemed structurally unsafe (or in need of further assessment) leading to limited access (Hatton, 2015; Kachali et al., 2012; Stevenson et al., 2012). Even without causing access issues, surrounding damage can be a major problem for the tourism industry since tourism businesses rely on the health of the "destination" as a whole (Fitchett, Hoogendoorn, & Swemmer, 2016). Misinformation about the progress of recovery or incomplete or sensationalist media coverage can affect the perception of, and likelihood of travel to, impacted tourist destinations (Ghaderi, Mat Som, & Henderson, 2015; Luo, Wan, & Liang, 2014). This is relevant to areas like Galveston that rely on out-of-town dollars in addition to the resident population. In addition, government action or regulation can affect businesses after a disaster. At the state or local level, the permit process and redevelopment planning after a disaster will affect the type and timing of reconstruction (Graham, 2007; Sapountzaki, 2005). Similarly, fuzzy regulations from federal agencies and the uncertainty of how these may affect building codes could also slow recovery as businesses and households hesitate to invest in any new construction (Runyan, 2006).

More broadly, however, the overall business climate and characteristics of the community can affect recovery. Much like previous financial condition can influence post-disaster business success, pre-disaster market trends set the initial trajectory for a business and influence recovery (Chang, 2010). Hurricane Ike, for example, coincided with the 2008 financial crisis which likely affected business recovery in several ways. It could decrease private banks' willingness to lend as well as affected spending habits of consumers. Even without a major financial crisis, however, the overall business climate was cited as an important factor in recovery during Hurricane Andrew and the Loma Prieta Earthquake (Webb et al., 2000).

As discussed previously, community populations dictate both supply (in terms of labor and production) and demand (in terms of consumers). A report following the Canterbury earthquakes in New Zealand writes about migration and population concerns: "The first (concern) is that if a large enough number of people leave, regardless of age and skill level, the remaining population may not be sufficient to drive the general economy of Christchurch/Canterbury. The second concern is that people with the skills required for the rebuild leave, creating a skills shortage" (Stevenson et al., 2012). Businesses might struggle to find employees and customers due to issues ranging from relocation, temporary housing decisions, and inequitable housing recoveries, to rent increases and gentrification during disaster recovery (Pais & Elliott, 2008; Peacock, Van Zandt, Zhang, & Highfield, 2014; Zhang et al., 2009). There is well-documented evidence that social vulnerability indicators matter in terms of household recovery in that recovery is not even for different socio-economic groups (Dash, Morrow, Mainster, & Cunningham, 2007; Levine, Esnard, & Sapat, 2007; Peacock, Morrow, & Gladwin, 1997; Phillips, 1993; Van Zandt et al., 2012). Businesses located in areas of slower household recovery, or in areas of higher dislocation, may have more difficulty in staffing and having enough customers to maintain a profit. Therefore, including demographic information about the community can help to capture these inequities and how those might impact a business.

2.3. Theoretical Perspectives

In order to have robust models on business recovery, the empirical literature suggests that variables should be included that can capture a business's ability to capture and maintain critical business inputs (i.e. capital, labor, suppliers, and customers) and make decisions in recovery in the face of changing circumstances. Models should also include area characteristics in order to control for recovery inequalities and overarching trends that may affect a business's survival. The last step, then, is to account for what is known on organizational theory. This dissertation makes use of two theoretical perspectives. Because this research is looking at assistance provided by organizations to organizations, these perspectives uniquely inform this research by providing context on the motivations of these organizations in the recovery context, the role of resources (in general) in organizational strategy, and how organizations react to and are affected by the external environment.

2.3.1. Institutional Logics

The institutional logics perspective is a meta-theory that serves as a "framework for analyzing the interrelationships among institutions, individuals, and organizations in social systems…each institutional order of the interinstitutional system distinguished unique organizing principles, practices, and symbols that influence individual and organizational behavior" (Thornton, Ocasio, & Lounsbury, 2012, p. 2). Whereas previous research neo-institutional theory provided a theory for institutional homogeneity through isomorphism (DiMaggio & Powell, 1983; Meyer & Rowan, 1977), institutional logics allow for a more influential individual actor (Friedland & Alford, 1991). Whereas neo-institutional theory is successful at a higher level of scale with an aggregate unit of analysis, institutional logics integrates societal-level culture with individual and firm-level heterogeneity (Thornton et al., 2012).

For example, there are several institutional orders that define the interinstitutional system—family, community, religion, state, market, profession, corporation—and each are guided by a central institutional logic. Individual and organizations may be more centered in any of these given institutional orders which allows for variation in culture (p. 43). Thornton et al. (2012) explain: "organizational fields are made up of a variety of organizations that have their values anchored in different societal-level institutional orders. For example, Catholic Hospitals (religion), the American Medical Association (professions), Medicare (states), and Humana Inc. (corporation and market), all have a huge stake in the provision and payment for health care" (pp. 44-45). These logics have "both material practices and symbols that comprise its organizing principles and that are available for individuals and organizations to elaborate" (Thornton, 2004, p. 42). Thornton continues, "the pure ideal types approximate to a greater or lesser extent hybrid types that are observable in the real world" (Thornton, 2004, p. 42). For example, two industry-level subsets of the more general institutional logics can be observed in the historical evolution of the publishing industry: the editorial logic and the market logic (grounded in the societal-level professional and market logics) (Thornton, 2004).

From the disaster literature side, there have been several theoretical conceptualizations of recovery (Chang, 2010; Drabek, 2012; Nigg, 1995; Quarantelli, 1999; K. Tierney & Oliver-Smith, 2012). In particular relevance to this research, Bates and Peacock (1989, p. 358), drawing from Bolin and Bolton (1983, p. 358), distinguish between indigenous or independent recovery and exogenous or dependent recovery: "the idea is to think of the recovery process in terms of (1) the origin of the resources employed in the recovery process, such as money, materials, labor and management, and (2) the organization of activities carried out in the recovery process." Looking at these distinctions more broadly, I argue contribution that these processes are dictated, if not predicted, by the influence of three institutional logics influencing the cross-scale dynamics of organizational recovery: the community logic, the state logic, and the market logic. This analysis assumes the market logic is a constant as all commercial businesses must survive by market principles. Table 2 represents the ideal types of the three institutional logics influencing disaster recovery with the categorical elements of each logic represented on the y-axis

Table 2 Ideal Type Institutional Logics Instantiated in Business Recovery After Natural Disasters.

	State Logic	Community Logic	Market Logic (Meta-logic)
Basis of Strategy	Viability	Sustainability	Profitability
Root Metaphor	Recovery as Obligation	Recovery as Normalcy	Recovery as Investment
Economic System	Welfare Capitalism	Cooperative Capitalism	Market Capitalism
Geographic Distance	National	Local	Global
Stakeholders	Taxpayers	Members	Shareholders
Organizational Form	Bureaucratic Hierarchy	Relational Network	Market structure
Exchange Relationships	Arm's Length	Embedded	Faceless
Perception of Time	Time as Legitimacy	Time as a Tool	Time as a Resource

Research has examined the impact of the community logic on organizational behavior (Lee & Lounsbury, 2015; Marquis & Battilana, 2009; Marquis, Lounsbury, & Greenwood, 2011). Community can be based on membership (e.g. shared values, activity, or beliefs) or geographic proximity (Thornton et al., 2012). In this case, the community logic after a natural disaster refers to the local geographic community that was impacted. After a disaster, the community logic encourages a policy of building back. The community logic is the desire for a community to "return to normal" and to restore the previous way of life. In this way, the community logic is similar to concepts related to people-place relationships that have been identified in allied fields of study, including place identity, sense of community, sense of place and place attachment (Low & Altman, 1992; McMillan, 1996; Proshansky, 1978; Tuan, 1974). These concepts illustrate the idea that people find meaning in their environment (e.g., place attachment) and the environment stimulates meaning within themselves (e.g., place identity). These concepts have been studied in relation to the disaster recovery process, for example the positive psychological impact of restoration (Silver & Grek-Martin, 2015), and the high amount of place attachment, identity and dependence of residents that chose to return to a disaster area (Chamlee-Wright & Storr, 2009). This spatial aspect of the community logic often manifests as a common sense of belonging bounded by a geographic place, and explains why for some, it is not acceptable to build back just something or build back anywhere, it is acceptable to build back in the same geographic area in a way that represents the established community ideal in order to address feelings of dislocation and disorientation (Cox & Perry, 2011). For residents of the Ninth Ward after Katrina, "contentment, well-being, and even self could only be found in New Orleans" (Chamlee-Wright & Storr, 2009). Recovery, under the community logic, might represent a cooperative activity where community members assist each other in their clean-up and rebuilding, i.e., the "honeymoon phase," (Silver & Grek-Martin, 2015).

By contrast, the state logic is guiding the recovery dynamics at the national scale. The state logic represents the Federal Government under obligation to aid communities after a natural disaster. The United States, for example, has seen a steady strengthening of this logic in the last century, no doubt influenced in part due to political opinion; for example, Rubin (2012, p. 122) comments, "Each president's declarations (of a presidential disaster) reveal something about that president as a person, as a public executive, and as a politician." Hurricane Katrina serves as a recent example of the solidification of the state logic and the dominant opinion that the Federal Government has a responsibility to disaster impacted communities, at the very least in terms of resources. In general, current legislation mandates federal involvement after a disaster when recovery needs surpass local capacity (FEMA, 2011). Regardless of whether the state logic is perpetuated by politics or altruism, the state logic desires a viable community as an outcome. The difference between the instantiation of state and community logics, however, is that the state does not care about the return of a particular way of life, but rather the general return of an economically and socially functioning political entity.

The market logic has a role in recovery, albeit as a meta-logic. Similar to the logic filtering identified by Lee and Lounsbury (2015), the market logic interacts with the state and community logics in recovery. The market logic would encourage rebuilding only as it relates to the broader economic goal of profitability. The market logic might not encourage rebuilding at all—for example, the risk of a future disaster may outweigh the costs of investing more infrastructure and resources into the area. Money and resources funneled into the community are therefore investments rather than donations. The market logic may also view disasters in a positive light. As in Schumpeter's notion of creative destruction (Reinert & Reinert, 2006; Schumpeter, 1942a), a disaster may offer the opportunity for a business to trim down unprofitable activities, become more efficient, and replace outdated technology. A natural disaster has even been shown to increase economic activity, perhaps due to the influx of relief workers and the short-term construction boom (Leiter, Oberhofer, & Raschky, 2009; Monllor & Altay, 2016; Tanaka, 2015; Hirofumi Uchida et al., 2014; H. Uchida et al., 2015). Such an increase in economic activity is not necessarily uniform. Different sectors bear the impact of disasters differently and small businesses with fewer resources are less able to withstand the external shock (Dahlhamer & Tierney, 1996; Scanlon, 1988). Whereas the community logic might be concerned with this complexity and the idea of "winners and losers" (Scanlon, 1988) of a natural disaster, the community desires the recovery of the community as a whole—the market logic makes no distinction beyond the aggregate net benefit. However, actors identified by both the community and state logics must comply and interact with the market logic. Individual businesses must make a profit and organizations at all levels are interested in the economic prosperity of the community, if motivated by different reasons.

In addition, recovery is naturally temporal, and temporal structures, as summarized by Reinecke and Ansari (2015, p. 622), "are replete with cultural values and interests (Schein, 1992) and shape what problems appear salient, how those problems are coped with, and what constitutes a satisfactory solution (Huy, 2001; Zaheer, Albert, & Zaheer, 1999)." Previous research has provided an alternative theory of time and organizations by combining temporal structures with the institutional logics perspective (Orlikowski & Yates, 2002). Whereas Rowell, Gustafsson, and Clemente (2016, p. 308) suggest that practices enact values of time which are encompassed by temporal orientations, this research suggests that logics provide the value structure and thus the temporal orientation of organizations. These in turn shape practices and, in this case, the way in which recovery is addressed.

For example, in the ideal type analysis, the state as perceives time as legitimacy. For the federal government under the state logic, longer wait times abet deliberation. For the state logic, the stakeholders are taxpayers—they have a stake in the actions of the government, especially when government resources are taken from taxpayer funds. As described in Uzzi (1996), the community logic operates through embedded ties and therefore is characterized by a relational network; the market logic and state logic are emblematic of arms-length ties (Powell, 2003). In a disaster scenario, embedded ties are an asset only to the community logic because they increase trust and social capital. According to the state logic, embedded ties can be construed as unethical and representing special interests; or, as in the case of the market logic, they can be construed as irrational because they can cloud judgement (Uzzi, 1996). Therefore, the government must utilize arms-length ties and bureaucratic hierarchy to establish transparency—all of which takes time. A planning or economic development organization under a community logic, however views times as a tool as they coordinate futures into a shared trajectory (Tavory & Eliasoph, 2013); community actors are constantly balancing short-term needs of individual community members with the long-term sustainability of the community, itself, and may use their embedded ties and social capital to achieve these goals.

The market logic, however, sees time as a resource (Das, 1991; Raaijmakers, Vermeulen, Meeus, & Zietsma, 2015). Scholars have identified the problem of time compression as characteristic to the recovery phase of natural disasters (Olshansky et al., 2012); whereas in normal time, changes to the built environment, policy decisions, information flows, financing, etc. occur incrementally and over longer periods of time, after a disaster these must be accomplished in, and are compressed to, much shorter timespans. For a business under the market logic, capital resources may be replaced incrementally under normal time, but during after a disaster and time compression inventory, machinery, and even the building itself might need to be replaced all at once. The longer a business waits, the longer the business cannot achieve its basis of strategy of profitability, giving a sense of immediacy to its survival. Whereas Hurricane Ike to state actors is merely one disaster event of many, businesses in Galveston describe the hurricane as permanently splitting their organization of time into "before Ike" and "after Ike" —the state does not feel the same temporal pressure the market actors do.

To summarize, organizations providing aid to businesses after a natural disaster are limited in their effectiveness contingent on their association with the recovery ideal types. Their timing, characteristics, and lens from which effectiveness and legitimacy is viewed by the organization, itself, will vary based on the y-axis attributes identified in Table 2. This culminates to makes the assistance more or less attractive to recovering businesses and more or less supportive of long-term survival and recovery.

2.3.2. Resource Dependence

The second perspective I draw upon in this research is resource dependence. Resource dependence theory argues that "the key to organizational survival is its ability to acquire and maintain resources" (Pfeffer & Salancik, 2003, p. 2). For almost all organizations, this requires some interaction with the external environment, as most organizations cannot be entirely self-sustaining. As outlined in Section 2.2.1., for-profit organizations depend on several critical inputs such as capital, labor, customers, and infrastructure (the physical premise, utilities, telecommunications, etc.). Organizations also rely on each other. Businesses specialize and outsource various portions of their operations, relying on supply chains to function. The environment, however, is undependable:

> "The fact that organizations are dependent for survival and success on their environments does not, in itself, make their existence problematic. If stable supplies were assured from the sources of needed resources, there would be no problem. Problems arise not merely because organizations are dependent on their environment, but because this environment is not dependable. Environments can change, new organizations enter and exit, and the supply of resources becomes more or less scarce. When environments change, organizations face the prospect either of not surviving or of changing their activities in response to these environmental factors." (Pfeffer & Salancik, 2003, p. 3)

Organizational vulnerability, therefore, stems from the potential of an environmental change to create uncertainty in resource acquisition. Organizational behavior under this assumption is motivated by the external environment and an organization's desire to exert control over the supply of resources. Often this involves strategic positioning in relation to the dependence of other firms, as an organization upon whom a large number of organizations rely on is better-off than an organization who itself relies on a large number of organizations. In general, the Pfeffer and Salancik

(2003) offer three factors determining the dependence of one organization on another: 1) the criticality of the resource to the organizations operation and survival; 2) the second is the amount of discretion the organization with the resource has in its allocation and use; and 3) the number of alternatives and/or the extent of control of the resource holding organization (p. 45-46).

This has several implications for this research, notably how resource dependence shapes cross-scale dynamics after a disaster. After a disaster event, the environment is abruptly changed. Businesses, households, and infrastructure are often extensively damaged, creating a scarcity in labor, capital, and utility resources among others. Telecommunications disruptions can limit the flow of information and knowledge becomes a limited resource. Likely, existing resource dependencies within organizations are disrupted if a critical number of partners are within the disaster area. Resource dependence, therefore, becomes a spatial as well as conceptual phenomenon (Zhang et al., 2009). This becomes an issue for organizations under the community logic in particular. Recalling Table 2, the geography of the community logic is local, the market is global, and the state is national. Because of the local impact of the disaster, community organizations may become dependent on—or more dependent—on market and state organizations.

I compare this idea against the three determinants of resource dependence, using the example of capital. Capital, as discussed in Section 2.2.1, is critical for an organization’s operation and survival. Also touched on in previous sections, federal investment in recovery is significant. Additionally, the state has almost full discretion on how disaster recovery capital is used. The red tape and high oversight are well-documented criticisms of federal programs for disaster recovery (Furlong & Scheberle, 1998). To look at it theoretically, Yuchtman and Seashore (1967) established one of the earliest models of the environment as a resource controller (Wry, Cobb, & Aldrich, 2013). In their paper, a poor bargaining position was a precursor or potential determinant of dependence. Consider the observation of Olshansky, Hopkins, and Johnson (2012):

> "Time compression affects power relationships at many levels. Consider the seeking of reconstruction funding... In order to persuade others to provide that funding, the disaster victims need to present an estimate of their financial needs and a plan that demonstrates that they will spend the funds wisely. The funding entity—whether a bank, insurance company, national government, or international aid agency—will provide the funds, but subject to conditions negotiated between the two parties. The disaster victims have the weak negotiating position, because, due to time compression, they need to start receiving funds as quickly as possible. Paradoxically, the conditions of receiving the external funding usually include promises of transparency and accountability, which can slow the flow of funds over time, even if initiated quickly." (122)

The first part of this statement corroborates the concepts identified Lawrence, Winn, and Jennings (2001), where negotiation abets slower temporal pace and disaster victims may respond by relinquishing their power and agency to hasten the process. This research, therefore adds a logic dimension to motivate the paradox identified by Olshansky, Hopkins, and Johnson (2012, 122). Referring back to Table 2, values and perceptions of time for each logic, therefore, lend themselves to particular temporal orientations during recovery: the market leans towards a present- or near-future orientation, the state is distant-future oriented, and the community balances the two. Relenting negotiating power defaults to the logic of the state and consequently, resource dependence.

Lastly, resource dependence is also subject to the number of alternatives and/or the extent of control of the resource holding organization. Until now, I have ignored the potential for resource dependence on the market. Indeed, private insurance greatly exceeds federal payout after disasters (Lindsay, 2010). However, the decision to buy insurance is made prior to the disaster and the resulting resource dependence. The market's role as a recovery, not mitigation, entity takes the form of private loans as discussed in Section 2.3.1. Because the state does not require profit, recovery assistance takes the form of grants or low-interest loans. This gives the state control over the resource because their form of capital is more desirable than market loans, whose rates would be higher to generate profit. The use of these perspectives, particularly institutional logics and resource dependence, supports the findings of the empirical literature. When it comes to critical inputs, it is not simply the amount of the resource but also the characteristics of that resource.

To summarize, disasters disrupt the existing environment, which consists of various resource dependencies across organizations. Drawing from our discussion of recovery logics, organizations under the community logic are more likely to become dependent on external partners under the state and market logics. Federal assistance, therefore, has consequences for long-term organizational survival thereby justifying research into its effectiveness.

3. CONCEPTUAL MODEL AND HYPOTHESES

Taking the literature and theoretical perspectives together, I use this section to derive the hypotheses to be tested. The literature review first used the empirical literature on businesses and disasters to identify factors influencing business performance. This review showed that business performance is influenced by external factors that are to some extent outside of the business's control, internal factors including characteristics of the business and factors within its direct control, the characteristics of the hazard itself, and provision of and characteristics of assistance to the business.

To illustrate, consider the discussion from Zhang et al. (2009) where businesses, as well as their suppliers and customers, can be inside or outside the disaster area. Businesses can be impacted by their own personal damage (internal characteristics and hazard characteristics, e.g. capital asset vulnerability), but also impacted by customer or supplier interruption if those inputs are inside the disaster area (external factors). I build upon their work to include assistance organizations and the institutional logics at a spatial and conceptual scale to integrate the theoretical perspective in the existing empirical literature:

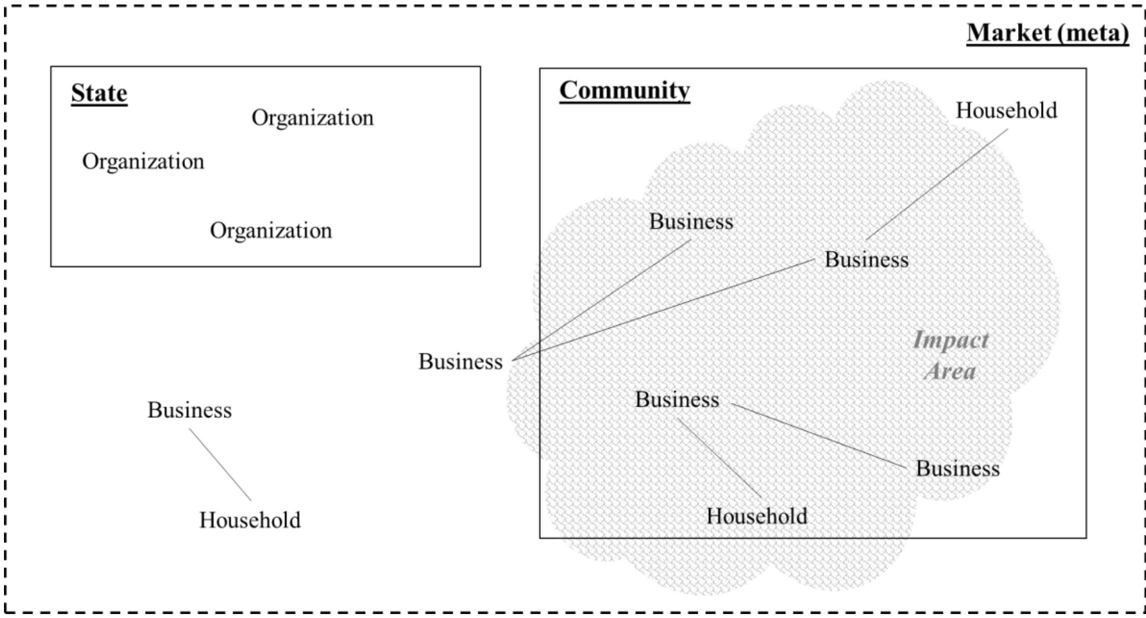

Figure 1 Business Linkages as Resource Dependences in the Institutional Logic Context.

Like Zhang et al. (2009) illustrated, businesses can be inside or outside the disaster area and linked with businesses and households inside or outside the disaster area (pg. 41). Businesses also have some blend of the market and community logics, with one being the predominant logic after a disaster. The connections between businesses and households are resource dependencies. As discussed in Section 2.3.2, disasters disproportionately affect businesses in the community logic due to the geographic distance category on its y-axis; however, businesses can be in the geographic community and still be dominated by the market logic. Businesses in general, however, see their resource networks disrupted by the disaster impact which changes their resource dependencies. The lines connecting the businesses and households become weaker or are destroyed outright.

From here, Figure 2 illustrates how the external environment responds with available assistance:

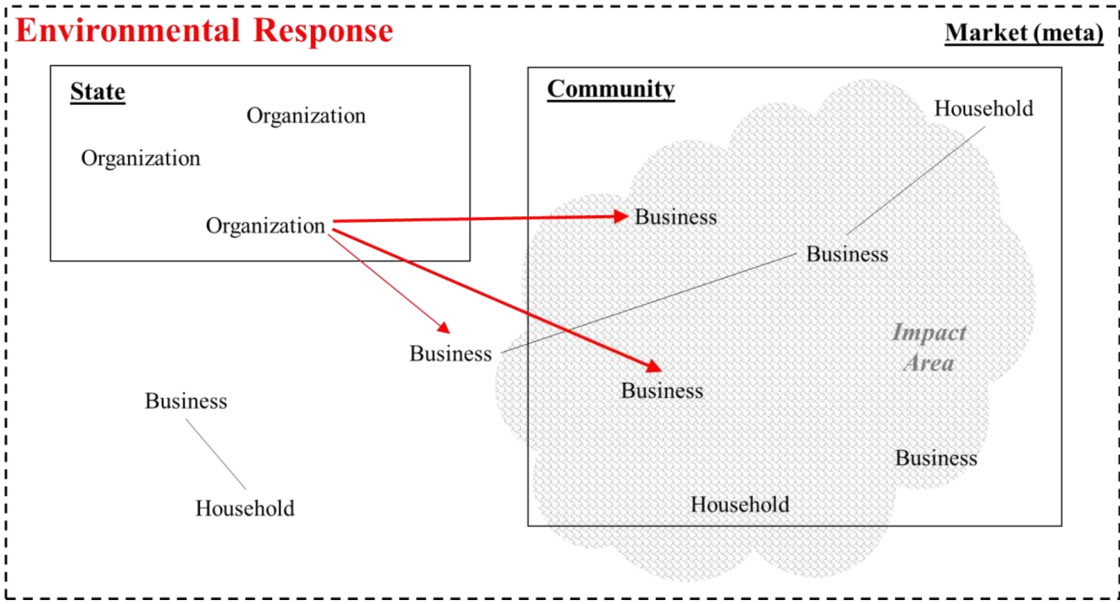

Figure 2 Environmental Response to Disasters.

Organizations under the state logic, due to their root metaphor, feel an obligation to assist impacted communities through welfare capitalism. Some businesses are approved for loans from the SBA, for example. Businesses, through the SBA, can be approved for loans for direct (e.g. physical) and indirect (e.g. interruption) damage as a result of the disaster. Households may also receive loans from the SBA or through individual assistance from the Federal Emergency Management Agency. For businesses, however, the empirical literature has suggested that loans may not be and effective form of assistance to capital-vulnerable businesses (Dahlhamer, 1998) and that businesses have been dissatisfied with the federal assistance process (Furlong & Scheberle, 1998).

Therefore, I consider the reciprocation of the business as separate decision. The decisions made by individual businesses are represented by Figure 3:

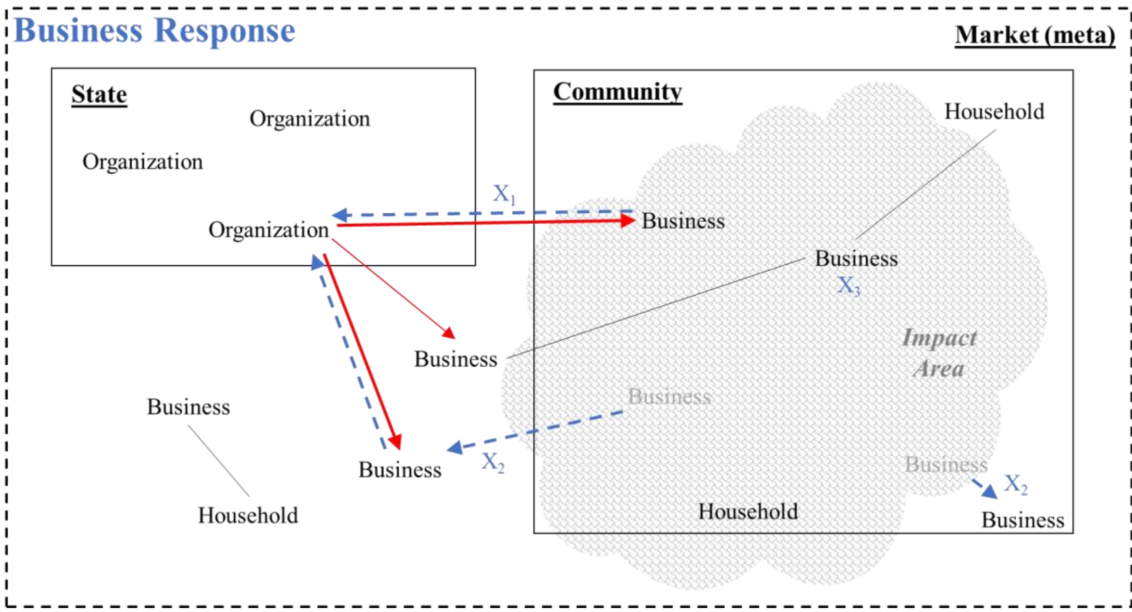

Figure 3 Business Response to Disasters.

Businesses may choose to become dependent on the state in lieu of their previous resource networks (X_1). Businesses may also choose to move and establish different resource networks (X_2), or stay in place and repair their previous resource networks (X_3). This can be facilitated by, hindered by, or irrelevant to their relationship with the state. Where a business moves, however, can indicate their dominant logic (i.e. community or market). In addition, through moving creates uncertainty, staying in place may also hurt a business if the community has permanently changed.

The last step is to include the temporal element: combining Figures 1-3 creates a process model of recovery. To reiterate, the research questions posed at the beginning of this dissertations were:

Research Question 1. Which businesses benefit from the SBA loan program?

Research Question 1.1. What determines loan amount?

Research Question 1.2. Which businesses are more likely to use SBA loans in recovery?

Research Question 2. Do SBA loans improve survival probabilities in the long term?

I place this research questions in the process model illustrated by Figure 4:

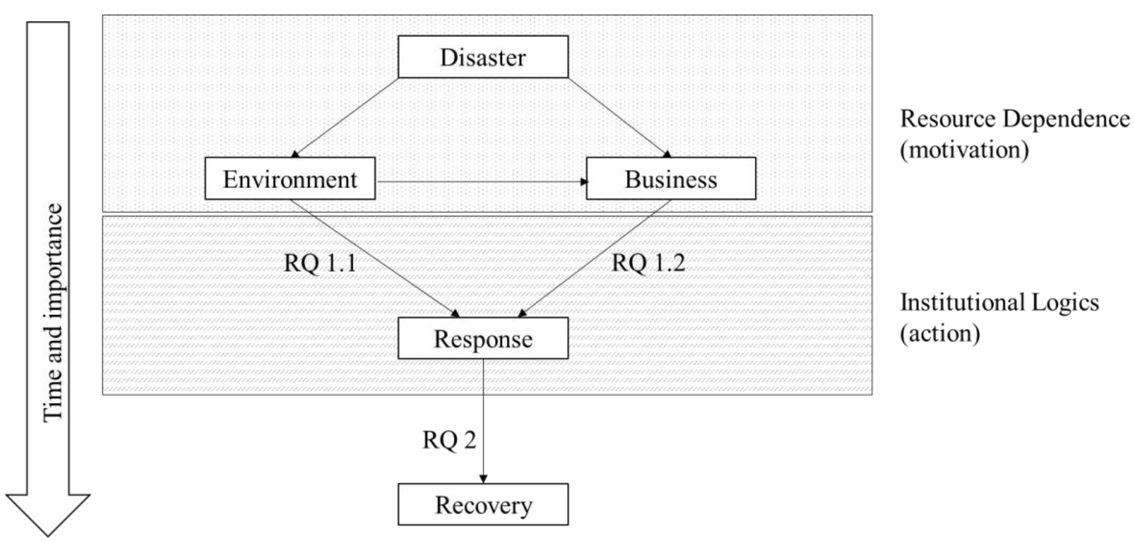

Figure 4 Process Model Contextualizing the Research Questions.

The process model illustrates how disasters affect the individual business as well as the environment. Disasters changes resource dependencies and thereby how the business interacts with its environment. Considering this new disaster-impacted environment and resource dependence landscape, the environment may respond with assistance (Research Question 1.1) and businesses may respond by accepting this assistance (Research Question 1.2). These decisions, controlling for resource dependence, are influenced by institutional logics. Accepting assistance (Research Question 2), then, potentially affects survival probabilities.

From here, I re-introduce the empirical factors introduced by the literature review and generate specific hypotheses. The final conceptual framework, Figure 5, blends the performance model in the literature review, as well as the theoretical conceptualizations in this chapter. Extending from Figure 4, it illustrates the relationship between the theories and empirical factors of business performance, and how they relate to long-term recovery. It also shows more nuance in how the various theoretical perspectives work together, as they are not perfectly independent

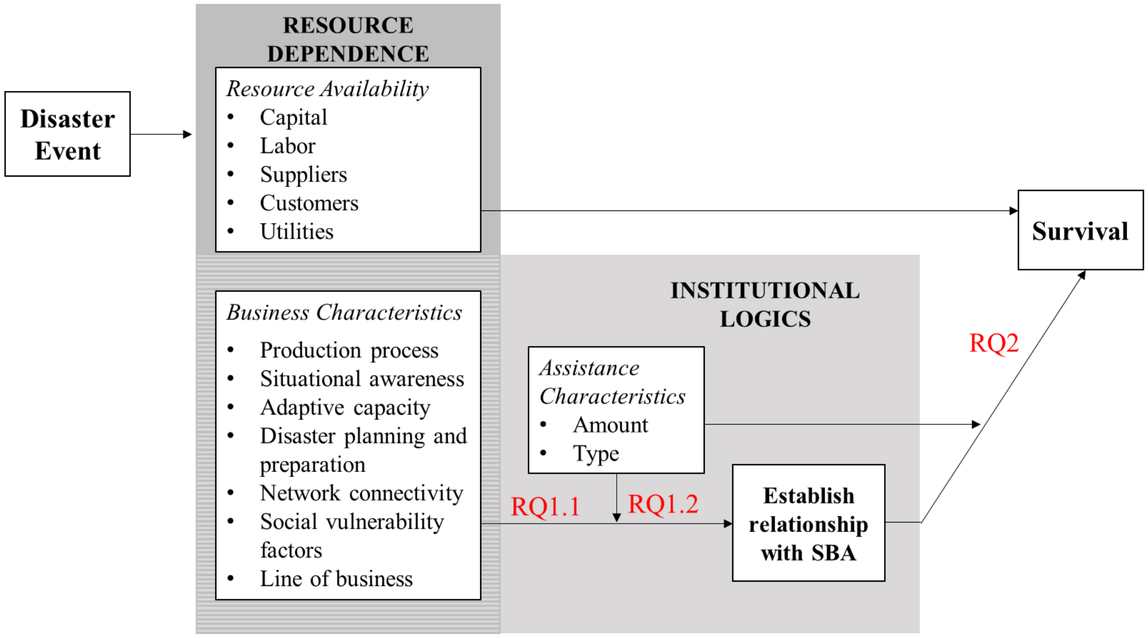

Figure 5 Conceptual Model.

Beginning from the left side of the model, I again illustrate how the disaster event affects the environment and the business in the context of post-disaster resource dependence as illustrated in the previous Figures 1-3. However, I now include the performance factors identified in the business disaster literature, such as critical inputs and external factors (see Section 2.2.1. and 2.2.3., respectively), as characteristics or determinants of resource dependence after a disaster event. This means that businesses are impacted by disasters and vulnerable post-disaster due to the disruption to their resource availability as well as the business characteristics that affect their capacity to recuperate those resources and connections. For businesses that are unable to re-establish their resource connection may draw from external sources. The SBA, however, is an organization that provides such assistance; I explore the motivation and action of the SBA in Research Question 1.1 by looking at loan amount. SBA, because they control the resources, also have more discretion with how the resource is utilized. SBA is grounded in the state logic meaning its economic system is welfare capitalism. In that sense it's blending the ideals of the state and community, where assistance is defensible philanthropy—the state provides assistance, but the assistance must be paid back, the assistance is loans, but the interest rate is low, etc. However, I discussed that because of the nature of their perception of time, the community relinquishes its bargaining position after disasters. A foreseeable consequence would then be that the SBA would prioritize repayment ability rather than need. Therefore:

Hypothesis 1. The larger the business, the more likely it will be approved for higher loan amounts.

Hypothesis 2. The older the business, the more likely it will be approved for higher loan amounts.

In addition, Olshansky et al. (2012, p. 176) suggest that disaster time compression affects power relationships where disaster victims have a weak negotiating position with aid providers because of their need to receive funds quickly. This corroborates the ideas of Lawrence, Winn, and Jennings (2001), where negotiation abets slower temporal pace and disaster victims therefore respond by relinquishing their power and agency to hasten the process. Relenting negotiating power defaults to the logic of the state, where time is legitimacy. Therefore:

Hypothesis 3. Deliberation time has a positive relationship with loan amount.

Businesses also lean toward a dominant logic, which affects their characteristics. For example, a business under the community logic may choose to remain small in the face of market pressures because it wishes to remain a community business. I also argued that organizations under the community logic, due to their geographic distance, are more likely to become dependent on external partners under the state and market logics such as the SBA. This also means that businesses who are less centered in the community logic and more market-driven will be less dependent. Research Question 1.2 explores the motivations behind why a business ultimately chose to take or reject a loan after being approved for it. Following the theory, one might expect that businesses that are more centered in the community logic are more likely to accept SBA loans. Businesses who have remained small as they age may indicate a rejection of market pressures, and are more likely to follow a community logic. Conversely, corporations—because of their obligation to shareholders—are more likely to follow a market logic. Therefore:

Hypothesis 4. Businesses that are smaller and older are more likely to accept SBA loans.

Hypothesis 5. Corporations are less likely to accept SBA loans.

Additionally, one existing theory of why assistance may be ineffective is the additional indebtedness from assistance such as SBA loans hindering recovery (Dahlhamer & Tierney, 1998). I hypothesize that higher levels of damage and higher approval amounts make taking a loan riskier in terms of payback ability and less attractive to a business. Research Question 1.2, by examining business decision-making in terms of establishing a relationship with the SBA, includes whether businesses are sensitive to this potential debt burden. Therefore:

Hypothesis 6. Businesses with higher damage are less likely to choose disbursement.

Hypothesis 7. Businesses approved for higher loan amounts are less likely to choose disbursement.

Also stemming from the empirical business and disaster literature is the importance of capital in business disaster recovery (Zhang et al., 2009). Capital is clearly an important factor in business survival and recovery after disaster events since all businesses must be profitable in order to survive, but the literature is mixed on the role of assistance programs as a source of capital. Research Question 2 looks at whether SBA loans affect survival probabilities in the long term; in other words, can they successfully be substituted for previous resource linkages. Using a different methodology aimed at program analysis, such as a matched analysis, which uses study design to control for potentially confounding variables, may give more clarity (Pearce, 2016). This creates groups of businesses whose difference can be predominantly explained by loan status. Given the new methodology, I propose:

Hypothesis 8. Businesses that receive SBA loans are more likely to survive.

4. RESEARCH DESIGN

This chapter then moves the discussion to the methodology that will be used to answer the research questions and test the hypotheses; Namely, the research context, data sources and collection, analytical method, and data reliability and validity will be elaborated on in detail.

4.1. Research Context

This research uses the case of Galveston, TX after Hurricane Ike to examine the influence of loans on long-term business outcomes. Hurricane Ike made landfall in Galveston, TX on September 13, 2008 as a Category 2 Hurricane (FEMA, 2009). Storm surge levels on the island reached up to 20 feet during high tide, with 110 mph sustained winds (FEMA, 2009). As of 2018, Hurricane Ike has remained the sixth-costliest hurricane in U.S. history, with the National Hurricane Center estimating that it caused approximately $30 billion in damages (NHC, 2018). Figure 6 illustrates the track of Hurricane Ike and the resulting inundation levels in Galveston County.

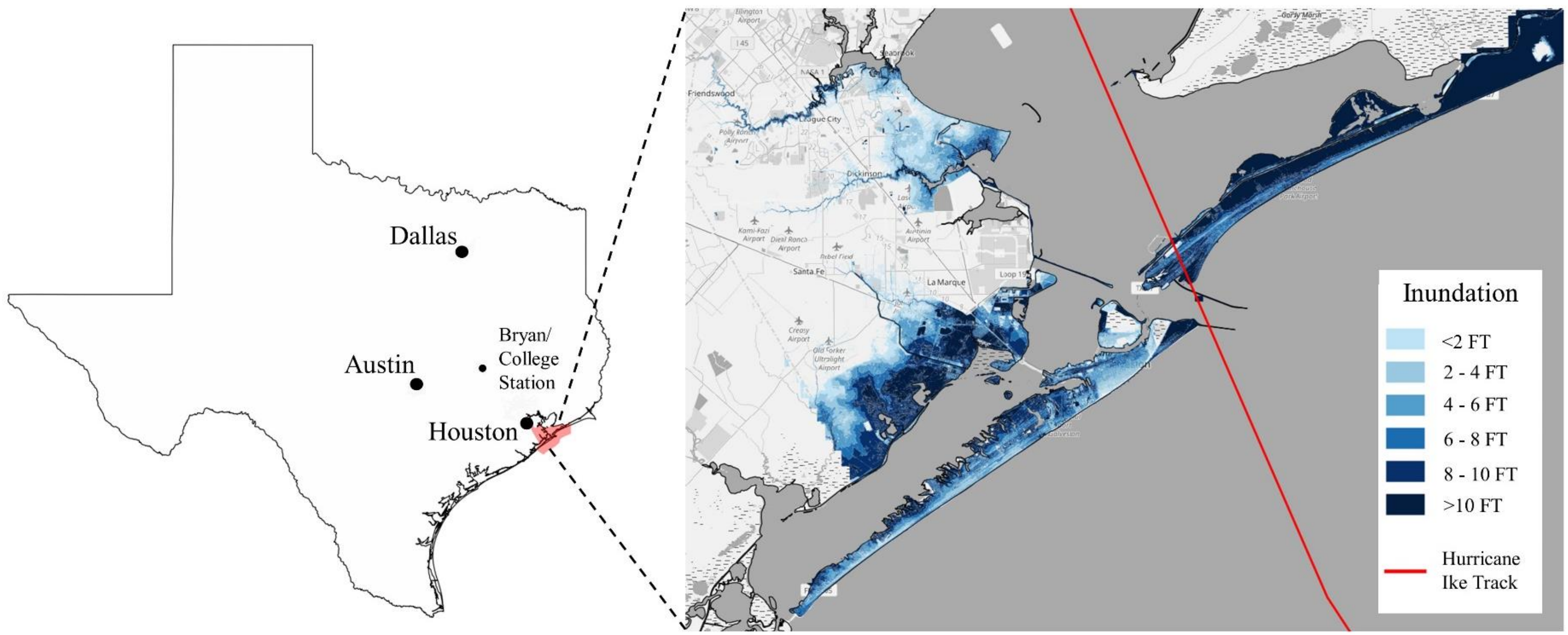

Figure 6 Map of Hurricane Ike Impact and the Study Area.

Hurricane Ike was devastating to the business community. In the initial impact report, FEMA cites impact estimates from the Houston-Galveston Area Council that claimed that, even excluding some of the more severely impacted areas such as Galveston Island, “more than 53,000 employees were put out of work; more than 3,800 businesses were interrupted; and more than 18,000 businesses were damaged in Galveston County” (FEMA, 2009) (p.34). On the island itself, it was estimated that 75-80 percent of the 2,500 businesses on Galveston Island were severely damaged as a result of the storm (IEDC & BCLC, 2009, p. 6). Hurricane Ike is an ideal event to examine long-term recovery of businesses due to the scale of the impact as well as the timing of the event. This research has been conducted almost ten years since the hurricane.

The SBA Disaster Loan Program, as illustrated by the literature review in Section 2.1, is the largest and oldest program available to businesses after a disaster and provided the bulk of non-insurance recovery assistance to businesses in Galveston. The SBA offers two types of recovery assistance, disaster assistance loans and economic injury loans to cover both physical damage and business interruption (SBA; SBA). A summary of these loans is provided in Table 3.

Table 3 SBA Loan Program Description

Loan Type	Interest Rate	Loan Term	Amount	Eligibility of Applicant	Funds can be used …
Business Physical Disaster Loans	4% if business can't get credit elsewhere, maximum 8%	Up to 30 years	Up to $2 mil.	Private or non-profit business located within a declared disaster area	To repair or replace real property, machinery, equipment, fixtures, inventory, leasehold improvements
Economic Injury Disaster Loans	4%	Up to 30 years	Up to $2 mil.	Small business, small agricultural cooperative, private non-profit	For working capital

The SBA's disaster assistance loans are similar to traditional, private sector loans but with a set low-interest rate. The SBA Disaster Loan Program is annually budgeted and does not rely on supplemental appropriations from Congress like other forms of disaster relief; it also deals directly from the federal level to the individual business and has its own loan monitoring and processing centers. This program is stable and independent, and it is therefore unsurprising that the SBA is considered a primary agency responsible for the Economic Recovery Support Function in FEMA's National Disaster Recovery Framework (FEMA, 2011). This research focuses on the role of these loans in long-term business recovery and survival since it is the largest, most consistent, and most well-known form of assistance available to individual businesses after a disaster event.

4.2. Data

This research makes use of both secondary and primary data to get the necessary information on business characteristics, loan information, area demographics, flood and wind damage information, and operational status of the businesses for this study. In general, the research will make use of two samples. The first sample consists of all eligible businesses in Galveston County that were approved for an SBA loan, or the treatment group, which will be used for Research Question 1.1 and Research Question 1.2; the second is a database of businesses that did not receive a loan which serves as a control group when exploring Research Question 2.

4.2.1. Secondary Data

The bulk of the data used in this research comes from secondary sources. I use data from the SBA, ReferenceUSA, Texas Comptroller of Public Accounts, U.S. Census, and data created by other researchers to generate my sample and track business outcomes.

Loan information at the individual business level was provided directly from the SBA through three separate Freedom of Information Act (FOIA) requests in 2016 and 2017. The resulting dataset includes information for every business that was approved for and received a loan after Hurricane Ike in Galveston County. Specific variables include the applicant and their mailing address, the damaged property address, number of employees at the business, business sector (North American Industry Classification System (NAICS) five-digit code as well as applicant write-in description), organization type, and loan characteristics (term, interest rate, amount, and disbursal timing and amount). There were 555 businesses included in the database. Although I also requested information on all businesses that applied and withdrew or were denied, the SBA was unable to provide that information. I did, however, receive a summary of denial and withdrawal codes for Galveston County that I have provided in Appendix A. A total of 1,177 businesses (including non-profits) were denied an SBA loan. The two most common reasons for denial were unsatisfactory credit (622 denial codes) and lack of repayment ability (485 denial codes). Some businesses (448) withdrew their applications. The most common reason for withdrawal was that the requested information was not furnished (158 withdrawal codes). This likely is capturing businesses that abandoned the application process.

Some cleaning also had to be done to the SBA database. Five businesses had damaged property addresses outside of Galveston County although the county field said "Galveston," which I believe was just a data entry error. Additionally, upon closer inspection of the remaining 550 businesses that were in the SBA database, I noticed that almost half the businesses were in the real estate sector (NAICS two-digit code 53). Because the dataset included write-in descriptions of the sector, it was possible to see that many of the business loans were for vacation home properties. This warranted a closer inspection of businesses in the real estate sector. A breakdown of Sector 53 with example write-in responses is provided in Table 4 below.

Table 4 Sector 53 and Teasing-out Vacation Homes by Description

NAICS Code	NAICS description	Example applicant write-in	Mean No. of Employees	Std. Dev.	Freq.
531110	Lessors of Residential Buildings and Dwellings	Beach House Rental	1	2.7	228
531120	Lessors of Nonresidential Buildings (except Miniwarehouses)	(Anywhere from Vacation Rental Property to Medical Clinic)	3.2	5.7	21
531190	Lessors of Other Real Estate Property	Rental of Covered boat Storage	0.8	1	4
531210	Offices of Real Estate Agents and Brokers	Real Estate	3.1	6.6	7
531311	Residential Property Managers	Vacation Rents/Property Mgmt.	2.3	2.5	3
531390	Other Activities Related to Real Estate	Property Management & Resale	0	0	3
532120	Truck, Utility Trailer, and RV (Recreational Vehicle) Rental and Leasing	Mobile Home and Travel Trailer	0	0	1
532292	Recreational Goods Rental	Golf Cart Rentals	2.5	0.7	2
532299	All Other Consumer Goods Rental	Music Equipment for Rent	2	0	1
533110	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	Rental Houses	0	0	1
Total			**1.26**	**3.15**	**271**

I also provide some attributes of the businesses in each sector in Table 5:

Table 5 Sector 53 and Teasing-out Vacation Homes by Attributes

NAICS Code	Corporation	Limited Partnership	LLC	Partnership	Sole Proprietorship/ Individual	Total
531110	6	3	11	4	204	228
531120	3	3	3	0	12	21
531190	0	0	2	0	2	4
531210	4	0	0	0	3	7
531311	0	0	1	0	2	3
531390	0	0	2	1	0	3
532120	1	0	0	0	0	1
532292	1	0	0	0	1	2
532299	0	0	0	0	1	1
533110	0	0	0	0	1	1
Total	**15**	**6**	**19**	**5**	**226**	**271**

From the two tables, it’s likely that Sector 531110 and 522110 are mostly vacation homes, which is supported by the fact that the vast majority are owned by sole proprietors. Galveston Island in particular has a large number of seasonal properties. These businesses were excluded from this research because they are a unique type of business and do not behave like other for-profit businesses. Also, owners of commercial properties—from whom another business might rent space—received SBA loans and are represented by Sector 531120 and 531190. These were excluded because of the ambiguity in assigning these types of businesses a status like “open” or “closed”—this would not be measuring the function of the business, but likely the restoration of the structure since the damaged property address is the rental property, which I believe makes it incompatible with the rest of the observations and intention of the analysis. Real estate brokers and agents were included in the analysis, so the sector is represented; the cells highlighted in Table 4 all remained eligible for analysis and were not excluded. Lastly, businesses that were listed as nonprofits in their organization structure (n=34) were excluded from the analysis as this research is concerned with for-profit businesses. The final count of eligible businesses in the dataset was 262. These businesses make up the treated business dataset, the method for which will be described in Section 4.3.1.

These treated businesses will then be matched with control businesses (see Section 4.3.2.1). This requires a database of the business population in Galveston County at the individual business level. Two frequently-used databases are ReferenceUSA and Dun & Bradstreet. ReferenceUSA is a database provided by InfoGroup. Both databases are compiled from a large range of sources (ReferenceUSA claims 5,000 public sources and Dun & Bradstreet claims 30,000) and are continuously updated (Dun & Bradstreet; ReferenceUSA). ReferenceUSA businesses can be separated by whether or not they have ben are verified through telephone calls, and Dun & Bradstreet also advertises machine and manual quality checks (Dun & Bradstreet; ReferenceUSA). The verified dataset downloaded from the ReferenceUSA website had 11,479 businesses and the dataset purchased by Dun & Bradstreet contained 10,614 businesses. Both databases contain business information such as sales, branch status, employment, female ownership, and general contact information.

To determine which database to use, the databases were compared to the SBA database for quality, since the quality of SBA data is likely to be very high and theoretically the businesses in the SBA database should exist in both ReferenceUSA and Dun & Bradstreet databases. I matched the SBA dataset with both datasets by hand; to be considered a match, the ReferenceUSA/Dun & Bradstreet business and the SBA business required a perfect match of two of the following three items: business or owner name, damaged property address, and sector description. Of the 550 businesses, 173 could be found in the ReferenceUSA database, and 150 could be found in Dun & Bradstreet. I also checked the quality of the information. I compared employment and sector information provided to the SBA to the employment and sector information in ReferenceUSA and Dun & Bradstreet. The ReferenceUSA database was off by an average of 4.64 employees (maximum difference of 50) and Dun & Bradstreet was off by an average of 5.01 employees (maximum difference of 36). In terms of sector, ReferenceUSA matched the 6-digit NAICS code of the SBA database 46 percent of the time (70 percent when using the 2-digit sector) and Dun & Bradstreet matched 42 percent of the time (69 percent on the 2-digit sector). Although it still contains error, ReferenceUSA outperformed Dun & Bradstreet on all the metrics and was used for the control database in this research.

Information on estimated loss was also requested from the SBA, but the information was withheld. Therefore, to estimate the severity of damage, businesses needed to be assigned damage information. This research uses both surge and wind information that was spatially joined to businesses in both the treatment and control databases using GIS. The wind speed data is a shapefile that contains a high density or "mesh" of points with wind speed information provided by Bret Webb, Department of Civil Engineering, University of South Alabama. The wind field data was part of meteorological forcing information used to create a hindcast simulation of Hurricane Ike; the meteorological forcing was created by Oceanweather Inc. and obtained through the Southeastern Universities Research Association (SURA)-led U.S. Integrated Ocean

Observing System (IOOS)-funded Coastal Inundation Modeling Testbed (COMT) (Integrated Ocean Observing System; Oceanweather Inc.).

Two different data sources were used for flood depth information. The first is a shapefile of various polygons of flood depth ranges provided by Wesley Highfield, Department of Marine Sciences, Texas A&M University Galveston and developed by the Harris County Flood Control District. Extent and depth information is based on LiDAR elevation with surge data provided by the Federal Emergency Management Agency (FEMA), Louisiana State University Sea Grant, Harris County Flood Control District, Galveston County, the United States Geological Survey, the National Oceanic and Atmospheric Administration and Calcasieu Parish (Harris County Flood Control District). Business point data was intersected with the polygon to recorded flood depth range. The polygon data were in the matching and treatment-control group analysis 1) due to their natural coarsening, which lends well to the matching methodology to be described in Section 4.3.2.1, and 2) because the data are grounded in observational data and have been used in previous studies on Hurricane Ike (Xiao & Peacock, 2014). However, for the analyses that use only the treated business group, I use the flood depth information generated by the Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) hydrodynamic models used to simulate Hurricane Ike. The simulated flood information was a raster file from which point values were taken for each business. These flood depths are highly correlated with the polygon flood depths (pairwise correlation coefficient of 0.85 ($p>.001$) and allow for more precise flood depth information without having to rely on midpoint values. This is also done at the suggestion of the data providers, since the wind data and flood data are closely related (the wind field was part of the meteorological forcing for the surge model). More detail on the relationship between the two flood variables can be found in Appendix B.

Lastly, for area characteristics, I used block group data from the 2000 U.S. Decennial Census which was spatially joined to the business. Dependent variable information—whether the business was open or closed—was gathered through primary data collection with some assistance from permit information provided by the Texas Comptroller of Public Accounts, since businesses must be registered with the state of Texas for sales tax and franchise tax purposes. This will be discussed more in the following section.

4.2.2. Primary Data and Data Collection

The major dependent variable of this study, business survival, required primary data collection. The protocol for determining the status of each business consisted of five stages: a preliminary search, phone calls, in-person visits, permit search, and confirming closure. Data collection was done between August and October of 2017.

The first stage, preliminary search, was done prior to field visits to get an initial sense of the status of each business based on an internet search. Each business was searched by name to see if there was a current website, *Google My Business Listing*, or other social media presence. The business address was also entered into *Google Maps* and examined in *Google Street View* to see if the signage matched the business information. If an online presence was found for the business, relevant information such as address and phone number was cross-checked for accuracy and to determine if a business had moved. Each business was coded based on the certainty of the information, for example a business was coded with a “1” if the status of the business could be determined without a doubt based on the online information. This was rare and only occurred in cases when a business posted on its social media within the last month and had a current website or had a statement on its website that the business had closed. A business was coded as a “2” if it seemed like the business was open or closed with a minor degree of certainty—for example had the same name on *Google Street View* in the same year and a website that did not have regularly updates, or was reported closed by Yelp or Google. Businesses coded with a “3” had statuses that were unable to be determined externally, for example some businesses could not be found on *Google Street View*, had no website, or the information seemed out of date.

Businesses coded as a “2” or “3” proceeded to the phone call stage. All business that had a record in the ReferenceUSA database had a phone number which was verified during Stage 1. If a business was not in ReferenceUSA, sometimes a phone number was available for the business. Phone calls were made to each business that had a phone number to ask whether or not the business was open and if the business answered, it was coded as a “1.” Businesses that were suspected open and had an answering machine that matched the record of the business were re-coded or remained as “2.” Businesses that had a non-working number and were suspected closed were also re-coded or coded as a “2.” Businesses that could not be reached kept their previous coding.

Businesses that remained coded as a “2” or “3” were then visited in person. The geocoded locations used to determine flood depth and wind speed were transferred to *Google MyMaps* to assist data collection as the record could be both easily navigated to as well as be updated in the field. In eight cases, the geocoding of the business was incorrect even if the address was correct and the business had not relocated. These businesses had their flood depth and wind speed updated to match the correct location. Businesses that were open when visited were coded as a “1.” If a business was not at the location, a neighboring business or the current business was asked if they knew the status of the business. In some cases, the status of the business could still not be determined by in-person visits due to safety issues, particularly when the business was home-based. Homes were not visited if there was a “No Trespassing” sign, had an unchained dog, or was an apartment building with no access. These businesses kept their original coding.

As a final method of determining the status of the business, I used the Franchise Tax (Taxable Entity) Search as well as the Sales Taxpayer Search provided by the Texas Comptroller of Public Accounts to search for the remaining businesses coded as a “2” or “3” (Texas Comptroller of Public Accounts; Texas Comptroller of Public Accounts). Once this was complete, businesses that were still coded as a “2” (e.g. they could not be found in either database) were assigned an operating status based on the most likely status of the business according to the evidence. Because there were five stages of data collection, there was usually enough evidence to indicate a likely status. In addition, the more impossible it is to find the business, the more likely the business is not in operation, as a business must have some availability or presence in order to function. Businesses still coded as a "3," which in this case meant there was no record of the business, were excluded from the analysis. There were 18 businesses still coded as "3" at the time of the analysis. Six of those eight businesses claimed money for a residential property— which they listed as a real estate property or new home construction—with the actual real estate businesses unable to be located. These most likely should have been excluded during the cleaning of the SBA data. The remaining 12 businesses simply could not be reached because no business name or number could be found aside from the applicant's own name and the house was inaccessible due to signage or safety reasons. One business requested to not be included in the study.

This research was very sensitive in declaring a true business closure. To ensure data quality, the final step in the data collection process was to verify closure status both to make sure the business had not simply moved, as well as try to reduce survivor bias in this research since open businesses are easier to determine (Schrank, Marshall, Hall-Phillips, Wiatt, & Jones, 2013). Closed businesses were searched for the Sales Taxpayer Search, the Taxable Entity Search, and in the 2017 ReferenceUSA database. The Sales Taxpayer Search and ReferenceUSA indicate whether a business has moved or re-opened in a new location, which was recorded as part of the data collection. Every business that was coded as had their evidence reviewed again as well as had an additional internet search done to ensure the data was accurate. This process resulted in an additional variable of whether a business moved, whether the business moved within or outside its original city, and whether it downsized or moved all operations to an existing location.[1]

Lastly, during data collection, adjustment needed to be made at various points due to the error in the ReferenceUSA database. When cleaning the matched businesses, 18 controls needed to be substituted for another business due to having no physical address even though there were coordinates attached to the business (n=3), not being an eligible business such as vending machines, ATM’s, etc. (n=5), or repeat observations (n=10). During data collection, an additional 11 controls were replaced with substitutes due to not having existing during Hurricane Ike but were still in the 2008 database. To substitute controls, businesses in the same strata were randomly selected, mirroring the original matching strategy. Three ineligible controls did not have any other businesses in their strata, resulting in three matched pairs being excluded from the analysis.

4.3. Analytical Methods

I employ a variety of analytical methods to answer the research questions. Specific estimation details such as variable choice and specific equations for each model will be presented in Chapter 5 in concurrence with the model results. However, this section will present a broader summary of the analysis techniques used in this research.

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[1] Example coding decisions include: bought out (coded as closed), single owners like realtors or hair salons now practicing as part of a group (coded as open, but downsized)

4.3.1. Research Question 1: Treatment Group Analyses

Many of the research questions can be analyzed using on the treatment sample of businesses. Research Question 1, how the SBA functions from the perspective of both the provider and the receiver of loans, utilizes descriptive statistics to see how businesses that are approved for loans differ from the general business populations. The specific sub-questions utilize linear regression and logistic regression to look at what determines loan amount (Research Question 1.1) and which businesses chose to accept the loan (Research Question 1.2), respectively. With respect to Research Question 1.1, Dahlhamer (1994) found that businesses that were likely to be eligible for commercial loans were more likely to receive SBA loans, concluding that SBA loans were approved based heavily on ability to repay. I extend this analysis to lean amount, examining whether damage or repayment ability had a stronger relationship with how much money a business was approved for. Because the dependent variable of interest is loan amount (in dollars), I propose ordinary least squares regression, which takes the general form:

$$Y=B_0+B_1X_1+B_1X_1+\ldots+B_nX_n+\varepsilon$$

Where Y represents the dependent variable, in this case loan amount, B_0 represents the intercept, B_1 represents the regression or slope coefficient for each intendent variable, X_i, and ε represents the error term. Independent variables include damage characteristics, area characteristics, business characteristics, and loan type.

Once a business is approved for a certain loan amount, the business can choose whether or not to accept the loan (i.e., the loan is disbursed to them), which is the concern of Research Question 1.2. Because this is a binary choice, I use logistic regression to predict whether a business chose to receive the loan. Using the same notation and form as the equation above, replacing Y with P to represent probability and constraining the outcome to fall between 0 and 1, the form becomes:

$$p=\frac{e^{B_0+B_1X_1+B_1X_1+\ldots+B_nX_n+\varepsilon}}{1+e^{B_0+B_1X_1+B_1X_1+\ldots+B_nX_n+\varepsilon}}$$

Or:

$$\text{logit}=\ln\left[\frac{p}{1\text{-}p}\right]= B_0+B_1X_1+B_1X_1+\ldots+B_nX_n+\varepsilon$$

4.3.2. Research Questions 2: Treatment-Control Analysis

To estimate the impact of the SBA loan program on business recovery, or Research Question 2, I will use quasi-experimental design to estimate the difference between these two groups. Because I want to estimate the effect of a specific treatment, but cannot randomly assign the treatment (businesses choose to take a loan), a quasi-experimental design is appropriate. Creating a control group of businesses that are as similar to the businesses that chose to apply for the various programs as possible reduces the selection bias. This allows the researchers to be more confident that the effects of the treatment have not been confounded by pre-treatment differences (Cook, Campbell, &

Shadish, 2002). For example, Dahlhamer and Tierney (1998) found a negative association between aid and recovery, but clarify in the discussion that those businesses that received aid were also more likely to be damaged, which may be confounding the result.

4.3.2.1. Matching

Matching is a common technique used to emulate experimental design in observational data. This is especially useful for disaster research since it’s impossible to predict when and where a disaster will be (nor can we create one). Covariates in both the treatment and control groups are matched such that the empirical distributions of the two groups are more similar (Iacus, King, & Porro, 2012). If the two groups are perfectly balanced, controlling for the covariates is no longer necessary and the difference in means is the treatment effect; approximately balanced data will still need a model to control for the covariates, but the analysis will have less statistical bias and model dependence (Ho, Imai, King, & Stuart, 2007).

There are two general classes of matching methods: Monotonic Imbalance Bounding (MIB) and equal percent bias reducing (EPBR) (King & Nielsen, 2016). Two of the most common matching methods, propensity score matching (PSM) and Mahalanobis distance matching (MDM), fall under the latter category. MDM uses a distance equation to minimize the distance between covariates (King & Nielsen, 2016; Xiao & Drucker, 2013). PSM uses logistic regression to estimate the probability of being “treated” based on the pre-treatment characteristics (covariates)—matching is then done

to treatment and control observations with similar propensity scores. Coarsened exact matching (CEM), in the Monotonic Imbalance Bounding class, allows the researcher to create coarsened "groups" of variables from which an exact match can be found.
The next natural question is which is of these methods is superior? Iacus et al. (2012) identify the major dilemma in matching methods, which is how to best achieve a balance between the treated and control groups:

> "…in many observational data sets, finding a matching solution that improves balance between the treated and control groups is easy for most covariates, but the result often leaves balance worse for some other variables at the same time. Thus, analysts are left with the nagging worry that all their ''improvements'' in applying matching may actually have increased bias and model dependence." (p.2)

To elaborate, King and Nielsen (2016) discuss the differences in methods in relation to the research designs they emulate. MDM and CEM approximate a fully blocked experimental design (treated and control groups blocked on the observed covariates) because the parameters can be adjusted to create exact matches; PSM approximates a completely randomized experimental design (random with respect to the covariates). King and Nielsen (2016) cite several sources supporting the notion that "a fully blocked randomized experimental design has more power, more efficiency, lower research costs, more robustness, less imbalance, and — most importantly from the perspective here — lower model dependence and thus less bias" (p. 12). The logic then transfers to strategies such as MDM and CEM versus PSM (King & Nielsen, 2016).

The authors then use both simulations and tests of published data to examine the effects of each matching technique on reducing imbalance. In the first simulation, the authors examined whether MDM and PSM pruned in the "correct order" (i.e. starting from the highest level of imbalance to the lowest) and if they could distinguish between randomized experimental observations and a matched pair randomized experiment—PSM could not recover the matched pair experiment although MDM could (p. 15). Secondly, the authors examine the effect of continued matching which showed that MDM continued to reduce model dependence whereas PSM eventually began to introduce more model dependence (p. 20) because it attempts to match globally instead of locally. This is further supported when using data from previously published studies: as more data is pruned (i.e., the worst score matches are dropped), CEM and MDM trend downward, whereas PSM trends upwards (King & Nielsen, 2016).

There are several conclusions from this analysis. First, is that bias can be minimized through any three of these methods if done correctly. Propensity score is efficient up to the point when randomization is approximated (p. 20). Secondly, propensity score can be done through several matching algorithms (Caliendo & Kopeinig, 2008) and the analysis done by King and Nielsen (2016) was done using a specific type of propensity score matching (i.e. one-to-one greedy matching). However, the authors believe the issues with propensity score matching will arise regardless of technique (King & Nielsen, 2016, p. 11). The benefits of MDM and CEM are that they can emulate an arguably superior experimental design (blocked) and will improve with continued pruning; CEM, specifically, can specify a desired level of imbalanced ex-ante. Regardless of matching technique, the most important take-away is the importance of testing and report covariate imbalance before and after matching to ensure that bias and model dependence are being reduced—a simple t-test will be insufficient (Iacus et al., 2012). These matching techniques and covariate imbalance reports can all be done through STATA, which is the primary analytic software used in this research (King, Blackwell, Iacus, & Porro, 2010; Leuven & Sianesi).

For this research, I will match using CEM to achieve a quasi-experimental design. Using CEM matching will allow me to control for selection bias and reduce model dependence by minimizing covariate imbalance (King & Nielsen, 2016). Many of my variables of interest are categorical which lend themselves well to a stratification approach. Additionally, there is some error in the database that will be used to find the controls, so having coarsened parameters will allow for the range of error to be included in the matching process.

As mentioned, CEM is characterized by temporarily "coarsening" data so exact matches can be found (for example, instead of exact number of employees, matching on categories such as 0-5, 5-10, 10-20, etc.). Strata are created that include the same coarsened values of the variables of interest. If there are more treated units than controls within a stratum or vice versa, a weight is assigned to balance the sample (however, to make the data more manageable I will be matching one-to-one). Those strata that don't include at least one control and one treatment observation will be dropped (assigned a weight of zero).

As discussed in Section 2.1, two studies looked at the factors influencing whether a business applied for and received an SBA loan (Dahlhamer, 1994; Josephson & Marshall, 2016). Table 6 summarizes these variables and whether or not they were able to be controlled for in this research through matching:

Table 6 Variables Affecting Whether or Not a Business Applies for and Receives an SBA Loan

Variable		Outcome: Source[1]	Controlled for through matching[2]	Notes
Damage and location	Location	Applied for a loan: - Received a loan: D	S	Damage limits the location of matches, but this research does not include a spatial variable
	Damage	Applied for a loan: JM Received a loan: JM	Y	Flood depth categories
	Coastal	Applied for a loan: JM Received a loan: -	S	This research controls for flooding which primarily occurred near the coast, but a coastal-specific variable was not included
Owner characteristics	Age	Applied for a loan: - Received a loan: D	N	Not provided at owner level
	Gender	Applied for a loan: JM Received a loan: JM	Y	This is provided by ReferenceUSA
	Income	Applied for a loan: JM Received a loan: JM	S	Not provided at owner level, but this research has at least one financial variable
	Education	Applied for a loan: - Received a loan: JM	N	Not provided at owner level
	Stress	Applied for a loan: JM Received a loan: -	N	Not provided at owner level
	Race	Applied for a loan: - Received a loan: JM	N	Not provided at owner level
Business characteristics	Home-based business	Applied for a loan: JM Received a loan: -	Y	This is provided by ReferenceUSA
	Revenue	Applied for a loan: JM Received a loan: JM	S	Business sales volumes are provided by ReferenceUSA
	Number of employees	Applied for a loan: - Received a loan: JM	Y	This is provided by ReferenceUSA and the SBA data
	Years in operation	Applied for a loan: - Received a loan: D, JM	N	This is provided in the SBA data, but mostly missing in the ReferenceUSA data (not reliable)
	Owned (vs. rented)	Applied for a loan: - Received a loan: D	S	This research only controls for whether the business is a franchise

Table 6 (continued)

Variable		Outcome: Source[1]	Controlled for through matching[2]	Notes
Other financial characteristics	Credit available elsewhere	Applied for a loan: - Received a loan: D	S	This research controls for branches, which may have additional sources of assistance and resources
	Insurance	Applied for a loan: JM Received a loan: JM	N	Not provided; this information was requested from FEMA in 2016 but is still being processed/gathered

[1]D= Dalhhamer (1994), JM= Josephson & Marshall (2016)
[2]Y=Yes, N=No, S=Somewhat

Also shown in Table 6, this research is able to match businesses on damage, business characteristics, and some owner and financial characteristics. This controls for many of the variables influencing whether or not a business applies for or receives an SBA loan. This research, because it relies on secondary data for matching, does not have detailed information on owner or manager demographics. However, those owner characteristics that were most important (i.e. significant predictors of both application and loan receipt) were at least partially controlled for. I also match on business sector to try and capture some of the missing variability between businesses. Although I don't have a good measure for repayment ability, employment size is a good indication of a business' financial situation. Combined with the business sector, it can serve as a good measure of where the business is amongst its peers as this will match the business to a similar-sized business.

For the mechanics of the matching, I sector was coarsened to two-digit NAICS codes; flood depth was coarsened to no damage, less than two feet, between two and six feet. and over six feet, which is slightly more coarse than the categories already in the data (Harris County Flood Control District); wind speed was coarsened to the damage categories in the Beaufort Wind Scale; and employment was coarsened to less than five employees, 5-10 employees, 10-25 employees, 25-50 employees, 50-100 employees, and over 100 employees. Employment was coarsened to at least groups of five because applicant-reported employment numbers and ReferenceUSA-reported employment numbers were off by an average of 4.64 people. Sales was coarsened to less than $500K, between $500K and $1mil., between $1mil. and $2.5mil, between $2.5mil. and 5mil., between $5mil. and $10mil., between $10mil. and $20mil. and over $20mil. Lastly, businesses were exact matched on branch status, female ownership or management, and home business status.

Deciding on the levels of coarsening was done either on a theoretical basis (e.g., wind speed), due to error in the data source (e.g. employment), or by existing data groupings (e.g. flood depth and sales), and decisions on variable inclusion in the matching process was made based on the literature. However, it could be argued that decisions on which matching variables and how to coarsen them can be subjective and can introduce bias. Therefore, I have presented a sensitivity analysis, or a more quantitative approach to deciding on which variables and coarsening to use, in Appendix C.

4.3.2.2. Matched analysis

Matched case-control samples violate the assumption of a simple random sample, as the probability of selecting one case is not independent of the selection (or not selection) of any other case (Menard & Menard, 2010). Therefore, the assumptions for simple logistic regression are also violated. One way to address this issue would be to create a dummy variable for each of the strata generated by the matching process (Menard & Menard, 2010; Pearce, 2016). However, this becomes an issue when strata are small (e.g., one case and one control for each stratum), known as a sparse data problem. The number of parameters increases at the same, or similar, rate as the sample size (Hosmer Jr, Lemeshow, & Sturdivant, 2013). For this research, for example, there are 109 strata which would require 108 dummy variables for only 282 observations. A more efficient approach, if not a required approach, is to use conditional logistic regression (Pearce, 2016). Conditional logistics regression groups data by strata and calculates the likelihood relative to each group (i.e., uses a conditional likelihood) and is often used in case-control studies (Pearce, 2016). Hosmer Jr et al. (2013) provide a derivation of the conditional likelihood. However, recently, Kuo, Duan, and Grady (2018) examined the differences between unconditional and conditional logistic regression models in case-control data. Their paper offers a more functional form of the two models citing Hosmer Jr et al. (2013) which I reprint here. The unconditional model is represented by:

$$\text{logit}(\pi)=\beta_0+\beta_e x_e+\beta_m^K x_m+\beta_o^K x_o, \quad \text{(Kuo et al., 2018, Eq.1)}$$

Where π represents the probability, an example in this research being the probability of survival. $\boldsymbol{X}_m = \{\boldsymbol{X}_{m1}, \boldsymbol{X}_{m2}\}$ is a vector of matching variables—variables in $\boldsymbol{X}_{m1}$ are exactly matched and variables in $\boldsymbol{X}_{m2}$ are interval matched—and X_o is a vector of unmatched variables to include in the model (Kuo et al., 2018). For this research, $\boldsymbol{X}_{m1}$ might represent whether the business is female-owned, a home business, or a branch, $\boldsymbol{X}_{m2}$ might represent number of employees, sales, and damage information, and X_o might represent area characteristics (census variables). X_e is an exposure variable indicating case-control status (in this research, whether or not the business received an SBA loan) with S being the id of matching sets; $s = i$ for subjects in the ith matching set for $i = 1, 2, \ldots, n$ (Kuo et al., 2018). The β's, as conventionally defined, are the regression coefficients. The conditional model is represented by:

$$\text{logit}(\pi)=\beta_{0i}+\beta_e x_e+\beta_{m2}^{K} x_{m2}+\beta_o^{K} x_o, \quad \text{(Kuo et al., 2018, Eq.2)}$$

Where β_{oi} denotes the contribution to the logit of all terms constant within the ith matching set (Kuo et al., 2018). In line with the examples provided by Hosmer Jr et al. (2013), I use the STATA command CLOGIT to estimate the matched analysis (conditional logistic regression).

Although the matching process is primarily designed to put businesses into treatment and control groups based on SBA loan status, this matching can also be used to provide evidence for whether moving affects survival since this data was collected. However, moving will be used as an independent variable (X_o) rather than the basis for matching. For this research design, the matching is done prior to data collection, which determines whether the business moved and where. However, this should not be an issue for several reasons. The first is that the matching technique in its essence, is matching businesses based on potential access to resources, thereby controlling for resource access through research design rather than purely in the regression. Adding the moving variable, therefore, is effectively answering whether moving is a significant predictor or survival controlling for SBA loan status and access to resources. This makes sense considering that moving likely does require access to resources. Moving might entail establishing or solidifying a new customer base, which would require marketing resources, or updating or constructing the building or machinery needed for operation on top of the expenses and opportunity costs related to the process of moving.

Existing research on business mobility after disasters is relatively sparse but supports the matching variable choice used in this research. Siodla (2014) looked at firm relocations after the 1906 San Fernando earthquake and found that damage and sector were important factors in the almost ten-year timespan of their analysis. Although technology has changed the way firms chose their locations since 1906, it seems reasonable to believe that these decisions will still vary by industry. Wasileski, Rodríguez, and Diaz (2011) looked at post-disaster firm relocations after both the Loma Prieta earthquake and Hurricane Andrew several years after the event and confirmed the importance of sector in whether a business moved. In addition to sector, significant variables included building construction type, whether the property was owned, business financial condition, and damage. This study can control for financial condition and damage. Building construction, in the study conducted by Wasileski et al. (2011) relates to structural vulnerability which may be captured by the damage and exposure variables; ownership of the property is unfortunately unavailable in the data sources for this research but highlights the importance of controlling for resource access and financial condition.

4.4. Data Validity and Reliability

This section concludes Chapter 4 with a discussion on threats to the reliability and validity of the study through the sample and matching process.

One potential impact on data quality is the incomplete matching when answering Research Question 2 and Research Question 3, since not all 262 businesses could be matched with a control, as well as the substitutions and additional exclusions made during the data collection process. First, as discussed in Section 4.3.1., matching aims to reduce the differences between covariates, or covariate imbalance in order to reduce bias (King & Nielsen, 2016). Concern with existing matching methods can arise if imbalance reduction is not recorded or reported, particularly when finding a matching solution may potentially reduce imbalance in some variables while increasing it in others (Stefano Maria Iacus, King, & Porro, 2008). I examine the covariate imbalance before and after matching using the imbalance measure defined by Stefano Maria Iacus et al. (2008). In this measure, variables are discretized (no change to categorical variables and automated univariate histogram method for continuous variables) and cross-tabulated ($X_1 \times \cdots \times X_k$) for the treatment and control groups; the k-dimensional relative frequency is recorded and the imbalance measure is the absolute difference across all cell values, similar to L1 distance (Iacus et al., 2008, Eq. 5). The imbalance prior to matching in our sample is presented in Table 7.

Table 7 Imbalance Before Matching.

Multivariate L_1 distance: 0.88
Univariate imbalance:

	L_1	Mean	Min.	25%	50%	75%	Max.
Flood depth	3.22	0.00	3.00	5.00	2.00	0.00	3.22
Wind speed	4.69	0.00	1.45	2.85	5.82	-1.57	4.69
Number of employees	-2.88	1.00	0.00	1.00	1.00	-1530.00	-2.88
Sales ($100,000)	-6.2	0.55	1.3	0.71	2.2	-13000	-6.2
2-digit NAICS	-2.51	11.00	0.00	0.00	0.00	-18.00	-2.51
Female-owned or managed	-0.05	0.00	0.00	0.00	0.00	0.00	-0.05
Home business	-0.05	0.00	0.00	0.00	0.00	0.00	-0.05
Branch	0.10	0.00	0.00	0.00	0.00	0.00	0.10

The imbalance after matching is presented in Table 8:

Table 8 Imbalance After Matching.

Multivariate L_1 distance: 0.59
Univariate imbalance:

	L_1	Mean	Min.	25%	50%	75%	Max.
Flood depth	0.05	0.18	0.00	2.00	0.00	0.00	0.00
Wind speed	0.10	0.20	0.00	0.95	0.81	0.37	-0.13
Number of employees	0.03	-0.24	0.00	0.00	0.00	0.00	-10.00
Sales ($100,000)	-0.05	0.00	0.00	0.56	-0.24	-5.00	-0.05
2-digit NAICS	0.01	0.07	0.00	0.00	0.00	0.00	0.00
Female-owned or managed	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Home business	0.01	-0.01	0.00	0.00	0.00	0.00	0.00
Branch	0.00	0.00	0.00	0.00	0.00	0.00	0.00

As illustrated by the tables, the multivariate imbalance was reduced to 0.59 from 0.88 and all univariate distances were reduced, indicating that the matching procedure was successful. Additionally, the imbalance reduction was not uneven and at the expense of some covariates over others which may have been a concern for other matching techniques.

I also examine the differences between the treated businesses that were able to be matched, the overlap with ReferenceUSA, and the original 262 treated businesses in terms of sector distribution in Table 9:

Table 9 Matching Success: Matched Sample vs. Eligible SBA Sample by Sector.

		Original sample		**Overlap with RUSA**		**Matched sample**		**Dif.**		
Super Sector	**Description**	Obs.	%	Obs.	%	Obs.	%	Original-RUSA	Original-Match	Match-RUSA
11	Logging	9	3.44	2	1.22	1	0.71	-2.22	-2.72	-0.51
21	Mining	2	0.76	1	0.61	0	0.00	-0.15	-0.76	-0.61
22	Utilities	0	0.00	0	0.00	0	0.00	0.00	0.00	0.00
23	Construction	28	10.69	13	7.93	9	6.43	**-2.76**	**-4.26**	-1.50
31-33	Manufacturing	10	3.82	6	3.66	6	4.29	-0.16	0.47	0.63
42	Wholesale	5	1.91	5	3.05	2	1.43	1.14	-0.48	-1.62
44-45	Retail	48	18.32	37	22.56	34	24.29	**4.24**	**5.97**	1.72
48-49	Transportation/ warehousing	7	2.67	4	2.44	4	2.86	-0.23	0.19	0.42
51	Information	1	0.38	0	0.00	0	0.00	-0.38	-0.38	0.00
52	Finance/insurance	7	2.67	5	3.05	4	2.86	0.38	0.19	-0.19
53	Real estate/rental	17	6.49	5	3.05	3	2.14	**-3.44**	**-4.35**	-0.91
54	Professional, Scientific, and Technical Services	30	11.45	18	10.98	16	11.43	-0.47	-0.02	0.45
55	Management	1	0.38	1	0.61	0	0.00	0.23	-0.38	-0.61
56	Administration	7	2.67	4	2.44	2	1.43	-0.23	-1.24	-1.01
61	Educational services	1	0.38	1	0.61	1	0.71	0.23	0.33	0.10
62	Health care and social assistance	19	7.25	14	8.54	14	10.00	1.28	2.75	1.46
71	Leisure and Hospitality	11	4.20	5	3.05	5	3.57	-1.15	-0.63	0.52
72	Accommodation and Food Services	32	12.21	24	14.63	24	17.14	**2.42**	**4.93**	2.51
81	Other services	27	10.31	19	11.59	15	10.71	1.28	0.41	-0.87
	Total	**262**	**100**	**164**	**100**	**140**	**100**	**-**	**-**	**-**

In terms, of sector, the treated businesses that were both able to matched and exist in the ReferenceUSA were underrepresented in the real estate businesses and construction sectors, and overrepresented in the retail and accommodation/food service sectors. However, this is due to the overlap error in the ReferenceUSA data as opposed to the matching methodology. I believe this will not affect study quality since this research is more concerned with between-match variance as opposed to overall variance, as well as the fact that there is still representation within those sectors. I also present the difference in the continuous variable distribution in Table 10:

Table 10 Matching Success: Matched Sample vs. Eligible SBA Sample by Continuous Variables.

	Original sample		**Overlap with RUSA**		**Matched sample**		**One sample t-test**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	t	p
# of Employees	6.8	10.7	8.5	11.8	8.0	11.8	-0.46	0.65
Flood Depth (midpoint, ft.)	5.6	3.8	5.2	3.6	5.1	3.6	-0.30	0.77
Average windspeed (m/s/s)	25.4	7.8	25.2	7.4	25.1	7.0	-1.35	0.18
Sales	N/A	N/A	1187.9	1790.1	1008.6	1664.2	-1.28	0.20
	n=262		n=164		n=140			

When comparing the mean of the sample to the treated business population mean, there is no significant difference.

5. RESULTS

This chapter discusses the results of the analyses.

5.1. Which Businesses Benefit from the SBA Loan Program?

The first analysis looks at how the SBA loan program functioned in Galveston after 2008 Hurricane Ike in terms of participation. According to a report to the U.S. Congress, around 22 percent of businesses that applied for an SBA loan after Hurricane Ike were approved. Approval rates for SBA business loans ranged between 20 and 50 percent for similar Hurricane during that time, with Hurricane Katrina's approval rate landing at around 45 percent, Hurricane Irene around 26 percent, and Hurricane Sandy around 24 percent (Velázquez, 2013). According to the data in this research, 550 businesses (including non-profits) were approved for either a physical disaster loan or an economic injury loan; 1,042 were denied, yielding an approval rate of closer to 35 percent. However, excluding nonprofits (n=34) and vacation homes (n=229), the approval rate does end up being around 22 percent. A map flooded businesses based on the ReferenceUSA data and flood depth from the Harris County Flood Control District is presented in Figure 7. A map of SBA-approved businesses is then overlaid on the business population of Galveston County in Figure 8.

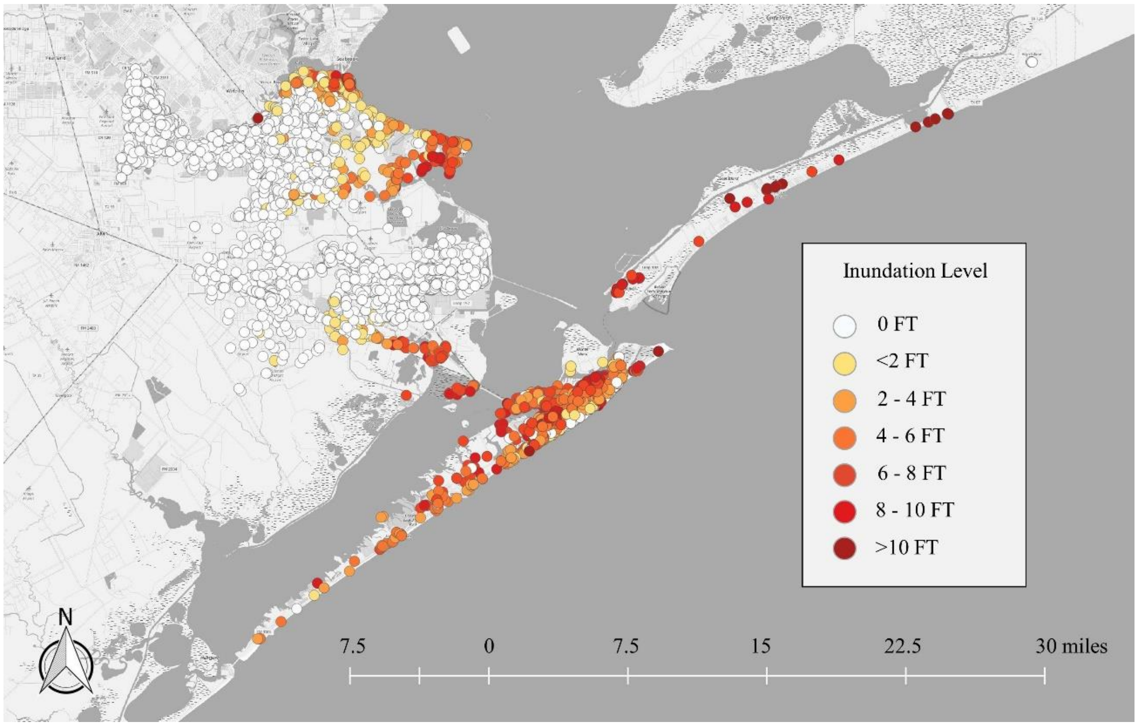

Figure 7 Businesses in Galveston County by Flood Depth.

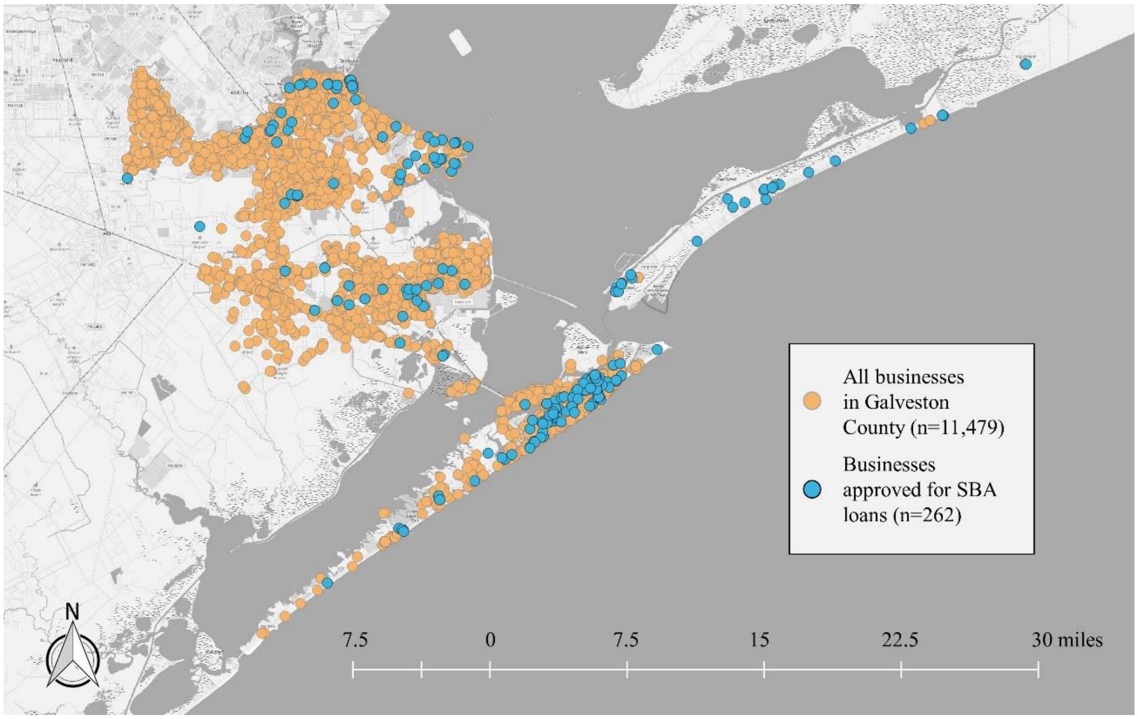

Figure 8 All Businesses in Galveston County and SBA-Approved Businesses.

As illustrated by the maps, there is not a clear, discernable geographic pattern to businesses that were approved for an SBA loan, though it does appear that SBA-approved businesses tend to be in flooded areas. This, of course, makes sense. A comparison of businesses that were approved for SBA loans to the Galveston business population and Hurricane Ike-flooded businesses is looked at in more depth in Appendix D.

For the remainder of the descriptive statistics, I use the sample selected for this study as detailed in Section 4.2.1 (nonprofits, vacation homes, businesses outside of Galveston, and other businesses whose status relates more to the restoration of the structure as opposed to the functionality of a business excluded, n=262 remaining). A map of these businesses is presented in Figure 9. Businesses that are colored light green were approved for a loan but did not accept the loan, whereas those businesses with a darker green coloration chose to have loans disbursed. The pattern is not visually clear, motivating the need for regression analysis on which businesses chose disbursement.

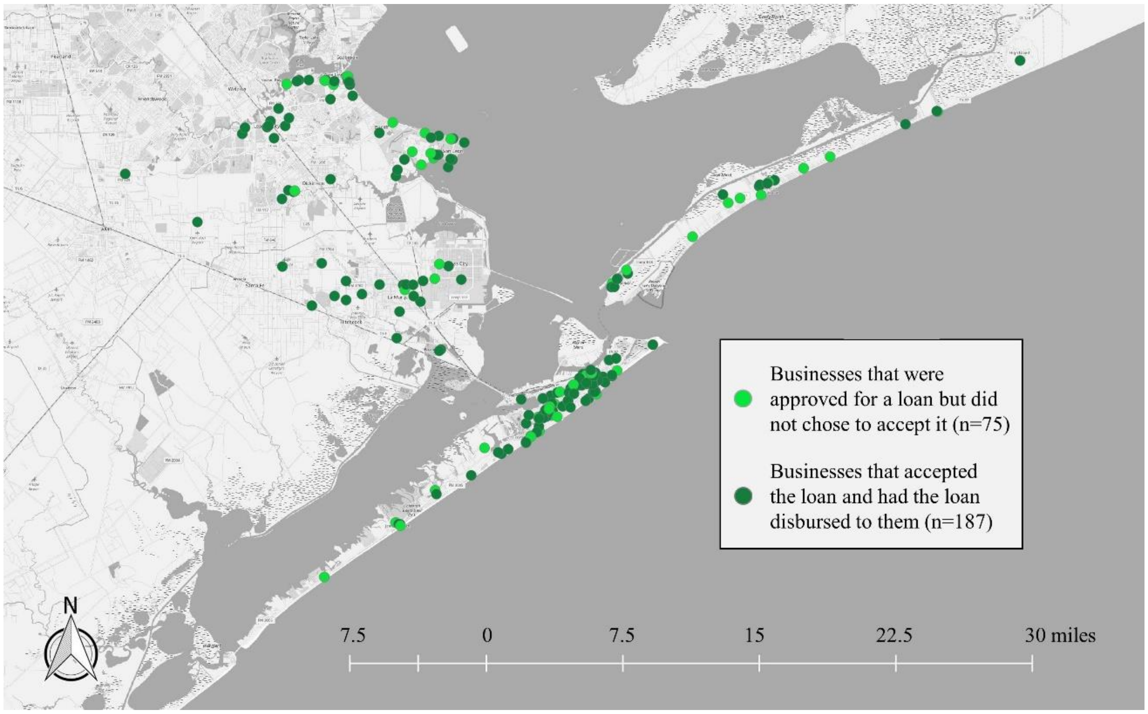

Figure 9 Sample of Businesses Approved for SBA Loans by Disbursement Decision.

Additional descriptive statistics relating to the types of businesses that were approved for SBA loans, and the characteristics of the loans they were approved for, are presented in Tables 11 and 12, below:

Table 11 SBA Descriptive Statistics: Continuous Variables.

Variable	Label	Obs.	Mean	Std. Dev.	Min	Max
Loan Term (years)	loanterm	262	17.7	10.4	0.8	30.0
Approved Loan Amount ($1000)	amount	262	142.9	188.7	0.7	1252.6
Amount Disbursed ($1000)	disb_amount	187	128.1	211.3	1.4	2000.0
Percent disbursed of approved	per_disburse	187	95.6	55.3	3.2	492.4
Applicant Delay (days after Ike loan accepted)	appdelay	262	88.9	81.0	11.0	479.0
SBA Delay (days between loan accepted and approved)	sbadelay1	262	26.4	15.6	2.0	108.0
SBA Delay 2 (days between loan approved and disbursed	sbadelay2	186	59.2	75.7	7.0	607.0
Total time to approval	delaytotalapp	262	115.2	82.2	25.0	537.0
Total time to disbursal	delaytotaldisb	186	176.2	120.5	42.0	781.0
Under Current Management (years before Ike)	management	254	10.7	8.7	0.0	41.7
Age of business (years established before Ike)	age	255	14.0	13.9	0.0	106.8
Number of employees	size	262	6.8	10.7	0.0	60.0
Flood depth (ft.)	flood_dmg	262	5.3	3.5	0.0	17.4
Average maximum wind speed (m/s)	wind_dmg	262	25.4	7.8	0.0	40.6
Density (1000 people/mi^2)	density	262	3.2	3.1	0.0	11.3
Median household income ($1000)	income	262	35.0	14.6	9.7	80.6

Table 12 SBA Descriptive Statistics: Categorical Variables.

Variable		Label	n	%
Loan Type	Physical	phys_dummy	244	93%
	Economic Injury	eidl_dummy	18	7%
Organization Type	Corporation	corp_dummy	116	43%
	Limited Partnership	lp_dummy	6	2%
	LLC, LLP, OR LLE	llc_dummy	33	12%
	Partnership	part_dummy	2	1%
	Sole Proprietorship/ Individual	sole_dummy	105	39%
Home Business	Yes	homebusiness	71	27%
Business had money disbursed	Yes	disburse	187	71%
Sector	Manufacturing or Construction	man_const	38	15%
	Retail or Wholesale	retail	53	20%
Interest rate	4%	4per	256	98%
	8%	8per	6	2%

Businesses that received a loan were an average of 14 years old with an average of seven employees. Years of current management was slightly less than the age of the business, with current management having run the business for an average of 11 years. Corporations made up 43 percent of businesses that were approved for a loan, and 39 percent were sole proprietors. The average flood depth experienced by the businesses was 5.3 feet, and the average (maximum) wind speed was 25 meters per second (or approximately 57 miles per hour).

Business loans were $143,000 on average, with a minimum of $700 and a maximum of two million. Loan terms, or amount of time the business had to pay back the loan, were an average of 17.7 years. A majority of loans (93 percent) were physical disaster loans with an interest rate of four percent (98 percent). It took an average of 89 days, or approximately three months, for businesses to get an application into the SBA. Once the application was accepted, it took an average of 26 days for the loan to be approved, and another 59 days for the money to be disbursed. Not all businesses chose to accept the loan once it was approved—only 187 of the 262 businesses that were approved for a loan actually chose to have money disbursed to them. For those 187 businesses, the entire amount of time since Hurricane Ike it took to receive money was 176 days, on average.

Using these 262 businesses, I ran two regressions. To answer what determines eligibility for SBA loans (Research Question 1.1), I examined what factors influence the amount of money approved to the business. To answer which businesses are more likely to use SBA loans in recovery (Research Question 1.2), I examined what made a business choose disbursement.

5.1.1. What Determines Loan Amount?

The first model looked at the variables driving approved loan amounts. Although I didn't have information on loan denials, I could still use loan amounts to test the motivations of the loan program. This analysis tested some of the x-axis attributes of the recovery ideal types identified in Table 2. SBA assistance takes the form of loans, so there is a balance between whether loans should be purely aid-based (loan amounts are driven by damage) or if loan amount is based purely on repayment ability. This conflict represents the state logic balancing the ideals of the community and the market. Olshansky et al. (2012, p. 176) note that post-disaster time compression affects power dynamics in that borrows relent their negotiating position in order to receive funds faster. This means we expect to see the program following the logic of the state and repayment ability being positive predictor of loan amounts. Additionally, the state views time as legitimacy so longer deliberation times on the side of the SBA are also expected to be positively related to loan amount.

The initial analysis used untransformed loan amounts as the dependent variable but the analysis had problems with non-normality in the residuals as well as heteroskedasticity. Therefore, the decision was made to use the natural log form of the loan amount variable, which improved these diagnostic issues. This process is discussed in greater detail in Appendix F. Using the natural log also has benefits in terms of interpretation and answering the research because the variables have a potentially multiplicative relationship to the dependent variable; for example, a variable that is associated with an additional $5,000 approval amount to a business with a $5,000 initial approved loan has an arguably different effect than if the businesses had a $500,000 approved loan initially. Therefore, the variable influence can now be interpreted as a percentage rather than unit increase.

For damage, I use the wind field data and flood depth information used in the ADCIRC and SWAN models for Hurricane Ike. This provides flood depth (ft.) and maximum wind speed (m/s) experienced by the business. Business characteristics include age of the business (years), years the business has been under its current management, size of the business (number of employees), sector (specifically whether the business is a retail/wholesale business or manufacturing/construction), whether or not the damaged property is a residential property (indicating a home business), and whether the business is a corporation. Area characteristics, taken from the 2000 U.S.

Decennial Census at the block group level, include median household income ($1,000) and density (1000 people per square mile). Lastly, I include loan term (months), loan type (whether the loan was economic injury or a physical disaster loan), and approval delay (days between Hurricane Ike and application approved by the SBA) as loan characteristic variables. The descriptive statistics and variable labels are provided in Tables 11 and 12. The full OLS regression, therefore, takes the form:

$$\begin{aligned}\ln(\text{loanamount}) = {} & \beta_1 + \beta_2\text{flood\_dmg} + \beta_3\text{wind\_dmg} + \beta_4\text{management} + \beta_5\text{age} \\ & + \beta_6\text{man\_const} + \beta_7\text{retail} + \beta_8\text{size} + \beta_9\text{homebusiness} \\ & + \beta_{10}\text{corp\_dummy} + \beta_{11}\text{density} + \beta_{12}\text{income} + \beta_{13}\text{loanterm} \\ & + \beta_{14}\text{eidl\_dummy} + \beta_{15}\text{appdelay} + \beta_{16}\text{sbadelay1}\end{aligned}$$

In addition to testing the specific hypotheses, I can also look at which variable categories have the most explanatory power in the models when it comes to predicting loan amounts. This can also shed light on whether the SBA loan program leans more towards the market, where loans would resemble private loans, or towards the community, where loans would more closely resemble philanthropic assistance. If the former, one might expect business characteristics or repayment ability to explain the most variance, if the latter, damage might play a larger role.

The results of the regression analyses are presented in Tables 13 and 14. Models 1-4 present loan amounts as a function of damage, business characteristics, area characteristics, and loan characteristics, shown in Table 13. Model 5 is shown in Table 14 and is the full model with all variables included. I present the coefficients, the X-standardized coefficients, the standard error, and the p-value of the one-tailed test.

Table 13 Loan Amounts as a Function of the Various Variable Categories.

	Model 1			Model 2			Model 3			Model 4		
Variable	Coef.	S.E.	p-value	Coef.	S.E.	p-value	Coef.	S.E.	p-value	Coef.	S.E.	p-value
Constant	4.083	0.280	0.000	3.874	0.151	0.000	5.158	0.256	0.000	2.620	0.183	0.000
Damage												
Flood depth (ft.)	0.041	0.028	0.073 *									
Average maximum wind speed (m/s)	-0.003	0.013	0.407									
Business Characteristics												
Age (years)				0.016	0.007	0.007 **						
Length of current management (years)				-0.006	0.010	0.295						
Number of employees				0.027	0.007	0.000 ***						
Retail business				0.204	0.185	0.135						
Manufacturing/Construction business				0.179	0.201	0.187						
Home business				-0.978	0.170	0.000 ***						
Corporation				0.436	0.152	0.003 **						
Area Characteristics												
Density (1000 people/mi^2)							-0.036	0.028	0.099 *			
Median household income ($1000)							-0.024	0.006	0.000 ***			
Loan Characteristics												
Loan Term (years)										0.050	0.007	0.000 ***
Economic injury loan										-0.194	0.272	0.239
Applicant Delay										0.003	0.001	0.001 ***
SBA Approval Delay										0.018	0.005	0.000 ***
F	1.30 (p-value 0.275)			17.24 (p-value 0.000)			8.42 (p-value 0.000)			25.31 (p-value 0.000)		
Root MSE	1.329			1.111			1.299			1.136		
R-Squared	0.010			0.329			0.061			0.279		
Adjusted R-Squared	0.002			0.310			0.054			0.268		
N	266			254			262			267		

Coef.=Beta coefficient; S.E.=Standard error; p=value represents 1-tailed test

* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

Table 14 Full Model Predicting Loan Amounts.

	Model 5				
Variable	Coef.	Coef.*	S.E.	p-value	
Constant	3.258	-	0.389	0.000	
Damage					
Flood depth (ft.)	0.038	0.130	0.026	0.069	*
Average maximum wind speed (m/s)	-0.002	-0.014	0.010	0.431	
Business Characteristics					
Age (years)	0.016	0.231	0.006	0.004	**
Length of current management (years)	-0.006	-0.052	0.010	0.273	
Number of employees	0.019	0.198	0.007	0.005	**
Retail business	0.075	0.030	0.178	0.338	
Manufacturing/Construction business	0.075	0.027	0.191	0.348	
Home business	-0.811	-0.367	0.164	0.000	***
Corporation	0.300	0.149	0.149	0.023	**
Area Characteristics					
Density (1000 people/mi^2)	-0.041	-0.126	0.024	0.042	**
Median household income ($1000)	-0.008	-0.111	0.005	0.079	*
Loan Characteristics					
Loan Term (years)	0.036	0.374	0.007	0.000	***
Economic injury loan	-0.089	-0.023	0.276	0.373	
Applicant Delay	0.001	0.105	0.001	0.064	*
SBA Approval Delay	0.009	0.137	0.005	0.027	**
F	13.31 (p-value 0.000)				
Root MSE	1.019				
R-Squared	0.462				
Adjusted R-Squared	0.427				
N	249				

Coef.=Beta coefficient; Coef.*=Beta coefficient standardized on X;
S.E.=Standard error; p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

Model 1 looks at loan amount as a function of damage. Flood depth is a marginally significant predictor of loan amount (p<0.1), where a foot increase in flood depth is associated with a four percent increase in loan amount. As damage increases, it makes sense that more money is needed to repair and address the damages. Wind damage is insignificant, but this result is fairly unsurprising given that Hurricane Ike was primarily a flooding event. The F test suggests we cannot reject the null hypothesis that all the coefficients in the model are equal to zero, and the model only explains approximately 1 percent of the variation in loan amounts.

By contrast, Model 2 looks at loan amount as a function of business characteristics. Several business characteristics have a significant relationship with loan amount. Business that are older and larger are approved for more money, with each year the business has been established increasing loan amount by 1.6 percent ($p<0.05$) and each additional employee increasing loan amount by 2.7 percent ($p<0.001$). Home businesses were approved for 97.8 percent less money than businesses with a commercial storefront (p-value $p<0.001$) and corporations were approved for 43.6 percent more than other organizational forms ($p<0.05$). Interpreting these results, it may be that businesses that are larger, older, and accountable to stakeholders (e.g. corporations) are potentially less risky in the eyes of lender, however, without controlling for damage these variables could also be capturing higher damage costs which would to higher amounts, as well (Webb et al., 2002). Home businesses are likely to have other assistance, such as homeowner's assistance, which would decrease business loan amounts since the SBA will not duplicate benefits. In contrast to Model 1, the Model 2 is able to explain approximately 33 percent of the variation in loan amount.

Model 3 looks at loan amounts as a function of area characteristics. Both median household income and density at the block group level have a significant, negative relationship with loan amount. A $1,000 increase in median household income decreases loan amount by 2.4 percent ($p<0.001$) and each 1000 person increase per square mile leads to a 3.6 percent decrease in loan amount ($p<0.1$). These variables can indicate the level of access to resources a business might have at the individual level (median household income) and at the community level (density). The model using area characteristics can account for six percent of the variation in loan amount.

Model 4 looks at loan characteristics as a function of other loan characteristics. Loan term is highly significant<0.001) and positively related with loan amount. Each additional year the business has to pay back the loan increases loan amount by five percent. The two time-related variables are also highly significant, with each day after Ike it took for the application to be accepted leading to a 0.2 percent increase in loan amount, and each day of deliberation between accepting the application and approving the loan increasing loan amount by 1 percent. This is also unsurprising, given the value of time in state institutions. The type of loan, whether a physical disaster loan or an economic injury loan, was insignificant. Model 3 can explain close to 28 percent of the variation in loan amount.

Lastly, Model 5 is the full model. This model can explain 46 percent of the variation in loan amount. There was very little change from the smaller models to the full model in terms of which variables were significant. Flood depth is positively related with loan amount, with each additional foot of water increasing loan amount by 3.8 percent, however it is only marginally significant ($p<0.1$). Wind speed is not significant. Business age and size were positive, significant predictors of loan amount. Each additional year the business has been established increased approved loan amount by 1.6 percent ($p<0.05$) and each additional employee increased loan amount by 1.9 percent ($p<0.05$). Home businesses were approved for 81 percent less money ($p<0.001$) and corporations were approved for 30 percent more money ($p<0.05$). Years under current management and sector were insignificant. A $1,000 increase in median household income decreased loan amount by 0.8 percent ($p<0.001$) and each 1000 person increase per square mile yields a 4.1 percent decrease in loan amount ($p<0.1$). Lastly, each additional year on the term of the loan increased loan amount 3.6 percent ($p<0.001$), each additional day of applicant delay increased loan amount by 0.1 percent ($p<0.1$) and each additional day of SBA delay and deliberation increased loan amount by 0.9 percent ($p<0.05$). Loan type was again insignificant.

Looking at the evidence as a whole, one can make some observations on the strongest predictors, and get a sense of the motivations and priorities of the loan program from the side of the SBA. The theory suggests that there is a balance between whether loans should be purely aid-based (loan amounts are driven by damage) or if loan amount is based purely on repayment ability, namely the balance of the community and market logics. The model using business characteristics alone could explain 33 percent of the variation in loan amount whereas the model with only damage variables explained closer to 1 percent. This provides evidence to suggest that repayment ability may be better able to explain the variation in loan amount. It is possible, however, that without controlling for damage in Model 2, business characteristics are still indirectly capturing the magnitude of potential damage, since larger and more successful businesses potentially have more to lose in a disaster and consequently need more money (Webb et al., 2002). Therefore, I also report the X-standardized coefficients in the full model, which represent the relative magnitude of effect in relation to the other covariates (Poston Jr, 2002; Scott Long, 1997). Being a home business had the highest relative magnitude of effect, followed by loan term, business age, number of employees, and whether the business was a corporation. Four of the five variables with the highest magnitude of effect were business characteristics; flood depth was the seventh highest. This suggests that models using businesses characteristics are still better at predicting loan amount, even when controlling for the full set of variables. As a whole the evidence seems to suggests that, although meant as a form of disaster assistance, repayment ability may drive much of the decision-making in the loan program from the side of the SBA.

5.1.2. Which Businesses are More Likely to Use SBA Loans in Recovery?

The second model examines why a business ultimately chooses to participate in the SBA loan program and establish a relationship with the SBA. I hypothesized that business characteristics, such as dominant logic, might affect the likelihood that a business has a loan disbursed to them. Businesses who have remained small as they age, indicating a rejection of market pressures and a propensity to follow a community logic, may be more likely to take a loan due to disparate impacts to their resource networks. Conversely, corporations—because of their obligation to shareholders—are more likely to follow a market logic, less likely to have their resource networks disrupted, and be less likely to take a loan. In addition, the literature suggests that assistance to businesses may not be effective due to the debt burden of taking a loan in tandem with the rising expenses businesses face after a disaster. This analysis allows us to test whether loan amount and damage affects the decision of businesses to incur this debt. The model controls for area characteristics and other business and loan characteristics.

This analysis uses the same variables as the previous model, except now loan amount ($1,000, untransformed) is used as a predictor. The model, using logistic regression instead of linear regression, takes the form:

$$\begin{aligned}\text{logit(disburse)} = \; & \beta_1 + \beta_2\text{flood\_dmg} + \beta_3\text{wind\_dmg} + \beta_4\text{management} + \beta_5\text{age} \\ & + \beta_6\text{man\_const} + \beta_7\text{retail} + \beta_8\text{size} + \beta_9\text{homebusiness} \\ & + \beta_{10}\text{corp\_dummy} + \beta_{11}\text{density} + \beta_{12}\text{income} + \beta_{13}\text{loanterm} \\ & + \beta_{14}\text{eidl\_dummy} + \beta_{15}\text{appdelay} + \beta_{16}\text{sbadelay1} + \beta_{17}\text{age*size}\end{aligned}$$

The results of the logistic regression are presented in Table 15:

Table 15 Logistic Regression of Whether or not a Business Choses Disbursement.

	Model 6				
Variable	Coef.	O.R.	S.E.	p-value	
Constant	0.185	1.203	0.959	0.424	
Damage					
Flood depth (ft.)	-0.097	0.907	0.062	0.058	*
Average maximum wind speed (m/s)	0.001	1.001	0.024	0.492	
Business Characteristics					
Age of business (years)	0.032	1.033	0.020	0.059	*
Length of current management (years)	-0.022	0.978	0.025	0.188	
Number of employees	0.098	1.104	0.035	0.003	**
Retail business	1.178	3.249	0.455	0.005	**
Manufacturing/Construction business	0.802	2.230	0.486	0.050	**
Home business	0.111	1.117	0.376	0.384	
Corporation	-0.896	0.408	0.364	0.007	**
Area Characteristics					
Density (1000 people/mi^2)	0.073	1.076	0.059	0.109	
Median household income ($1000)	0.005	1.005	0.013	0.359	
Loan Characteristics					
Loan Term (years)	-0.020	0.980	0.016	0.104	
Economic injury loan	0.507	1.661	0.845	0.274	
Approved Loan Amount ($1,000)	-0.001	0.999	0.001	0.080	**
Applicant Delay	0.003	1.003	0.002	0.091	**
SBA Approval Delay	0.030	1.031	0.013	0.010	**
Variable interactions					
Age of business (years)*Number of employees	-0.002	0.998	0.001	0.006	**
$\chi 2$	31.63 (p-value 0.017)				
-2 log (L_1)	-260				
McFadden's Pseudo R-Squared	0.108				
N	249				

Coef.=Logit coefficient; O.R.=Odds ratio; S.E.=Standard error of the logit coefficient;
p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

Flood damage is negatively related to probability of disbursal. For every foot increase in flood depth, the odds of choosing disbursement fall by nine percent ($p<0.1$). Wind speed was not significant, perhaps again illustrating the nature of the hazard.

Business characteristics, in general, were significant predictors of whether or not a business chose to actually receive the loan. Older businesses and larger businesses were more likely to choose disbursal, with the odds of choosing disbursement increasing by three percent for each additional year of age ($p<0.1$) and 10 percent per one employee increase in staff ($p<0.05$). Size and age are often used as a proxy for organizational resources, so larger businesses choosing to take the loans might be capturing the idea that they are more comfortable in risking the accumulation of more debt, especially after a disaster when the future of the business is less certain. In terms of sector, retail/wholesale and manufacturing/construction businesses were both more likely than other sectors to accept the loan; being a retail/wholesale business resulted in a 224 percent increase in odds ($p<0.05$) and manufacturing/construction businesses resulted in a 123 percent increase in odds ($p<0.05$).

Loan characteristics were also significant in the model. The longer the loan term, the less likely a business was to accept the loan; odds of choosing disbursement decreasing by about 2 percent for each additional year needed for repayment. Perhaps contrary to expectation, the longer it took the business to both apply and be approved for a loan, the more likely the business was to take the loan; specifically, each additional day of applicant delay increased the odds of disbursal by 0.3 percent and each day of SBA delay increased odds of disbursement by 3.1 percent. To speculate, this may indicate that a business that waits longer to put in an application may have already made the decision to accept the loan if they were approved, since they had longer to assess their current and future business situation. A business putting in an application sooner may make the decision after the approval, or while the application is being processed. Or, lastly, it could simply indicate that the business was out of financial options by the time the loan was accepted. For SBA delay, it may simply compound the last point or indicate that more deliberation occurred. Because these variables were significant in this model as well as the model for Research Question 1.1, I made the decision to further explore which types of businesses were more likely to be delayed in Appendix E.

All of the theoretical variables from the hypotheses were also significant. Loan amount was negatively associated with the probability of disbursement. The odds of choosing to have the loan disbursed decreased by 0.1 percent for each additional $1,000 for which the business was approved. Corporations, the proxy for market businesses, had odds of choosing disbursement that were 59 percent lower than other types of businesses. The interaction between size and age, the proxy for community businesses, was also significant: smaller businesses were more likely to choose disbursal if they were older, conversely larger and older businesses were less likely to choose disbursal ($p<0.05$). This interaction is presented in Figure 10 for visual interpretation

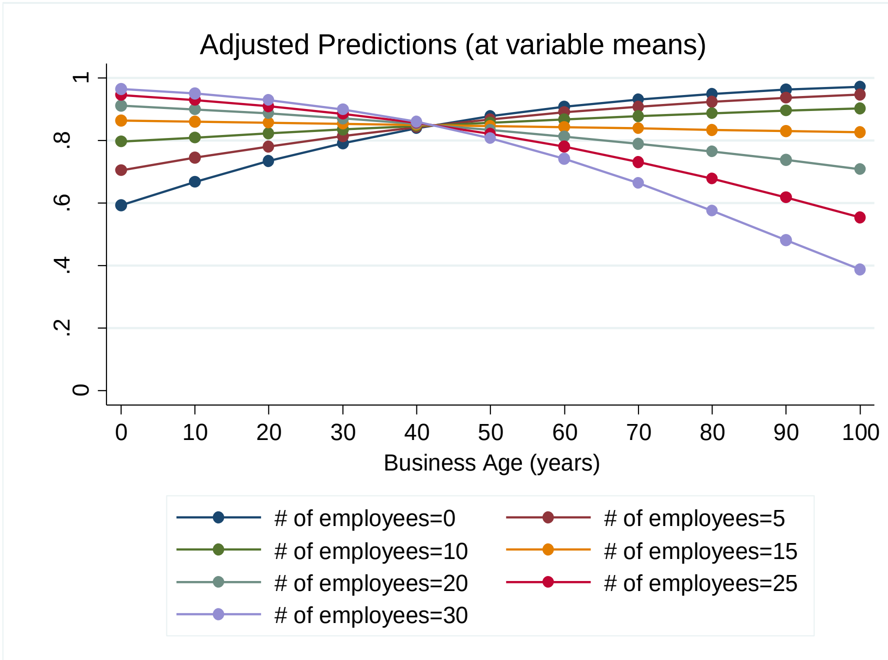

Figure 10 Adjusted Predictions for the Interaction Term in Model 6.

Lastly, I report a variety of model fit statistics, namely the sensitivity and specificity of the logistic regression in Table 16 and the receiver operating characteristics (ROC) curve in Figure 11. In general, the model correctly classifies 72.29 percent of the observations and has an area under ROC curve of 0.724. The model is more likely to predict a false positive (i.e. choosing disbursement) than a false negative.

Table 16 Sensitivity and Specificity of the Logistic Regression Predicting Disbursement.

Classified	D	~D	Total
+	171	59	230
-	10	9	19
Total	181	68	249

Classified + if predicted Pr(D) ≥ 0.5
True D defined as disbursement ≠ 0

Sensitivity	Pr(+ | D)	94.48%
Specificity	Pr(- | ~D)	13.24%
Positive predictive value	Pr(D | +)	74.35%
Negative predictive value	Pr(~D | -)	47.37%
False + rate for true ~D	Pr(+ | ~D)	86.76%
False - rate for true D	Pr(- | D)	5.52%
False + rate for classified +	Pr(~D | +)	25.65%
False - rate for classified -	Pr(D | -)	52.63%
Correctly classified		72.29%

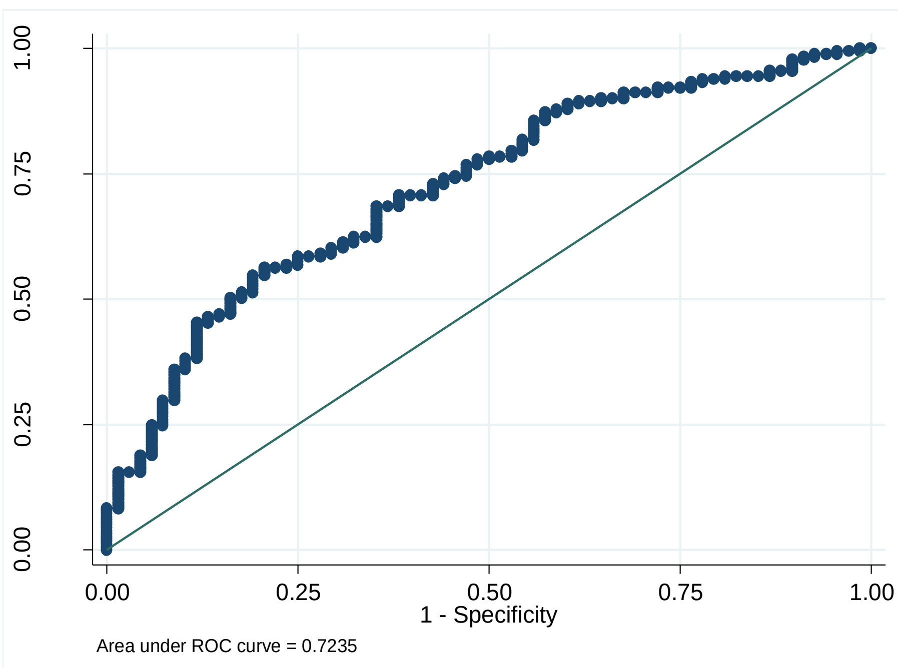

Figure 11 Receiver Operating Characteristic Curve (ROC) for Logistic Regression Predicting Disbursement.

In general, the evidence of the model suggests that businesses under different institutional logics have different likelihoods of choosing disbursement. Corporations, the proxy for organizations under a market logic, are less likely to take a loan. Referring back to Figures 1-3, Corporations are less likely to have all their resource networks destroyed in a disaster and may be able to rebuild their networks without relying on external assistance. Conversely, businesses under a community logic, for example the proxy of older businesses that have remained small (and thereby rejecting market pressures), whose networks are more likely to be disrupted, are more likely to take loans and establish a relationship with external organizations like the SBA.

There is also evidence to suggest that businesses chose to take or reject loans based on the potential debt burden. Loan amount and damage were significant, negative predictors of whether or not a business accepted the loan, which might be expected if that were the case. In addition, businesses that are well-equipped to deal with this debt also seem to have higher probabilities of taking a loan: larger businesses, older businesses, and manufacturing businesses (who likely see higher demand after a disaster) are more likely to take the loan. Retail is the only exception to this statement, with retail businesses being more likely to take a loan even though they are a traditionally vulnerable sector after a disaster (Alesch et al., 2001; Brunton, 2014; Webb et al., 2000).

5.2. Do Loans Improve Survival Probabilities in the Long Term?

The next set of analyses uses the matched case-control sample of businesses to examine whether or not receiving SBA loans and/or moving had a significant effect on business survival nine years after Hurricane Ike. As discussed in Section 4.3.2.2, this analysis requires the use of conditional logistic regression. Conditional logistics regression, as opposed to simple logistic regression, groups data by strata and calculates the likelihood relative to each group (i.e. uses a conditional likelihood) and is traditionally used in case-control studies (Pearce, 2016). The equation, reprinted from Kuo et al. (2018) takes the form of:

$$\mathrm{logit}(\pi)=\beta_{0i}+\beta_e x_e+\beta_{m2}^{K} x_{m2}+\beta_o^{K} x_o, \quad \text{(Kuo et al., 2018, Eq.2)}$$

Where π represents the probability of survival. $X_m = \{X_{m1}, X_{m2}\}$ is a vector of matching variables—variables in X_{m1} are exactly matched and variables in X_{m2} are interval matched—and X_o is a vector of unmatched variables to include in the model (Kuo et al., 2018). X_{m1} includes sector and whether the business is female-owned, a home business, or a branch, X_{m2} represents number of employees, sales, and damage information, and X_o represents the independent variables of density, median household income, and whether the business moved to a new location (excluding downsizing). Only X_{m2} is included in the conditional model because there will be no variation in X_{m1} within strata, but because I coarsened the continuous variables during matching—flood depth, wind speed, sales and employment—they must also be included as regressors

(Kuo et al., 2018). Lastly, X_e is an exposure variable indicating case–control status (in this research, whether or not the business received an SBA loan) with S being the id of matching sets; s = i for subjects in the ith matching set for i = 1, 2, …, n (Kuo et al., 2018). The β's, as conventionally defined, are the regression coefficients. Where βoi denotes the contribution to the logit of all terms constant within the ith matching set (Kuo et al., 2018).

The measurement of the independent variables follows that of the previous analysis. Density and median household income were taken from the 2000 U.S. Decennial Census at the block group level. Whether the business moved and their operating status were both collected primarily. Treatment status was designated by the SBA dataset and was broken down in further by whether the business was approved and didn't take a loan and whether a business was approved and had the loan disbursed. Employment and sales information was taken from the ReferenceUSA database. Wind data was created by Oceanweather Inc. and obtained through the SURA coastal and ocean modeling test bed study, and flood depth information was developed by the Harris County Flood Control District (Harris County Flood Control District; Integrated Ocean Observing System; Oceanweather Inc.). The strata for the matching sets was done through the CEM matching process (Section 4.3.2.1). Descriptive statistics are provided in Table 17 below:

Table 17 Descriptive Statistics for Conditional Logistic Regression.

Variable	Obs.	Mean	Std. Dev.	Min	Max
Dependent Variable					
Survived (yes=1; no=0)	280	0.66	0.47	0.0	1.0
Treatment Status					
Loan: Accepted/Not Disbursed (yes=1; no=0)	280	0.13	0.33	0.0	1.0
Loan: Accepted/Disbursed (yes=1; no=0)	280	0.38	0.48	0.0	1.0
No Loan (yes=1; no=0)	280	0.50	0.50	0.0	1.0
Damage					
Flood depth (ft.; midpoint)[1]	280	4.91	3.32	0.0	11.0
Average maximum wind speed (m/s)	280	24.96	6.81	0.0	40.0
Business Characteristics					
Number of employees	280	6.54	9.20	1.0	80.0
Sales ($1000)	280	1,008.90	1,710.82	55.0	15,616.0
Branch (yes=1; no=0)	280	0.04	0.19	0.0	1.0
Female owned or managed (yes=1; no=0)	280	0.20	0.40	0.0	1.0
Home dummy (yes=1; no=0)	280	0.07	0.25	0.0	1.0
Relocation					
Moved (yes=1; no=0)	280	0.16	0.37	0.0	1.0
Area Characteristics					
Density (1000 people/mi^2)	280	3.58	2.95	0.0	16.4
Median household income ($1000)	280	36.70	17.33	7.8	94.0

[1]Flood depth will be used as a continuous measure, see Appendix G

There were 140 groups (280 observations) with no missing data. Of the 280 businesses, 66 percent of them survived. A total of 13 percent of businesses were approved but ended up not taking the loan and 38 percent were approved and also took the money. Exactly 50 percent of the observations are controls and had no loan. Across all businesses the average flood depth was 4.9 feet, the average maximum wind speed was 24.96 m/s, the average number of employees was 7, and the average sales volume was $1,008,900. Approximately 16 percent of businesses moved to a new location. Generally, businesses were located in areas with an average of 3,580 people per square mile with an average household income of $36,700.

The results of the conditional logistic regression are presented in Table 15, below. The first model uses both treatment indicators (i.e. loan approval and loan disbursal) with their controls and the second model uses only treatment/control pairs of businesses that chose disbursement.

Table 18 Conditional Logistic Regression on Business Survival.

	Model 7					Model 8 (disbursed only)				
Variable	O.R.	Coef.	S.E.	p-value		O.R.	Coef.	S.E.	p-value	
Damage										
Flood depth (ft.)	0.920	-0.083	0.200	0.339		0.806	-0.212	0.212	0.156	
Average maximum wind speed (m/s)	1.077	0.075	0.046	0.055	*	1.043	0.041	0.050	0.197	
Business Characteristics										
Number of employees	0.934	-0.069	0.090	0.224		0.883	-0.124	0.105	0.119	
Sales volume ($1,000)	1.001	0.001	0.001	0.224		1.001	0.001	0.001	0.069	*
Treatment Status										
Loan approved but not disbursed	0.957	-0.044	0.536	0.468		-		-	-	
Loan disbursed	0.813	0.325	0.733	0.006	**	2.447	0.901	0.350	0.006	**
Area Characteristics										
Density (1000 people/mi^2)	0.901	-0.105	0.073	0.076	*	0.915	-0.088	0.080	0.134	
Median household income ($1,000)	1.012	0.012	0.013	0.172		1.012	0.013	0.015	0.216	
Adaptation										
Moved	2.805	1.032	0.529	0.026	**	3.904	1.339	0.644	0.018	**
$\chi 2$	18.88 (p-value 0.026)					18.40 (p-value 0.018)				
-2 log (L_1)	124					91.26				
McFadden's Pseudo R-Squared	0.13					0.168				
N	182[a]					144[b]				

O.R.=Odds ratio; S.E.=Standard error; p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$
[a]48 groups (98 observations) dropped because of all positive or all negative outcomes
[b]33 groups (68 observations) dropped because of all positive or all negative outcomes

In both models, having the loan disbursed was a significant, positive predictor of survival. Receiving a loan more than doubled the odds of survival. Being approved for a loan and refusing disbursement was insignificant in predicting survival. In terms of the independent variables, businesses that moved were much more likely ($p<0.05$) to survive in both models: in Model 7, odds of survival were 2.8 times higher for businesses who moved than those who didn't, and the odds were 3.9 times higher for businesses who moved in Model 8. Area characteristics were insignificant predictors in both models with the exception of density, which was marginally significant ($p<0.1$) in Model 7. Businesses in higher density areas were less likely to survive. Only a few of the continuous matching variables were significant. In Model 7, the differences in sales and wind speed within strata were marginally significant ($p<0.1$); sales and wind speeds were positively associated with survival probability. In Model 8, the sales variable is still marginally significant and a positive predictor whereas the effect of wind speed disappears. The magnitude of these effects is small due to the nature of how they were controlled for in the matching.

It is important to note that conditional logistic regression is meant to examine variability within groups, in this case our matching strata. However, if there is no variability within groups, the model has nothing to examine and it drops the observations within those groups. In the case of Model 7 and 2, 48 groups (98 observations) and 33 groups (68 observations) were dropped, respectively, due to observations all having the same dependent variable within strata. Of the 98 businesses that were excluded from Model 7, 84 of them were excluded for being all open. 14 were excluded for being all closed. Of the 68 businesses excluded from Model 8, 60 of them were excluded for being all open and only eight excluded for being all closed. To see which businesses were more likely to have the same outcome, and therefore be exclude from the analysis, I run a logistic regression to predict same outcome (open) and same outcome (closed) with different outcomes as the base category for the approved (Model 9) and disbursed

(Model 10) sets of businesses. These models are presented in Table 19. For simplicity, I report the results in terms of odds ratios.

Table 19 Logistic Regression Predicting Same Outcomes.

	Model 9					Model 10 (disbursed only)				
Variable	O.R.	O.R.*	S.E.	p-value		O.R.	O.R.*	S.E.	p-value	
Constant	0.937	-	0.049	0.088	*	0.653	-	0.883	0.377	
Damage										
Flood depth (ft.)	0.931	-21.2	0.049	0.088	*	0.940	-20.1	0.058	0.149	
Average maximum wind speed (m/s)	0.978	-14.2	0.024	0.178		0.956	-27.8	0.026	0.054	*
Business Characteristics										
Number of employees	1.031	32.7	0.019	0.050	**	1.027	32.3	0.018	0.063	*
Sales volume ($1,000)	1.000	18.0	0.000	0.168		1.000	4.8	0.000	0.406	
Branch	0.153	-29.5	0.131	0.015	**	0.192	-27.2	0.179	0.040	**
Female-owned or managed	1.397	14.3	0.495	0.173		2.331	40.3	1.021	0.023	**
Area Characteristics										
Density (1000 people/mi^2)	1.062	19.5	0.057	0.133		1.098	33.1	0.072	0.076	*
Median household income ($1,000)	1.010	18.5	0.009	0.148		1.012	24.2	0.011	0.136	
Status										
Moved	1.388	12.8	0.518	0.133		1.376	11.4	0.595	0.258	
Operating Status	4.802	110.1	1.685	0.000	***	6.454	139.3	2.929	0.000	***
$\chi 2$	51.97 (p-value 0.000)					47.18 (p-value 0.000)				
-2 log (L_1)	311					219				
McFadden's Pseudo R-Squared	0.14					0.18				
N	280					212				

O.R.=Odds ratio; O.R.*=percent change in odds standardized on X; S.E.=Standard error (O.R.);
p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

Both Models 9 and 10 show that there are variables that can significantly predict whether the group was excluded for having the same outcome. For Model 9, survival status, the number of employees the business had, flood depth, and whether the business was a branch significantly predicted whether the groups would be excluded (same outcome). If a business was open, they were 380 percent more likely to be in a group that was excluded from the analysis, and this was highly significant (p<0.001). A one-employee increase also significantly ($p<0.05$) increases the odds of being excluded by three percent. By contrast, being a branch significantly ($p<0.05$) decreases the odds of being excluded by 80 percent. Lastly, going up in flood depth category decreased the odds of being excluded by six percent. This was only marginally significant ($p<0.1$). Model 10, however, had more significant variables, with density, number of employees, wind speed, branch status, female-ownership or management, and survival status predicting exclusion. Density and number of employees were marginally significant ($p<0.1$) and increased the odds of being excluded by nine percent and three percent per unit increase, respectively. Whether the business was open significantly ($p<0.000$) increased the odds of being excluded by a huge 540 percent. Being female-owned or managed also significantly ($p<0.05$) increased the odds of being excluded by 137 percent compared to other businesses. A one m/s increase in average wind speed decreased the odds of exclusion by four percent ($p<0.1$) and branch status decreased the odds of exclusion by 80 percent compared to other businesses ($p<0.05$).

Lastly, I can look at the sector differences between excluded and included groups. This is presented in Table 20:

Table 20 Sector Differences Between Included Groups and Total Groups.

Sector	Accepted			Disbursed		
	All	**Included**	**%All-%Included**	**All**	**Included**	**%All-%Included**
11 Agriculture, Forestry, Fishing and Hunting	2	0	-1%	0	0	0%
21 Mining	0	0	0%	0	0	0%
23 Construction	18	10	-1%	14	8	-1%
31-33 Manufacturing	12	8	0%	12	8	0%
42 Wholesale Trade	4	2	0%	2	2	0%
44 – 45 Retail Trade	68	42	-1%	54	36	0%
48 – 49 Transportation and Warehousing	8	0	-3%	8	0	-4%
51 Information	0	0	0%	0	0	0%
52 Finance and Insurance	8	4	-1%	6	4	0%
53 Real Estate Rental and Leasing	6	2	-1%	4	2	0%
54 Professional, Scientific, and Technical Services	32	28	4%	28	24	3%
55 Management of Companies and Enterprises	0	0	0%	0	0	0%
56 Administrative and Support and Waste Management and Remediation Services	4	2	0%	4	2	0%
61 Educational Services	2	2	0%	2	2	0%
62 Health Care and Social Assistance	28	16	-1%	20	12	-1%
71 Arts, Entertainment, and Recreation	10	8	1%	10	8	1%
72 Accommodation and Food Services	48	36	3%	30	24	3%
81 Other Services	30	22	1%	18	12	0%
Total	280	182		212	144	

In general, the sector differences are not hugely problematic and are similar in both the accepted sample and the disbursed only sample. Transportation and warehousing businesses were excluded from the analysis completely. Professional, scientific, and technical services and accommodation and food services businesses were over-represented by around three to four percent of the total sector distribution.

To conclude, although the analysis excluded quite a bit of observations, I believe the analysis is still valid and the research question still adequately addressed; this analysis answers, if there is a difference in survival between similar businesses, whether we can attribute that difference to a loan. Models 7 and 8 provide evidence that having a loan disbursed significantly increased likelihood of survival within groups of similar (matched) businesses. Additionally, based on the evidence, most of the observations that were excluded were excluded for groups of businesses being open; the standardized coefficient was 110 in Model 9 and 139 in Model 10, which were both over three times higher than the second-highest standardized coefficient in terms of its magnitude. The fact that more businesses are excluded for both being open rather than closed is unsurprising when considering the matching technique. I matched businesses with controls based on their ability to be approved for a loan; loans are approved based on ability to repay and therefore the matching is also selecting businesses that are more likely to survive. From an interpretation side, excluding open businesses is potentially less concerning that excluding closed businesses. For businesses and policymakers concerned with the businesses in their community, failure is more of an issue than survival, and failed businesses were more likely to be included in the analysis.

Otherwise, businesses in the analysis of approved businesses were smaller, more likely to be branches, and with higher average flood depths. Businesses in the analysis of only businesses with disbursed loans were more likely were smaller, more likely to be branches, less likely to be female-owned or managed, and with higher average wind speeds and lower densities. However, the magnitude of these variables is quite small compared to the survival status variable. In addition, businesses were still included in the analysis that represented these variables, the distribution is simply different. The analysis is not meant to make conclusions on the distribution of all businesses, but rather the differences between similar (based on matching) businesses. One last way to get around this issue and not exclude groups would be to run a fixed effects linear probability model. This would make the outcomes slightly different in all groups. The results of running a fixed effect linear probability model (XTREG FE in STATA grouped by the matching strata) are shown in Appendix H. The results of this model still show treatment status as a significant, positive predictor of survival.

6. DISCUSSION AND CONCLUSIONS

To summarize, this research began with several questions:

Research Question 1. Which businesses benefit from the SBA loan program?

Research Question 1.1. What determines loan amount?

Research Question 1.2. Which businesses are more likely to use SBA loans in recovery?

Research Question 2. Do SBA loans improve survival probabilities in the long term?

I generated hypotheses that were motivated by both the empirical business and disaster literature and organizational theory, with the relationship between these presented in Figure 5. I then ran several statistical analyses to test these hypotheses and answer the research questions. The final section of this research will summarize of the findings by research question—specifically addressing the results of each hypothesis test that fell under the research question of interests—and a discussion on the implication of these findings in terms of planning, policy, organizations theory, and business and disaster research. Lastly, I conclude with limitations and suggestions for future research.

6.1. Summary of Findings

Research Question 1 was broken down into two parts. For Research Question 1.1 I ran an OLS regression to determine the factors that were most related to loan amount approved by the SBA loan program. In Section 2.3.1, I theorized that the SBA loan program falls under the logic of the state, defined by the y-axis characteristics identified in Table 2. After a disaster, the state balances the needs of the community with the overall needs of its constituents—its stakeholders extend beyond the affected area. Additionally, I argue that the community relinquishes its bargaining position after disasters and the SBA can, therefore, lean closer to the market to assuage taxpayer concerns of fiscal responsibility (the majority) rather than be purely philanthropic for the taxpayers in the damaged community (the minority). Therefore, it seems likely that the SBA loan program would prioritize repayment ability over need. I hypothesized:

Hypothesis 1. The larger the business, the more likely it will be approved for higher loan amounts.

Hypothesis 2. The older the business, the more likely it will be approved for higher loan amounts.

I also hypothesized that, due to the weak negotiating position of businesses after a disaster, the state logic becomes dominant and therefore longer times are preferable as they are more legitimate:

Hypothesis 3. Deliberation time has a positive relationship with loan amount.

The results of the OLS regression on loan amount supported Hypotheses 1-3 with number of employees, age, and SBA deliberation time being significant, positive predictors of loan amount. Other significant variables in the model included flood depth, whether the business was home-based, whether the business was a corporation, density at the 2000 census block group level, median household income at the 2000 census block group level, loan term, and applicant delay. Flood depth, corporate status, loan term, and applicant delay were positively associated with loan amount and home-based, higher density, and higher income were negatively associated with loan amount.

For Research Question 1.2 I ran a logistic regression on which businesses were more likely to establish a relationship with the SBA and take the loan for which they were approved. I suggested that organizations under the community logic, due to their geographic distance, are more likely to become dependent on external partners under the state and market logics. This also means that businesses who are less centered in the community logic and more market-driven will be less dependent. It is likely corporations are less centered in community logics since they are more likely to have other locations and external pressures from stockholders, and corporations are significantly less likely to take disbursement. Additionally, older businesses that have remained small indicate that they may be less profit-driven and more of a community business as defined in the planning sphere (Jacobs, 1961). Therefore, I specifically hypothesized:

Hypothesis 4. Businesses that are smaller and older are more likely to accept SBA loans.

Hypothesis 5. Corporations are less likely to accept SBA loans.

These hypotheses were also supported by the logistic regression. The interaction term between size and age was also significant: smaller businesses were more likely to choose disbursal if they were older, conversely larger and older businesses were less likely to choose disbursal. Corporations were less likely to choose disbursal compared to other organizational forms. Based on these proxies for the community and market logics, there is evidence to suggest that businesses under different institutional logics have different likelihoods of choosing disbursement and becoming dependent on state resources.

The debt burden hypothesis (James Dahlhamer, 1998) was also tested with the logistic regression. It stands to reason that businesses would be wary of higher loan amounts because they mean incurring more debt in an unreliable environment. I hypothesized:

Hypothesis 6. Businesses with higher damage are less likely to choose disbursement.

Hypothesis 7. Businesses approved for higher loan amounts are less likely to choose disbursement.

Hypothesis 6 and Hypothesis 7 were supported by the model. Loan amount and damage were significant, negative predictors of whether or not a business accepted the loan, which might be expected if businesses chose to take or reject loans based on the potential debt burden. Other significant variables in the model included business age, business size, business sector, applicant delay, and SBA delay. All of these variables had a positive relationship with probability of choosing disbursement.

Research Question 2 and Research Question 3 look at the types of actions businesses can after a disaster event that may affect their survival probabilities in the long run. The literature suggests that capital is extremely important for business recovery since businesses must be profitable to survive. There has been some doubt, however, of the ability of recovery programs to be effective replacements for this capital. I used a matching methodology to isolate the loan effect from potentially confounding variables and found that loans significantly improved survival probabilities. I hypothesized:

Hypothesis 8. Businesses that receive SBA loans are more likely to survive.

In addition, being able to move in the face of a changing environment post-disaster may be the difference in a business's survival since businesses are sensitive to changes in their customer base. I included whether a business moved as another variable of interest in the matched analysis, essentially controlling for resource access to see whether moving affected survival. Specifically, I ran a conditional logistic regression that examined the differences between similar businesses (i.e. the matched pairs) to see if loan status and mobility affected survival. I found that both choosing to receive a loan and moving were positive predictors of survival nine years after Hurricane Ike. Having higher sales was also a positive predictor of survival, however this was a matched variable and should be thought of as a control variable. This variable was likely significant (rather than damage and number of employees) since the range of acceptable values for this variable was wider when matching giving the model more variation to analyze.

6.2. Implications

The goal of this research was to take a holistic approach to the study of loan effectiveness, taking the perspective of both the loan provider and the receivers of the assistance to understand not only the outcome of interest, but also why that outcome occurs, and how the program may be realistically improved. This research found that SBA loans did improve survival probabilities in the long term, but certain businesses were more likely to receive higher loan amounts and were more likely to use the loans in their recovery.

This research contributes to existing knowledge by not only trying to better understand the effect of SBA loan on business recovery, but also understanding who the program serves and benefits. There is some evidence to support the notion that businesses that benefit from the SBA loan program were more resilient to begin with. Although denial information was unavailable, motivations of the SBA program could still be looked at through loan amounts. Larger businesses, older businesses, and corporations were approved for higher loan amounts and the model looking at loan amount as a function of business characteristics was able to explain close to 33 percent of its variation. Although flood damage also had a positive relationship with loan amount, the model looking at loan amount as a function of damage alone was only able to explain 1 percent of the variation in loan amount. When looking at the X-standardized coefficients in the full model, four of the five variables with the highest magnitude of effect were business characteristics; flood depth was the seventh highest. This suggests that businesses characteristics are still better predictors of loan amount, even when controlling for the full set of variables. This provides some support to the broader speculation that the SBA prioritizes repayment ability over need and the state logic dictates the relationship between the business and the SBA. Lastly, there were 1,158 businesses that were denied a loan, a majority of which were denied due to repayment ability (see Table 21). Although 555 businesses were approved for loan, a large portion of those businesses could be considered more real estate property as opposed to a for-profit business. Only 262 businesses were deemed eligible for this study making the SBA loan program quite exclusive.

Businesses also differed in whether or not they even chose to use loans in their recovery even if they were approved. Of those 262 businesses, only 187 (71 percent) actually had the money disbursed to them. In general, the model suggests that businesses may be aware of the debt burden of a loan during recovery. Businesses are less likely to take a loan if they are damaged and approved for higher amounts. Businesses are more likely to take the loans if they are in a better position to manage that burden, such as being larger or older. However, there is also evidence that businesses also take the loans because they have fewer alternative options (i.e. differences in resource dependencies). Corporations, the proxy for the market logic, were less likely to choose disbursement and smaller, older businesses, the proxy for the community logic, were more likely to choose disbursement.

These findings make sense given the logics framework used in this research, and the research has solidified many of the attributes presented in Table 2. The interests of the SBA extend beyond the disaster area and those affected by it. Its geography of stakeholders is national and as an organization it must be concerned with repayment ability as it relates to accountability. Therefore, the state must balance this need for accountability with its mission of providing assistance, which is even more difficult when the recipients are for-profit organizations. This results in loans that resemble market loans more so than philanthropic donations, which might be more acceptable for individuals or households within a capitalist framework. However, this also means that businesses may be in debt for up to thirty years (the maximum loan term allowable in the SBA disaster loan program), exacerbated by changing community demographics that can affect the business's market and potential revenue (Alesch et al., 2001). Loan characteristics were significant predictors of whether or not a business chose to take the loan once they were approved. Most notably, businesses were less likely to accept the loan as the loan amount increased, indicating that businesses are aware of, and act accordingly with, the debt burden hypothesis.

Additionally, this research provides empirical support that the state logic views time as legitimacy. Deliberation time—how long it took from when the SBA received the loan application to when it was approved—was positively associated with loan amount. Longer deliberation times allow the state to determine the likelihood the business will be able to repay the loan as well as reduce the likelihood that the SBA is not duplicating benefits, thereby achieving its obligation to the taxpayers. For the individual businesses, however, time is a resource. Each day a business waits for the funding necessary to re-open or recover, it risks losing its market share to its competitors as well as loses the profits it would have amounted if it were open for businesses. This may be particularly relevant for businesses in the construction or manufacturing sector. Alesch et al. (2001, p. 68), for example, writes about a carpet business after the Northridge earthquake:

> "The merchant applied for an SBA loan and was turned down. While it looked to us as though the business had been prosperous, tax records apparently showed that it was not sufficiently prosperous for the SBA to find the merchant loan-worthy. So there he was. The rebuilding of Northridge had begun. Large carpet wholesalers from across the country were swarming over building contractors like ants at a picnic, offering spectacular deals for large lot orders. Our merchant had no inventory to sell, wasn't positioned to compete with large wholesalers, and had just recently found a place into which he could move. The giant rebuilding boom passed him by as he was getting ready to do business."

The carpet business references here was unable to capitalize on the increased demand for new carpet after the disaster and instead lost its market to outside competitors. This may have long-term consequences, as customers replacing their carpets all at once are unlikely to do so again for several years, which could mean that this business may see a lower-than-average demand moving forward in its recovery on top of its capital expenses. This may be a reason why manufacturing/construction businesses were more likely to accept disbursement in Model 6. Although they are considered a more resilient sector due to this increased disaster-related demand (Webb et al., 2000), they are also vulnerable to timing. They may wish to re-open as soon as possible, even despite the potential debt burden of the loans. Although this example is of a business denied for a loan, this could also be relevant to a business who experienced longer delays compared to those within its industry.

Given this discussion, this research then leads to broader questions of whether the state can effectively provide assistance to businesses or even if it should. Though this research does not attempt to definitively answer these questions, it will discuss them briefly in terms of policy and planning. I conclude with limitations and directions for future research.

6.2.1. Policy

Historical dissatisfaction with federal funding makes sense through the lens of differing institutional logics as the expectations for the program will differ depending on whether the organization is guided by the state, market or community logic. It is possible that, given these logics, the state is ill suited to providing this kind of assistance and its role may need to be re-imagined. The state, because its view of time as legitimacy, may not be able to act quickly enough for businesses like the carpet business. Although businesses were more likely to take the loan if they were more delayed as shown in Model 6, model on delay time indicated that businesses that took longer to apply (of those that were approved) tended to be stronger businesses (see Appendix E). Those businesses who closed during the application process or were denied a loan outright were not captured by this analysis.

Additionally, this research has shown that the SBA loan program benefits those businesses who were more likely to be able to pay off the loan. The research also shows that even considering potential access to resources through matching, SBA loans were positively associated with odds of survival (see Model 8). Because businesses that were more damaged were less likely to take loans, an argument could be made the SBA loan program is no longer meeting its goal of welfare capitalism and is instead interfering with the market. By approving loans, the SBA is rewarding capital access in recovery and in a sense making a judgement on what constitutes business resilience. However, if only capital-based resilience is supported, then assistance could potentially increase inequities. Model 8 did not indicate that the median household income of the census block in which the business was located affected recovery, the model again only included those businesses approved for loans and their very similar control. Of the loan denial codes in Galveston County (see Appendix A), 94% were related to credit or repayment ability. This could impact low-income or disadvantaged neighborhoods already dealing with disproportionate impacts and unequal housing and household recoveries (Cutter, Boruff, & Shirley, 2003; Peacock, Morrow, & Gladwin, 1997; Van Zandt et al., 2012) and exacerbate issues relating to resources and power dynamics during recovery (Olshansky et al., 2012). These issues, now coupled with potential impacts to employment and opportunity access, could lead to a vicious cycle in these neighborhoods. Xiao and Nilawar (2013) illustrate how donut holes of low income and employment growth emerge in damaged areas. This research points towards loan denials for capital-deficient businesses, lower loan acceptance rates for higher damaged businesses, and higher survival odds for businesses that moved. Whether or not these phenomena are spatially related has consequences for recovery and will need to be examined in future research.

This then leads to the question of whether there are better ways for the federal government to assist businesses after a disaster. After Hurricane Ike, local banks in Galveston offered a bridge loan program that provided businesses with capital while the businesses waited for insurance or SBA loans to pay out. If formalized, this could be a form of iteration, which Olshansky et al. (2012) recommend to get around post-disaster timing issues. Iteration involves prioritization of decisions would be prioritized, meaning some decisions would be made immediately with little forethought, and some decisions, those requiring more deliberation, are made later (Olshansky et al., 2012). The SBA could back private loans for businesses with existing banking relationships and adequate credit history as determined by the original lender, meaning the money could be disbursed much more quickly. Those businesses without a previous banking relationship could apply to the SBA as usual. Another option would be for SBA, itself, to approve much smaller amounts of money more quickly—similar to the concept of bridge loans—with more relaxed requirements. The smaller loan amounts are potentially less subject to scrutiny from the taxpayers and have the potential to help more businesses stay afloat in the immediate aftermath since for them time is a resource. Later, businesses desiring more money can re-apply and the SBA would already have a relationship and repayment history with the business.

Rather than suggesting incremental changes to the existing program, a more radical option may be changing the form of federal assistance to businesses to resemble the earthquake support subsidy that was used after the Christchurch Earthquakes in New Zealand. Assisting business through a workforce retention program has the potential to address many of the limitations associated with the current strategy. This kind of program is essentially place-based in that it encourages businesses to continue employing its current people, and employees are encouraged to remain in the community with a source of income to begin making their own repairs. There could be a coordination with household assistance to combine resources towards this program; households and businesses are closely linked and affect each other's recovery decisions, so it would make sense to structure assistance around that relationship (Xiao & Van Zandt, 2012). Really, any form of assistance that makes use of the close relationship between businesses and households may be an appealing alternative for the state. Assistance could take the form of childcare vouchers and programs for employees who miss work after a disaster due to school closures and childcare issues. These types of programs allow the state to provide individual assistance that still helps businesses, which may be faced with less scrutiny.

6.2.2. Planning

Although it is important to ask whether the SBA can affectively assist businesses, there can be a discussion of which businesses should be assisted. One position is that assistance should go towards those with the highest likelihood of success; for instance, those unable to pay back a loan are unlikely to survive, and it is better to replace unsuccessful businesses (Schumpeter, 1942b). Based on the findings of this research and the previous discussion, SBA loans tend to fall into the latter category. Again, this behavior makes sense given the discussion on institutional logics and the way state institutions view their role in recovery. An alternative viewpoint is that we should support the recovery of all businesses, regardless of their capital resilience, because of their social impact on recovery (Xiao & Van Zandt, 2012) and role as community members as opposed to simply commercial entities (Xiao, Wu, Finn, & Chandrasekhar, 2018). Planners may be more likely to fall into the former category.

Therefore, although this research focuses on the role of federal assistance on business recovery, the findings have revealed a space for planners. Because the models provide evidence that the SBA highly values repayment ability, the SBA assisted a relatively small number of affected businesses. Assuming the number of businesses that applied for a loan was to some extent correlated to the need, the SBA still only assisted 22 percent of those that applied. This leaves a significant gap and unmet need that planners in a recovering city can address with local programs. This assistance does not need to be monetary. For example, programs that help businesses create an online presence and is promoted by the city can help businesses buffer some of the temporary demand shifts after disaster by diversifying their market area.

Recovery planning is still incredibly important, and this research stresses the need for including local businesses in this process. At a minimum, understanding recovery priorities, changes in regulations, etc. can help businesses in their decision-making. In addition, knowing the role of the SBA, their logic, and how the program is designed to function, is incredibly important in managing business expectations and minimizing future frustration (Furlong & Scheberle, 1998). If businesses know that approval rates are only around 22 percent, they may be more likely to invest in insurance or take mitigation measures. Planners can create toolkits and educational programs to promote these types of strategies. These can be as simple as making sure the business has contact information for customers and employees on the cloud, or as hands-on as helping businesses elevate and secure contents.

Secondly, Model 8 suggests that moving is positively associated with business survival. This could potentially raise issues from the planning and economic development perspective. Namely, these findings contribute to the debate of people-based vs. place-based economic strategies. Encouraging businesses may be beneficial at the individual level and moving can potentially help businesses become more resilient to future disaster events if they are encouraged to move to higher elevations or more inland. However, businesses have been shown to be important in recovery in that they also influence the return of households (Xiao & Van Zandt, 2012). Encouraging businesses to move out of the city by providing more flexible forms of assistance would potentially be a significant loss for a damaged community.

To reconcile this, having a recovery plan that prioritizes restoration and economic development in local commercial areas with less physical disaster risk may prevent some outmigration and spatial disparities identified in previous research (Xiao & Nilawar, 2013). Predicting business mobility after disasters and getting ahead of it by incentivizing moving within the same community may help in business retention. In addition, principles of planning that create desirable places, strengthen social networks, engage businesses in the process are going to build and strengthen the community logic in the business community. This may, in turn, encourage businesses to stay in the community. Xiao et al. (2018) found that businesses do indeed make recovery decisions based on community ties and attachments and may remain for reasons outside of the management and operation of the business. Strengthening the community logic may also encourage the community to support its businesses. Engaging the private sector in recovery, particularly community banks, led to the aforementioned bridge loan program that was able to supplement federal funding for businesses in Galveston after Ike (Simon, 2016).

6.3. Future research

This research opens up several domains for future research. Broadly, these might include the influence of loan characteristics (e.g. amount, loan term, loan type) on survival, the effect of loan characteristics on business mobility (i.e. whether loan encourage or discourage moving), and including organizational ecology as a theoretical control. To illustrate, I include these future research topics in the process model and conceptual model from Figures 4 and 5 in Section 3. These topics are presented in context of this research in Figures 12 and 13, below.

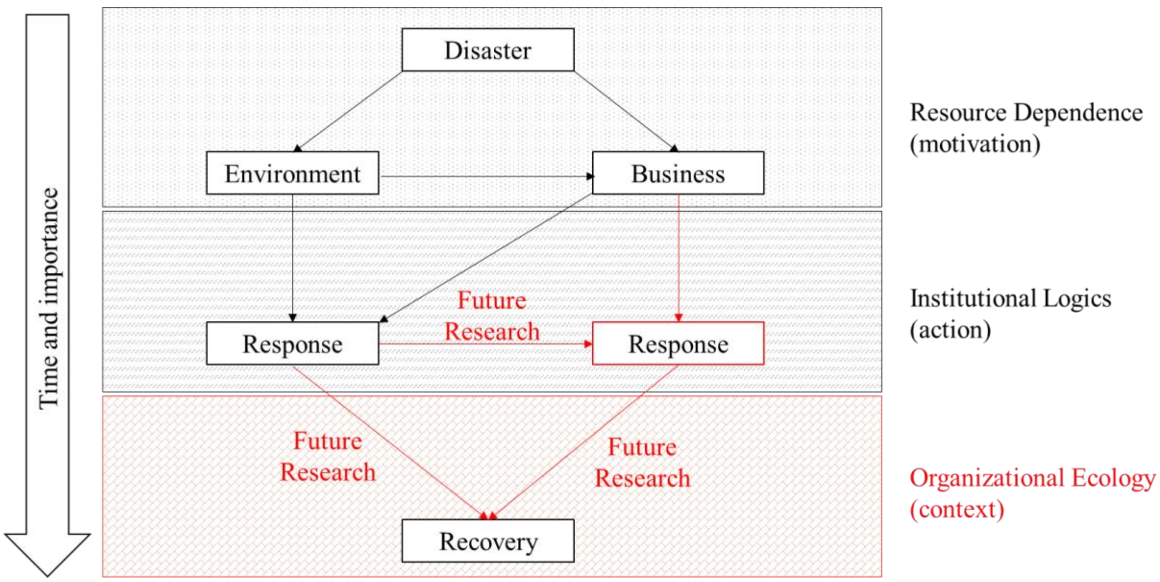

Figure 12 Modified Process Model for Future Research.

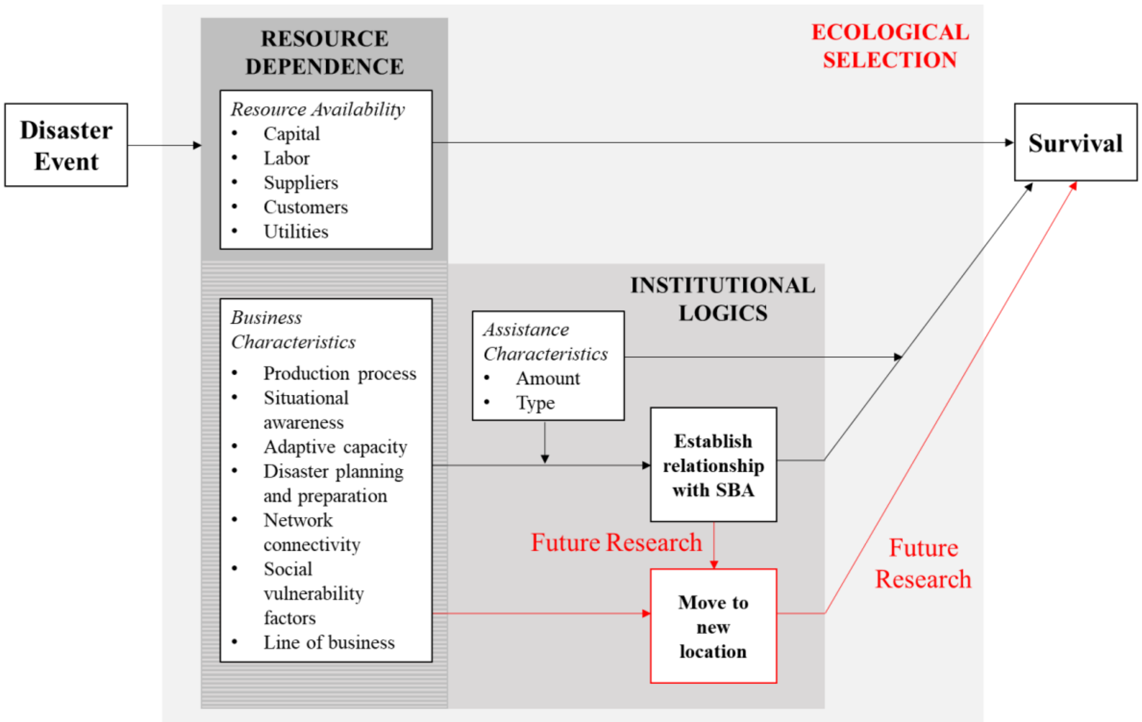

Figure 13 Modified Conceptual Model for Future Research.

The results of this research illustrate that moving is another course of action that a business may take in the face of a disaster and altered resource dependence, and accepting assistance may affect their likelihood of doing so. In addition, moving, controlling for resource dependence, may be influenced by institutional logics. For example, the market is made up of different kinds of resources. Some resources are exchangeable in that they are the same in Houston as they are in Galveston, for example—they move across place. Some resources are more worth more in different areas and are tied to place. However, institutional logics can also serve as a lens through which these resources are viewed. The same resource through the lens of the community logic is a way to sustain the community whereas through the market logic is an opportunity to capitalize elsewhere. The exchangeability of resources, therefore, affects that desirability of that resource to different logics. However, I also argued that businesses operating under different institutional logics have different resource dependencies after a disaster, and organizations under the community logic become more dependent on state organizations. State resources, however, are constrained by the nature of the state logic. For businesses, then, desirability must be weighed by the extent of their dependence. Logics will also motivate different actions on the same resource. Some businesses might take the money they receive and moved away, whereas some rebuild in the same community. Both types of businesses recognize a need to relocate, but varied in their degree of embeddedness within the community logic.

Logics and their consequences for a business's decisions about moving may also have an impact on their survival. One element of organizational ecology is the mortality (or selection) of firms within a population or community (Hannan & Freeman, 1993). Figure 10 illustrates how organizational ecology is a background process to the already observed phenomena. The organizational ecology perspective lends itself very well to the resilience and disaster management domain. Future research would move the scope of organizational ecology research from slow-onset phenomena and disturbances on longer timescales to acute hazards and extreme events. Specifically, it might examine to what types of firms are selected after a disaster in a context of altered resource dependence and how selection after disasters differs from non-disaster selection processes. Using Olshansky et al. (2012)'s theory of disaster time compression, we might expect to see similar firm selection but at a more rapid rate, and there is empirical evidence that disasters hasten firm demise in that businesses doing poorly prior to the event were much more likely to fail (Alesch et al., 2001). This, in turn, has implications for organizational diversity and resilience of impacted communities to future hazard events. In addition, there may be a spatial component to selection. Based on the spatial disparities identified by Xiao and Nilawar (2013), it is possible that businesses moving outside the impacted community are more likely to survive. Given that moving within or outside the original community is motivated by logics, this might indicate that logics have tangible effects on recovery outcomes and can act as their own form of organizational selection.

6.4. Limitations

Lastly, I discuss the limitations of this research. Perhaps the most significant is the lack of insurance information. Although this information was requested from FEMA, it was not furnished in time for the study. This will have to be included in future research. This likely affects whether or not a business applies for SBA loans, and would need to be controlled for both in the matching process and the models. Additionally, it would be better to include more controls in the matching so that issues of no within-group variance do not occur in the conditional logistic regression. However, the fixed effects linear probability model suggests that this did not affect the findings in a significant way. Lastly, this research relied on proxies for the community and market logics rather than survey-based or interview-based measures. It's possible that these proxies do not accurately represent these logics (or only partially represent them) and more research is needed on the operationalization of these concepts.

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APPENDIX A

SBA DATA: WITHDRAWAL AND DENIAL INFORMATION

Tables 21 and 22 show the count of denial and withdrawal codes for businesses applying for SBA loans in Galveston County after Hurricane Ike. Numbers in each category represent denial or withdrawal codes (a business can have more than one code) but application totals are presented at the bottom.

Table 21 SBA Denial Codes for Hurricane Ike in Galveston County.

Decision Codes		Business/ EIDL	Stand Alone EIDL	Non-profit
20	Repayment - Failed Minimum Income Test	-	-	-
21	Lack of Repayment Ability	428	45	12
25	Inadequate Working Capital After Loan	-	1	-
26	Unsatisfactory History on Existing or Previous SBA Loan	21	3	1
27	Federal Obligation	49	10	1
28	Unsatisfactory Credit (Based on Credit Bureau)	569	52	1
29	Unsatisfactory Credit (Other Than Credit Bureau)	5	-	1
30	No Disaster Damage (Physical)	8	-	-
31A	No Economic Injury (No Needs)	6	14	-
31B	No Economic Injury (Disaster Gross Margin Exceeds Normal)	2	-	-
31C	No Economic Injury (Custom Text)	-	1	-
32	Business Activity Not Eligible (EIDL)	4	2	1
33	Applicant Business Not Small (EIDL)	1	-	-
34	Credit Available Elsewhere (EIDL)	2	5	-
36	Ineligible Real Property (Secondary Home, Etc.)	5	-	-
37	Ineligible Personal Property	1	-	-
38	Not Eligible Due to Recoveries	4	-	2
39A	Flood Ins. Not Maintained (SBA Loan)	2	-	-
39B	Flood Ins. Not Maintained (Fed Regulated Lender)	10	-	-
39C	Flood Ins. Not Maintained (As Directed by FEMA)	-	-	-
40A	Not A Qualified Business (Not Rental)	24	4	1
40B	Not A Qualified Business (Rental)	49	2	-
41	Refusal to Pledge Available Collateral	1	-	-
42	Delinquent Child Support	6	1	-
43	Not Eligible (Character Reasons)	1	-	-
44I	Failed Min Income Test Based on Applicant's Income Alone	-	-	-
44R	Repayment Based on Applicant's Income Alone	1	-	-
45	No Decision Code	1	1	-
46A	Agricultural Enterprise (Not Eligible)	20	-	1
46C	Property in CBRA (Not Eligible)	1	-	-
46D	Not Eligible (Custom Text)	37	7	3
60D	Character Eligibility Determination - Decline	20	3	-
Count of Decision Codes		1,278	151	24
Distinct Count of Applications		1,042	116	19

Table 22 SBA Withdrawal Codes for Hurricane Ike in Galveston County.

Decision Codes		Business/ EIDL	Stand Alone EIDL	Non-profit
51	Withdraw - Requested Info Not Furnished	134	12	12
52	Withdraw - Applicant's Request	46	3	1
53	No Decision Code	19	7	1
54	Withdraw - Applicant's Request - Insurance or Other Recovery	22	1	0
55	No Decision Code	42	3	4
56A	Withdraw - Unable to Verify Property	20	0	0
56B	Withdraw - Custom Text	16	1	2
57	Withdraw - Consolidation of Multiple Applications	8	0	0
58	Withdraw - Consolidation of Related Applications	8	0	0
59	Withdraw - IRS Has No Record	69	6	3
60A	Character Elig. Determination - Otherwise Approvable Application	11	2	0
60W	Character Eligibility Determination - Withdrawal	9	1	0
61	Withdraw - Applicants Request Due to Market Rate	2	0	0
Count of Decision Codes		406	36	23
Distinct Count of Applications		390	36	22

1,177 businesses (including non-profits) were denied an SBA loan. The two most common reasons for denial were unsatisfactory credit (622 denial codes) and lack of repayment ability (485 denial codes). 448 businesses had their applications withdrawn. The most common reason for withdrawal was that the requested information was not furnished (158 withdrawal codes), perhaps capturing businesses that abandoned the application process.

APPENDIX B

COMPARING FLOOD DEPTH MEASURES

This section examines the differences between the polygon flood depth data provided by the Harris County Flood Control District (HCFCD) and the flood depth information generated by the Advanced Circulation (ADCIRC) and Simulating Waves Nearshore (SWAN) hydrodynamic models used to simulate Hurricane Ike. Table 22 looks at the distribution of flood depths from the ADCIRC/SWAN model compared to the HCFCD flood depth categories:

Table 23 Comparison of Flood Depth Measures.

Range	Obs.	Mean	Q1	Q2	Q3	Q4
0	76	0.06	0.00	0.00	0.00	3.54
< 2	14	0.89	0.00	0.89	1.31	2.21
2 - 4	41	3.42	1.83	2.89	5.08	11.25
4 - 6	71	4.37	3.40	4.75	5.40	10.92
6 - 8	98	6.83	5.76	6.61	7.63	17.44
8 - 10	71	7.88	7.37	8.04	8.23	13.42
> 10	14	9.82	8.38	10.58	12.39	13.72
	385					

Corr = .85 (p-value=0.0000)

The mean flood depth of the ADCIRC/SWAN model trends upwards with the HCFCD flood depth categories. The ADCIRC/SWAN model mean falls within the bounds for all HCFCD categories except for the higher flood depths (8 – 10 feet and > 10 feet) where the average is slightly lower than the bounds. The median, however, does fit within the bounds. The flood depth measures have a correlation of 0.85 (p-value 0.000). We can also visualize this graphically with the scatterplot provided in Figure 14.

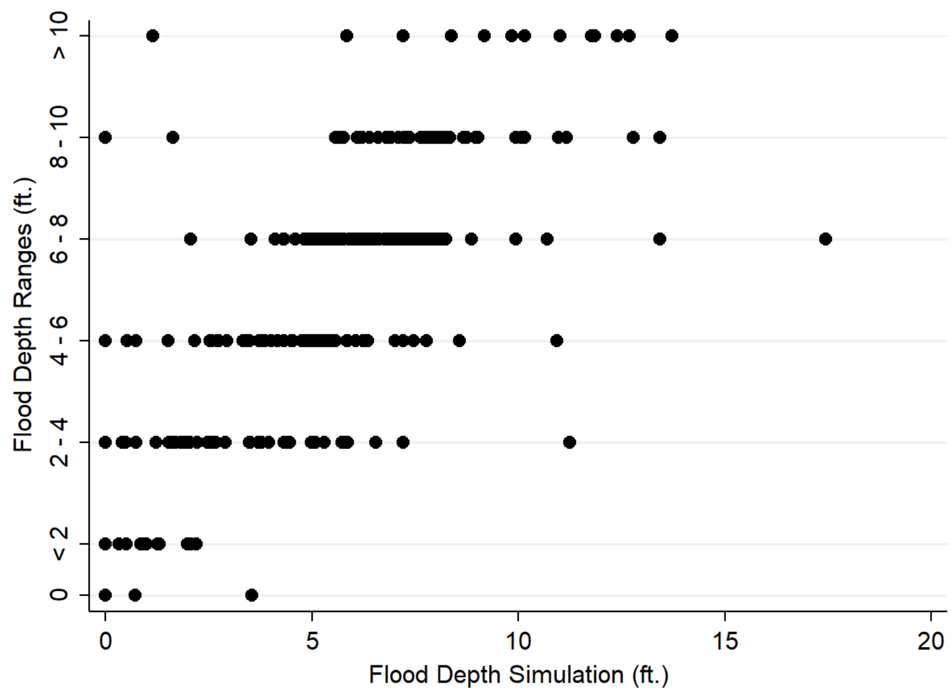

Figure 14 Scatterplot of Flood Depth Measures.

Looking at the measures graphically, it appears that a few low outliers from the ADCIRC/SWAN model are causing the mean for the "8 – 10 feet" and "> 10 feet" to be below the bounds (while keeping the median fairly accurate). This is likely only an issue for fewer than five observations in the dataset. When running the analyses in this dissertation, I ran both flood depth measures independently in each of the models and no significant differences in variable importance arose. The only difference would be in the interpretation of the coefficient values, where the ADCIRC/SWAN model values have an advantage given that they are truly continuous measures rather than increases/decreases in category.

APPENDIX C

MATCHING SENSITIVITY ANALYSIS

Choosing the coarsening of variables on which control variables are matched with treatment variables can be a subjective process. For this research, deciding on the levels of coarsening was done either on a theoretical basis (e.g. wind speed), due to error in the data source (e.g. employment), or by existing data groupings (e.g. flood depth and sales), and decisions on variable inclusion in the matching process was made based on the literature. However, it could be argued that decisions on which matching variables and how to coarsen them can introduce bias. This section presents an analysis of the sensitivity of the matching process to changes in variable coarsening.

The first table, Table 23 looks at how imbalance is reduced at different levels of variable coarsening as well as the number of matches able to be generated. Different matching attempts are broadly organized by 2-digit vs. 3-digit sector coarsening, then by whether branch status, female-owned/managed status, and home business status were included in the matching code. Lastly, employment, sales, flood depth, and wind speed were coarsened. Because CEM matching randomly chooses a match within the strata, two rounds of matching were run for each code. The one that reduced imbalance the most (bolded) was kept for further analysis.

Table 24 Imbalance Reduction and Number of Matches for 20 CEM Codes.

Sample ID	Description of sample change	Matches	Initial imbalance	Match 1	Match 2	Dif.
1	*2-digit NAICS*	149	0.810	0.564	**0.490**	0.320
2	coarsened employment to (0 10 50 100 2000)	151	0.810	0.682	**0.616**	0.194
3	coarsened sales to (0 500000 1000000 5000000 10000000 20000000 1000000000)	151	0.810	**0.556**	0.576	0.234
4	coarsened flood depth (0 3 16)	151	0.810	**0.589**	0.623	0.220
5	coarsened windspeed to over/under 96mph (cat 2 hurricane)	151	0.810	0.642	**0.623**	0.187
6	& branch, female, home (same)	144	0.881	0.674	**0.653**	0.228
7	&…coarsened employment	148	0.881	**0.669**	0.716	0.212
8	&…coarsened sales	146	0.881	0.685	**0.589**	0.292
9	&…coarsened windspeed	148	0.881	0.669	**0.635**	0.246
10	& coarsened flood depth	147	0.881	**0.735**	0.748	0.146
11	*3-digit NAICS*	120	0.822	0.608	**0.592**	0.231
12	coarsened employment to (0 10 50 100 2000)	127	0.822	0.677	**0.614**	0.208
13	coarsened sales to (0 500000 1000000 5000000 10000000 20000000 1000000000)	126	0.822	0.595	**0.571**	0.251
14	coarsened flood depth (0 6 16)	125	0.822	**0.608**	0.624	0.214
15	coarsened windspeed to over/under 96mph (cat 2 hurricane)	127	0.822	**0.559**	0.598	0.263
16	& branch, female, home (same)	109	0.887	**0.615**	0.624	0.272
17	&…coarsened sales	116	0.887	**0.638**	0.664	0.249
18	&…coarsened windspeed	117	0.887	**0.624**	0.718	0.263
19	&… coarsened flood depth	117	0.887	0.718	**0.632**	0.255
20	&… coarsened employment	114	0.887	0.658	**0.640**	0.247

The number of matches in the 20 coarsening levels ranged from 109 to 151. Matches were lowest when using sector and the three dummy variables. Matches were highest when super sector was used and any of the continuous variables was coarsened.

Imbalance was reduced between 0.15 and 0.32. Next, I examine how each of samples resulting from the matching codes are distributed across sectors. The percent businesses in each sector for each sample ID was subtracted from the percent businesses in each sector of the original n=267 sample. Then, the difference was averaged across sector to get a singular measure of sector deviance. This is presented in Table 24:

Table 25 Sector Deviation for All Samples.

	ID1	ID2	ID3	ID4	ID5	ID6	ID7	ID8	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	ID19	ID20
11	2.700	2.709	2.709	2.709	2.709	2.676	2.695	2.686	2.695	2.691	3.371	3.371	3.371	3.371	3.371	3.371	3.371	3.371	3.371	3.371
21	0.078	0.087	0.087	0.087	0.087	0.749	0.749	0.749	0.749	0.749	0.084	0.038	0.045	0.051	0.038	0.749	0.749	0.749	0.749	0.749
23	3.775	3.864	3.202	3.864	3.864	3.542	3.730	2.953	3.730	3.684	5.487	4.975	4.138	5.687	5.762	5.762	3.590	5.359	5.359	4.347
31-33	0.282	0.228	0.228	0.228	0.228	0.421	0.309	0.364	0.309	0.336	0.412	0.596	0.571	0.255	0.192	0.596	0.297	0.528	0.528	0.237
42	0.812	0.776	0.776	0.776	0.776	0.211	0.154	0.503	0.830	0.168	0.627	0.490	0.285	0.527	0.490	1.085	0.149	1.018	1.018	0.995
44-45	5.434	5.114	5.114	5.114	5.114	5.579	5.598	5.931	4.922	5.083	2.107	4.108	2.702	2.073	2.533	2.191	1.101	0.932	1.786	1.449
48-49	0.063	0.027	0.027	0.027	0.027	0.156	0.081	0.118	0.081	0.099	2.622	2.622	1.828	1.822	1.047	2.622	2.622	0.912	1.767	2.622
51	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375
52	0.734	0.690	0.690	0.690	0.690	0.156	0.757	0.118	0.081	0.780	0.712	0.528	0.553	0.578	0.528	0.260	0.036	0.058	0.058	0.010
53	3.011	3.056	3.056	3.056	3.056	3.589	3.664	3.627	2.989	3.646	3.034	3.217	3.192	3.167	3.217	4.792	4.643	3.803	4.658	4.613
54	1.247	0.727	0.727	0.727	0.727	0.874	0.499	0.341	0.499	0.420	1.348	1.401	1.507	1.615	1.401	0.613	2.670	2.545	2.545	2.927
55	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375	0.375
56	1.279	1.297	1.297	1.297	0.635	1.233	1.270	1.252	0.595	1.261	0.955	1.047	1.034	1.022	0.260	1.047	0.898	0.058	0.912	0.867
61	0.297	0.288	0.288	0.288	0.288	0.320	0.301	0.310	0.301	0.306	0.459	0.413	0.419	0.425	0.413	0.413	0.488	0.480	0.480	0.503
62	2.280	2.155	2.155	2.155	2.155	2.606	2.343	2.473	2.343	2.408	3.717	3.120	3.201	3.284	3.120	3.120	4.091	3.995	3.995	4.287
71	0.764	0.809	0.809	0.809	0.809	0.648	0.741	0.695	0.741	0.718	0.463	0.211	0.945	0.280	0.211	0.211	0.190	0.274	0.701	0.705
72	4.122	3.909	3.909	3.909	3.909	4.682	4.231	4.453	4.231	4.342	5.098	4.157	6.269	4.415	4.157	4.157	6.980	6.391	6.818	5.997
81	0.420	0.109	0.553	0.109	0.553	0.070	0.324	0.213	0.352	0.397	2.013	2.112	1.418	2.313	1.324	0.537	1.582	1.479	3.188	2.671
Avg. % off	1.558	1.477	1.465	1.477	1.465	1.570	1.566	1.530	1.455	1.547	1.848	1.842	1.790	1.757	1.601	1.793	1.900	1.817	2.149	2.061
Max value	5.434	5.114	5.114	5.114	5.114	5.579	5.598	5.931	4.922	5.083	5.487	4.975	6.269	5.687	5.762	5.762	6.980	6.391	6.818	5.997

In addition to the average percent off for all sectors, I also included the maximum value that any sector was off. I wanted to make sure that there weren't huge sector differences being lost in the averaging process. I then plotted the relationship between the maximum value a sector was off to the average difference across sectors. This is presented in Figure

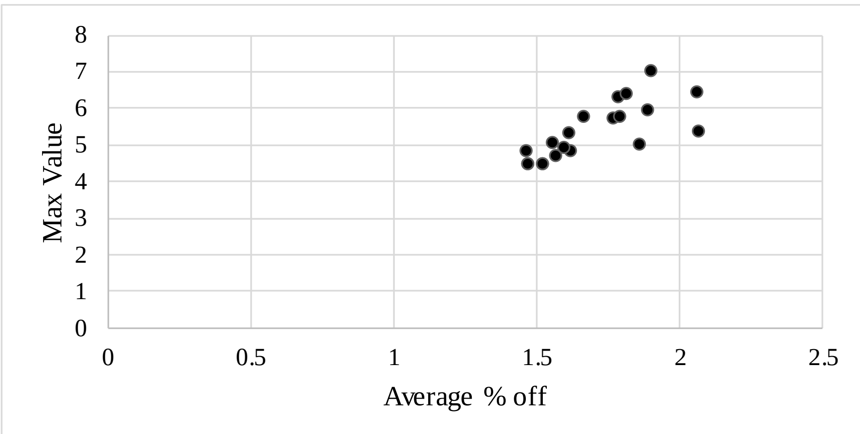

Figure 15 Relationship Between Average Percent Off and Maximum Value.

As illustrated, those samples with the highest average differences also had the highest maximum values so the average seems fine for an indicator. Finally, I took these measures and used them to create an overall distance from the original sample that could be minimized in Table 25. I used ratio of un-matched to the original sample, imbalance, sector average percent difference, and differences in mean for employment, flood depth, and wind speed and added them. The closest to zero is the best sample.

Table 26 Distance from Original Sample.

ID	Matches	Imbalance improvement %	Sector difference	Mean emp.	Mean flood	Mean WS	Distance	Rank
1	0.442	0.605	1.558	0.333	0.385	0.128	3.451	1
2	0.434	0.760	1.477	0.316	0.467	0.220	3.675	2
3	0.434	0.711	1.465	0.183	0.450	0.875	4.120	5
4	0.434	0.769	1.477	0.180	0.609	1.483	4.953	10
5	0.434	0.769	1.465	0.117	0.301	1.100	4.187	7
6	0.461	0.741	1.570	0.485	0.470	0.213	3.941	4
7	0.446	0.813	1.566	0.358	0.394	0.337	3.914	3
8	0.453	0.669	1.530	0.188	0.557	0.733	4.129	6
9	0.446	0.721	1.455	0.361	0.347	1.623	4.953	11
10	0.449	0.849	1.547	0.338	0.652	1.274	5.109	14
11	0.551	0.719	1.848	0.811	0.539	0.331	4.799	9
12	0.524	0.747	1.842	1.194	0.559	0.095	4.961	12
13	0.528	0.695	1.790	0.618	0.432	0.501	4.565	8
14	0.532	0.759	1.757	0.809	1.095	1.340	6.292	18
15	0.524	0.728	1.601	0.615	0.484	1.908	5.859	17
16	0.592	0.703	1.793	0.817	0.603	0.662	5.170	15
17	0.566	0.748	1.900	0.580	0.586	0.694	5.074	13
18	0.562	0.809	1.817	0.441	0.577	3.157	7.363	20
19	0.562	0.713	2.149	0.663	1.064	1.673	6.825	19
20	0.573	0.722	2.061	0.994	0.640	0.695	5.684	16

According to this methodology, ID 1 is the best sample. Coarsening employment also helped, which made ID 2 and ID 7 ranked next. The code that was actually used in this research was ID 6, which was still ranked 4th. However, from a theoretical standpoint, ID 6 is still beneficial because it includes branch, female ownership/management, and a home-based indicator. There is also an argument to be made that coarsening employment to 1, 10, and 50 loses a lot of variation in businesses considering the average is only around 6, making ID 2 and ID 7 less ideal, as well.

APPENDIX D

A COMPARISON OF BUSINESSES THAT WERE APPROVED FOR SBA LOANS TO GALVESTON BUSINESS POPULATION AND HURRICANE IKE-FLOODED BUSINESSES

I compare the sample of businesses that were approved for an SBA loan—with vacation homes and non-profits removed—to the overall business population in Galveston County. Specifically, sector distribution is compared to 2007 firm counts from both the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (only employing firms) as well as Nonemployer Statistics (NES) from the U.S. Census (non-employing firms). The comparison is presented in Table 26.

Table 27 Firms Receiving SBA Loans by Sector Compared to 2007 Total Firms (QCEW and NES).

Sector	SBA Firms	%	Employing Firms	Non-employing Firms	Total Firms	%	Dif.
11 Agriculture, Forestry, Fishing and Hunting	9	3.44	14	475	489	2.06	1.38
21 Mining	2	0.76	44	155	199	0.84	-0.07
23 Construction	28	10.69	470	2147	2617	11.01	-0.33
31-33 Manufacturing	10	3.82	189	304	493	2.07	1.74
42 Wholesale Trade	5	1.91	263	323	586	2.47	-0.56
44 – 45 Retail Trade	48	18.32	797	1712	2509	10.56	7.76
48 – 49 Transportation and Warehousing	7	2.67	173	835	1008	4.24	-1.57
51 Information	1	0.38	67	194	261	1.10	-0.72
52 Finance and Insurance	7	2.67	289	505	794	3.34	-0.67
53 Real Estate Rental and Leasing	17	6.49	291	1751	2042	8.59	-2.10
54 Professional, Scientific, and Technical Services	30	11.45	522	2531	3053	12.85	-1.40
55 Management of Companies and Enterprises	1	0.38	20	N/A	20	0.08	0.30
56 Administrative and Support and Waste Management and Remediation Services	7	2.67	262	1969	2231	9.39	-6.72
61 Educational Services	1	0.38	134	496	630	2.65	-2.27
62 Health Care and Social Assistance	19	7.25	486	1304	1790	7.53	-0.28
71 Arts, Entertainment, and Recreation	11	4.20	113	816	929	3.91	0.29
72 Accommodation and Food Services	32	12.21	559	317	876	3.69	8.53
81 Other Services	27	10.31	523	2527	3050	12.84	-2.53
Total	262		5216		18361		

Retail businesses and accommodation and food service businesses were more likely to have been approved for an SBA loan than other sectors. Conversely, businesses in administrative and support and waste management and remediation services were less likely to have been approved for an SBA loan. However, since I do not have individual-level data on businesses that applied, the reason could be either that businesses in those sectors were more likely to apply or that businesses in those sectors were more likely to be approved. I also note that real estate businesses approved for an SBA loan, when removing vacation homes, are proportional to the overall population of businesses in the county; 254 businesses, almost half of all businesses approved for a loan, were previously removed (refer to Section 4.2.1.) making them easily the largest and most disproportionate sector in the SBA sample had they remained in the sample.

QCEW data also includes employment information by sector, so I also include information on the size of businesses approved for SBA loans by sector. This information is presented in Table 27:

Table 28 Employment of Firms Receiving SBA Loans Compared to 2007 Total Firms (QCEW).

Sector	SBA Firms	Avg. Employee #	Total Firms	Avg. Employee #	Dif.
11 Agriculture, Forestry, Fishing and Hunting	7	3.71	14	3.07	0.64
21 Mining	2	27.50	44	12.89	14.61
23 Construction	25	8.08	470	15.39	-7.31
31-33 Manufacturing	10	6.40	189	36.35	-29.95
42 Wholesale Trade	4	4.50	263	6.77	-2.27
44 – 45 Retail Trade	42	6.31	797	13.81	-7.50
48 – 49 Transportation and Warehousing	6	12.67	173	16.96	-4.29
51 Information	1	5.00	67	11.72	-6.72
52 Finance and Insurance	6	4.83	289	14.43	-9.59
53 Real Estate Rental and Leasing	10	3.60	291	5.93	-2.33
54 Professional, Scientific, and Technical Services	28	6.46	522	5.24	1.22
55 Management of Companies and Enterprises	1	5.00	20	8.40	-3.40
56 Administrative and Support and Waste Management and Remediation Services	6	4.33	262	12.22	-7.89
61 Educational Services	1	13.00	134	70.66	-57.66
62 Health Care and Social Assistance	17	6.94	486	17.00	-10.06
71 Arts, Entertainment, and Recreation	8	11.88	113	22.14	-10.27
72 Accommodation and Food Services	32	11.91	559	21.99	-10.09
81 Other Services	24	7.29	523	4.86	2.43
Total	**230**		**5216**		

Average # of employees of SBA Businesses with >0 employees = 7.7
Average # of employees Galveston County (total) = 15.3

Businesses approved for an SBA loan were smaller than the average business in the county in all sectors except for agriculture, mining, professional services, and other services. Overall, businesses approved for an SBA loans were approximately 7-8 employees smaller than the average business in Galveston County. Although physical disaster loans were available to businesses of all sizes, it appears that businesses that applied and were approved for a loan ended up being smaller; it's possible that larger businesses don't need a loan or were able to find assistance elsewhere, but without the application data it is impossible to say for sure. This is especially interesting considering close to 1,000 of the ~1200 decision codes for denying an application were related to insufficient credit or lack of repayment ability; the literature review (Section 2.1) suggests that larger businesses are likely to have more resources (repayment ability). Therefore, it's most plausible that larger businesses did not apply. However, without the individual point data, it is also possible that smaller businesses were more likely to have been inundated and/or damaged.

To check this, then, I use the ReferenceUSA point data for Galveston County. Although the data has proven to be somewhat messy (see Section 4.2), it still gives the opportunity to compare SBA-approved businesses to only the businesses that were damaged as opposed to the overall business population. First, I removed the ReferenceUSA businesses whose geolocation was outside the county line, leaving me with 10,856 businesses. From there, I removed businesses whose sales were zero (indicating a non-profit, n=1,663), businesses with no flood damage based on the continuous flood depth measure (n=5,813), those in sector 22 (indicating a utility company, n=7), and those missing sector information (n=12). Table 28 shows the sector distribution of flooded businesses compared to the sector distribution of unflooded SBA businesses (n=219).

Table 29 Flooded Businesses Receiving SBA Loans by Sector Compared to Total Flooded Businesses (ReferenceUSA).

Sector	SBA Firms	%	Total Firms	%	Dif.
11 Agriculture, Forestry, Fishing and Hunting	9	4.11	6	0.18	3.93
21 Mining	1	0.46	7	0.21	0.25
23 Construction	23	10.50	274	8.15	2.35
31-33 Manufacturing	8	3.65	85	2.53	1.12
42 Wholesale Trade	5	2.28	101	3.01	-0.72
44 – 45 Retail Trade	44	20.09	604	17.97	2.12
48 – 49 Transportation and Warehousing	6	2.74	106	3.15	-0.41
51 Information	1	0.46	50	1.49	-1.03
52 Finance and Insurance	5	2.28	156	4.64	-2.36
53 Real Estate Rental and Leasing	16	7.31	234	6.96	0.34
54 Professional, Scientific, and Technical Services	27	12.33	369	10.98	1.35
55 Management of Companies and Enterprises	1	0.46	2	0.06	0.40
56 Administrative and Support and Waste Management and Remediation Services	5	2.28	141	4.20	-1.91
61 Educational Services	0	0.00	15	0.45	-0.45
62 Health Care and Social Assistance	14	6.39	490	14.58	-8.19
71 Arts, Entertainment, and Recreation	9	4.11	95	2.83	1.28
72 Accommodation and Food Services	25	11.42	345	10.26	1.15
81 Other Services	20	9.13	281	8.36	0.77
Total	**219**		**3361**	**100**	

As illustrated by the table, the sector distribution was similar for flooded SBA-approved businesses and total flooded businesses in the county. Sector 11, agriculture, forestry, fishing and hunting, was slightly over-represented and sector 62, health care and social assistance, was under-represented. I then look at size and damage of flooded SBA-approved businesses compared to total flooded businesses in the county in Table 29:

Table 30 Employment of Firms Receiving SBA Loans Compared To 2007 Total Firm Employment (QCEW).

	Obs.	Mean	Std. Dev.	Min	Max
ReferenceUSA					
Average flood depth	3,361	5.24	3.26	0	29.30
Average employment	3,361	7.86	21.91	1	500
SBA					
Average flood depth	219	6.29	2.80	0.32	17.44
Average employment	219	6.47	10.73	0	60

The average businesses that was both flooded and approved for an SBA loan had a higher flood depth and fewer employees than the average flooded business in the county. I then see if the “smallness” is consistent across sectors in Table 30:

Table 31 Flooded Businesses Receiving SBA Loans Employment Compared to Total Flooded Businesses (ReferenceUSA).

Sector	SBA Firms	Avg. Employee #	Total Firms	Avg. Employee #	Dif.
11 Agriculture, Forestry, Fishing and Hunting	9	2.89	6	2.50	0.39
21 Mining	1	10.00	7	5.57	4.43
23 Construction	23	7.22	274	6.78	0.44
31-33 Manufacturing	8	4.88	85	13.32	-8.44
42 Wholesale Trade	5	3.60	101	6.94	-3.34
44 – 45 Retail Trade	44	5.80	604	6.87	-1.07
48 – 49 Transportation and Warehousing	6	12.17	106	10.46	1.71
51 Information	1	5.00	50	7.94	-2.94
52 Finance and Insurance	5	3.00	156	6.16	-3.16
53 Real Estate Rental and Leasing	16	2.19	234	6.01	-3.82
54 Professional, Scientific, and Technical Services	27	6.56	369	3.74	2.82
55 Management of Companies and Enterprises	1	5.00	2	9.00	-4.00
56 Administrative and Support and Waste Management and Remediation Services	5	4.80	141	6.16	-1.36
61 Educational Services	0	0.00	15	6.87	-6.87
62 Health Care and Social Assistance	14	5.57	490	9.62	-4.05
71 Arts, Entertainment, and Recreation	9	8.89	95	8.63	0.26
72 Accommodation and Food Services	25	10.92	345	15.63	-4.71
81 Other Services	20	6.90	281	4.79	2.11
Total	**219**		**3361**		

SBA-Approved businesses were smaller in several sectors with the exception of sector 21, Mining, which only had one business for comparison.

APPENDIX E

REGRESSION ON LOAN DELAY TIMES

When answering RQ1.1 and RQ1.2, loan delay from both the applicant and the SBA were significant variables in both analytical models. However, it's unclear which types of businesses this variable might be capturing. There are several reasons why a business may be delayed in getting an application in to the SBA. The first might be that the business was highly damaged, meaning their paperwork is potentially destroyed and they have other recovery issues such as clearing out their business to attend to. The second, however, is that businesses that can afford to wait for assistance, do. Businesses may not apply for SBA loans until they find out how much their insurance will cover, whether they will receive assistance elsewhere, or even what the recovery situation will look like. Because these are two drastically different potential sets of businesses, I run a regression on factors associated with loan delay, separating the time into the applicant delay. I use the same variables as the models for RQ1.1 and RQ1.2, with the exception of the loan variables and interaction terms. The identical process outlined in Appendix F indicated that using the linear form of the time variables led to a violation of the assumptions of homoscedasticity and multivariate normality. The logged form of the variables, however, did not present these issues. This makes sense given that disaster time compression provides a theoretical justification for a multiplicative effect when it comes to wait times (Olshansky et al., 2012). I present the results in Table 31.

Table 32 OLS Regression on Applicant Delay (ln).

Variable	Coef.	Coef.*	S.E.	p-value	
Constant	4.127	-	0.273	0.000	
Damage					
Flood depth (ft.)	0.010	0.036	0.021	0.307	
Average maximum wind speed (m/s)	-0.001	-0.006	0.008	0.466	
Business Characteristics					
Age of business (years)	0.008	0.119	0.005	0.042	**
Length of current management (years)	-0.014	-0.120	0.008	0.039	**
Number of employees	0.014	0.153	0.006	0.005	**
Retail business	-0.076	-0.030	0.141	0.296	
Manufacturing/Construction business	0.193	0.069	0.153	0.105	
Home business	-0.108	-0.049	0.129	0.202	
Corporation	0.247	0.123	0.115	0.017	**
Area Characteristics					
Density (1000 people/mi^2)	-0.003	-0.009	0.019	0.442	
Median household income ($1000)	-0.005	-0.074	0.004	0.111	
Delay					
Applicant Delay	-	-	-	-	
F	2.95 (p-value 0.001)				
Root MSE	0.821				
R-Squared	0.120				
N	249				

Coef.=Beta coefficient; Coef.*=Beta coefficient standardized on X; S.E.=Standard error; p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

The results show that business age, management history, size, and corporate status are all significant predictors of applicant delay ($p<0.05$). Each additional year the business has been established, the number of days to acceptance increases by 0.08 percent, each additional employee increases days until acceptance by 1.4 percent, and corporate businesses versus other types of businesses have 24.7 percent more days until acceptance. Years of current management is the only significant variable that has a negative relationship with application delay; days to acceptance is reduced by 1.4 percent for every year under the current management. Surprisingly, damage was insignificant. The age, size, and corporation variables suggest that the businesses that are more likely able to function longer in a deficit and more likely to have insurance have the longest delay times. The negative significance of the management variable may indicate that, controlling for resources, more managerial experience would help navigate the paperwork that has often been described as cumbersome or burdensome (Furlong & Scheberle, 1998; Runyan, 2006).

I next look at factors related to SBA approval delay, or the time it took from the application acceptance date to the date the loan was approved. This looks at which types of businesses might receive longer deliberation. Again, I use the same variables as the previous model. I present the results in Figure 32:

Table 33 OLS Regression on Applicant Delay (ln).

Variable	Coef.	Coef.*	S.E.	p-value	
Constant	3.387	-	0.169	0.000	
Damage					
Flood depth (ft.)	-0.006	-0.021	0.012	0.312	
Average maximum wind speed (m/s)	0.003	0.022	0.005	0.294	
Business Characteristics					
Age of business (years)	-0.003	-0.039	0.003	0.175	
Length of current management (years)	0.004	0.036	0.005	0.191	
Number of employees	0.006	0.059	0.003	0.052	*
Retail business	-0.186	-0.074	0.085	0.015	**
Manufacturing/Construction business	0.012	0.004	0.093	0.451	
Home business	-0.178	-0.081	0.078	0.012	**
Corporation	0.249	0.124	0.070	0.000	***
Area Characteristics					
Density (1000 people/mi^2)	-0.017	-0.052	0.011	0.069	*
Median household income ($1000)	-0.005	-0.074	0.002	0.021	**
Delay					
Applicant Delay	-0.001	-0.117	0.000	0.000	***
F	4.04 (p-value 0.000)				
	0.17				
Root MSE	0				
	0.12				
R-Squared	8				
N	249				

Coef.=Beta coefficient; Coef.*=Beta coefficient standardized on X; S.E.=Standard error; p=value represents 1-tailed test

* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

The results show a somewhat different set of significant variables. Being a retail business, being a home businesses, density, median household income, and applicant delay reduced the time it took for the SBA loan to be approved; being a home business reduced days to approval by 17.8 percent compared to storefront businesses (p<0.05), retail businesses reduced days to approval by 18.6 percent compared to other sectors (p<0.05), each $1,000 increase in median household income decreased days to approval by 0.5 percent ($p<0.1$), and each additional day of applicant delay decreased days to approval by 0.1 percent ($p<0.001$). Larger businesses and corporations had longer wait times, with each additional employee increasing days to approval by 0.6 percent ($p<0.1$) and a decrease in days to approval of 24.9 percent for corporations compared to other businesses ($p<0.001$).

It still seems like delay tends to be correlated with stronger businesses, even on the side of the SBA. Home businesses and retail businesses likely want assistance the quickest. Corporations and larger businesses are more likely to have other resources, which will need to be checked before an approval is made. The significance of median household income and density may be related to information sharing and more complete and correct applications, which would reduce processing time controlling for the other variables (damage and resources). A similar logic could be applied to applicant delay, where the longer it took for the application to be accepted, the more complete the application since resources and damage are controlled for.

To conclude these two analyses, it appears that delay generally tended to be related to businesses that *could* be delayed.

Lastly, Galveston had a bridge loan program after Hurricane Ike that provided bridge funding to businesses that were likely to receive SBA loans or insurance payouts. This presents an issue for using delay variables as an indicator of timeliness of funds in predicting survival, since the delay is not accurately capturing delay for all funding. Therefore, I do not use these variables in any of the other models. I believe this is not as much of an issue for the loan amount models and disbursement decision models. It should not affect loan amounts since the bridge loan program is not meant to supplement funds, just speed up the timing. Additionally, the theoretical variable in this model is the SBA timing, which should not be significantly affected, but this requires the model to have a control for applicant delay. For disbursement decision-making, the variable is not trying to capture time to first funding, but rather the certainty of the business' financial landscape (businesses are more likely to know if insurance payouts are going to go through, they will receive private funding [including the bridge loan], etc., the longer time goes on) as well as the rigor of the application process, itself.

APPENDIX F

JUSTIFICATION FOR TAKING THE LOG OF LOAN AMOUNT IN SECTION 5.1.1.

Table 33 presents the results of the linear regression on raw (untransformed) loan amounts.

Table 34 Predictors of Loan Amount ($10,000), Untransformed.

Variable	Coef.	S.E.	p-value	
Constant	-54.412	59.955	0.183	
Damage				
Flood depth (ft.)	3.063	3.958	0.220	
Average maximum wind speed (m/s)	0.614	1.592	0.350	
Business Characteristics				
Age (years)	4.629	0.940	0.000	***
Length of current management (years)	-3.088	1.550	0.024	**
Number of employees	4.439	1.078	0.000	***
Retail business	10.029	27.436	0.358	
Manufacturing/Construction business	8.841	29.401	0.382	
Home business	-54.193	25.247	0.017	**
Corporation	6.714	23.009	0.386	
Area Characteristics				
Density (1000 people/mi^2)	-1.871	3.641	0.304	
Median household income ($1000)	0.004	0.825	0.498	
Loan Characteristics				
Loan Term (years)	3.443	1.037	0.001	***
Economic injury loan	-43.816	42.543	0.152	
Applicant Delay	0.176	0.127	0.084	*
SBA Approval Delay	1.748	0.696	0.007	**
F	9.15 (p-value 0.000)			
Root MSE	157.04			
R-Squared	0.371			
N	249			

From there, I saved the residuals to a new variable, “r.” I produce the kernel density estimation, comparing the residuals to a normal density. This is presented in Figure 16. I also produced a normal probability plot in Figure 17. Both results indicate non-normality in the residuals, which would violate the multivariate normality assumption of OLS regression.

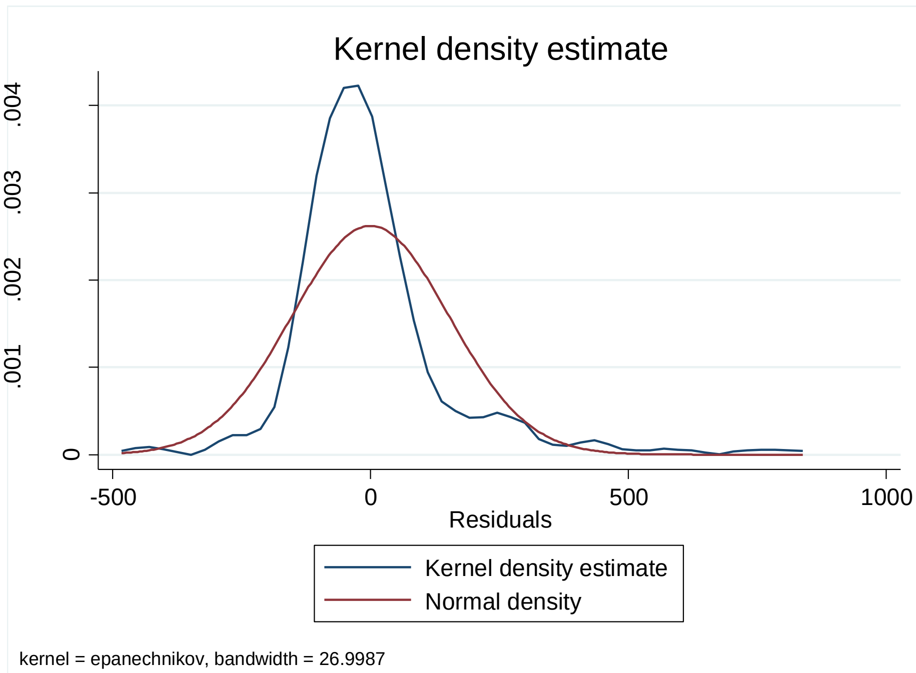

Figure 16 Kernel Density Estimation for Regression on Untransformed Loan Amount.

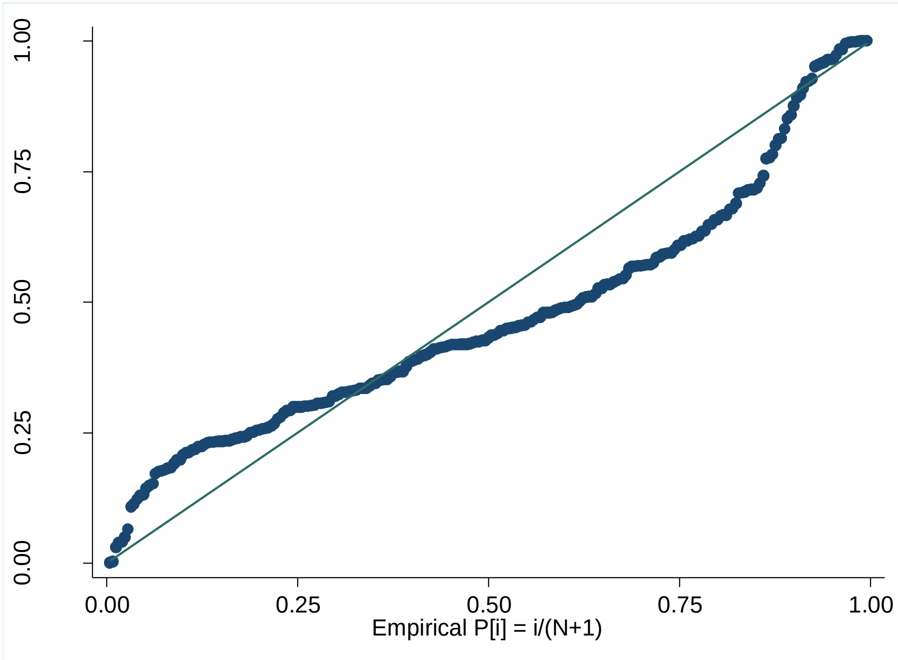

Figure 17 Normal Probability Plot for Regression on Untransformed Loan Amount.

To test the normality of the residuals, I also conducted a Shapiro-Wilk *W* test for normal data. The null hypothesis is that the data is normally distributed; the results in Table 34 indicate that we reject this hypothesis.

Table 35 Shapiro-Wilk Test for Regression on Untransformed Loan Amount.

Variable	Obs.	W	V	z	Prob>z
r	249	0.84501	28.011	7.752	0.000

I then plot the fitted values against the residuals to see if there is heteroskedasticity, as presented in Figure 18. The variance does not appear uniform. I then test the null hypothesis that the variance of the residuals is homogenous, another assumption of linear regression, using the Breusch-Pagan test. We reject the null, as shown in Table 35.

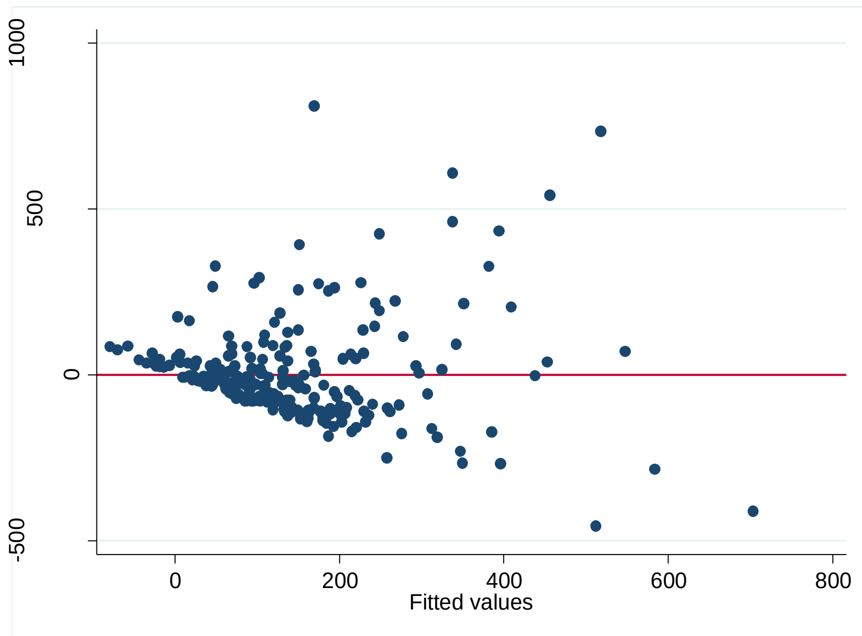

Figure 18 Fitted Versus Residual Values for Regression on Untransformed Loan Amount.

Table 36 Breush-Pagan Test of Constant Variance for Regression on Untransformed Loan Amount.

chi^2	$Prob>chi^2$
193	0.000

Because the previous regression violates the assumptions of homoscedasticity and multivariate normality, I examined the scatterplot of the continuous variables to get a sense of the relationship with the dependent variable. These scatterplots are presented in Figure 19.

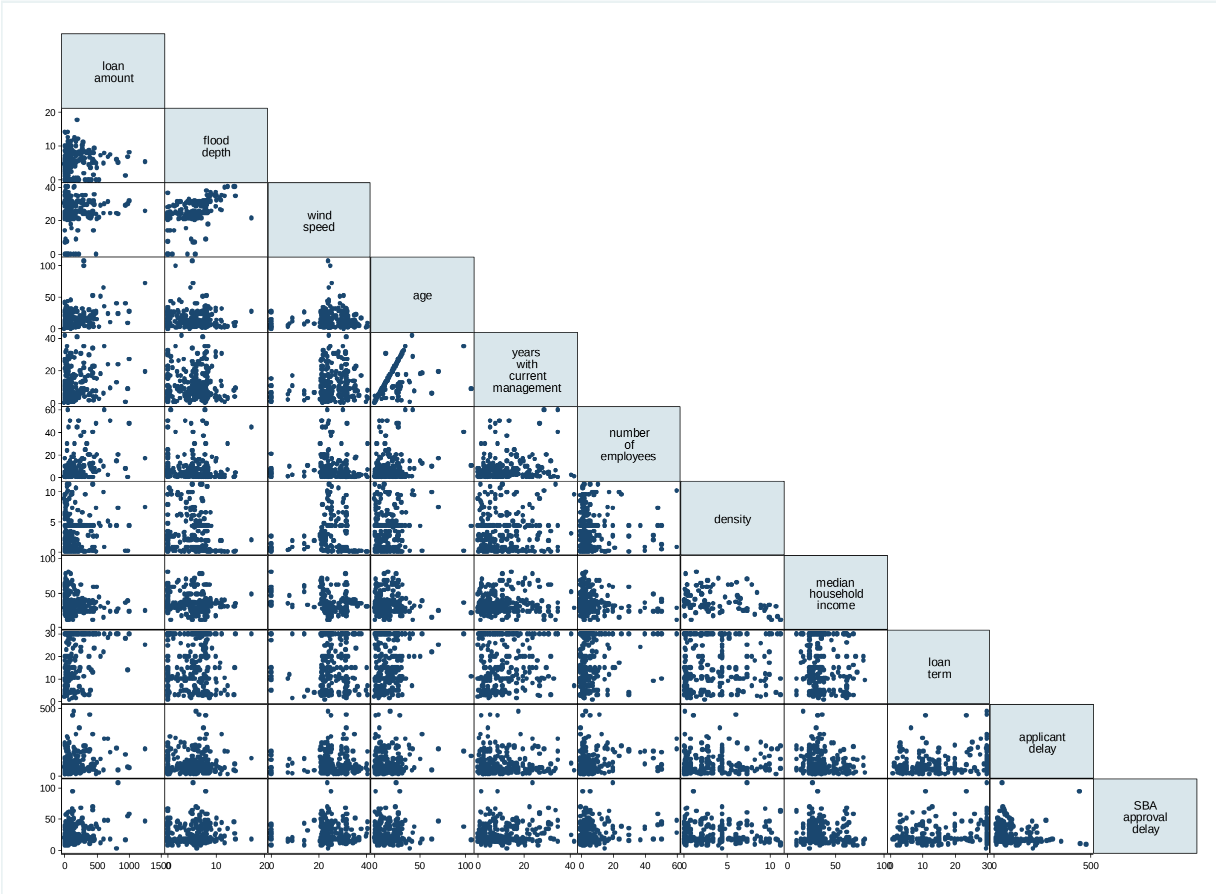

Figure 19 Scatterplot of Continuous Predictors and Untransformed Loan Amount.

It appears that there may be some non-linearity in several of the independent variable relationships with loan amount, with observations tending to cluster in the lower amounts. I then took the log value of loan amounts and re-ran the same tests.

Immediately looking at the same scatterplots in Figure 20, the relationships look a little more linear. The kernel density estimation and normal probability plot in Figure 21 and Figure 22 both indicate that the residuals are more normal. When testing this as a null hypothesis, we cannot reject that the residuals are normal, see Table 36.

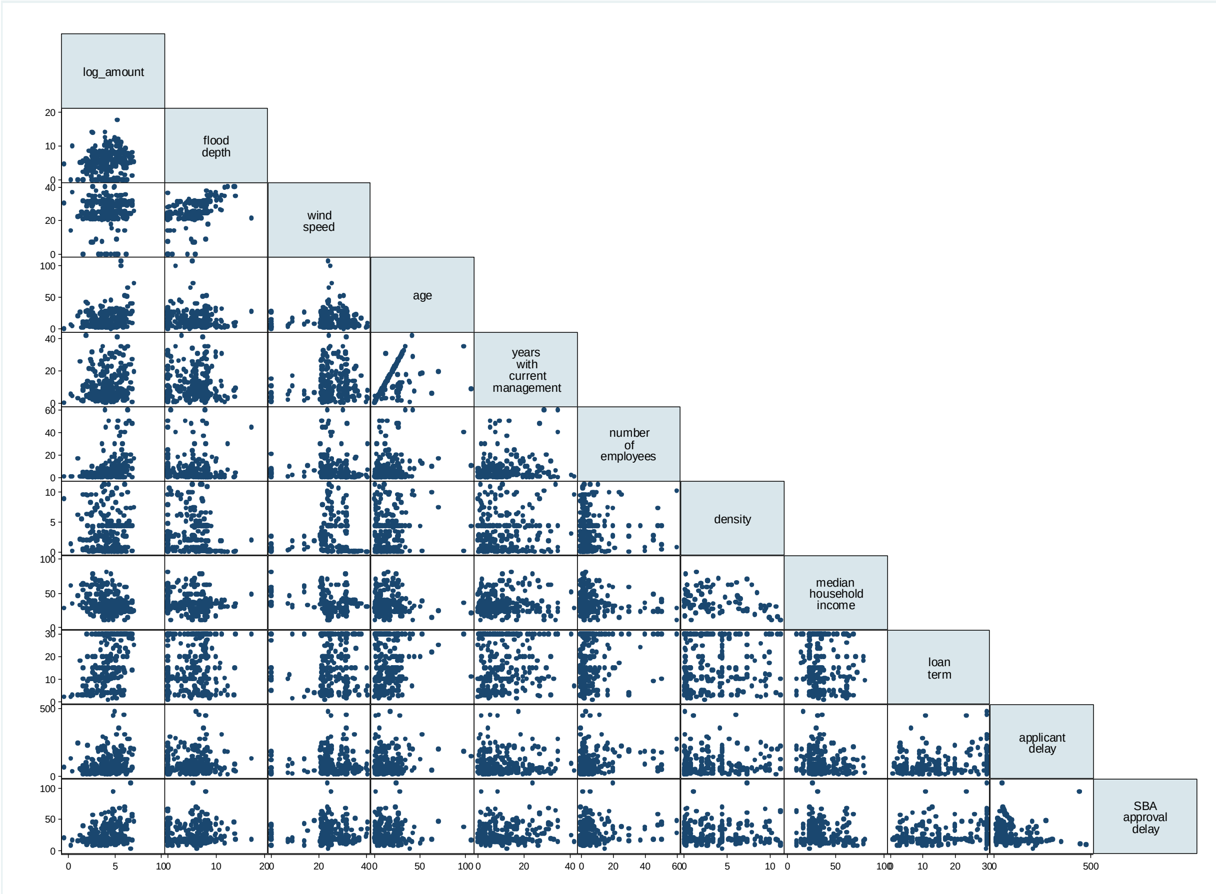

Figure 20 Scatterplot of Continuous Predictors and Logged Loan Amount.

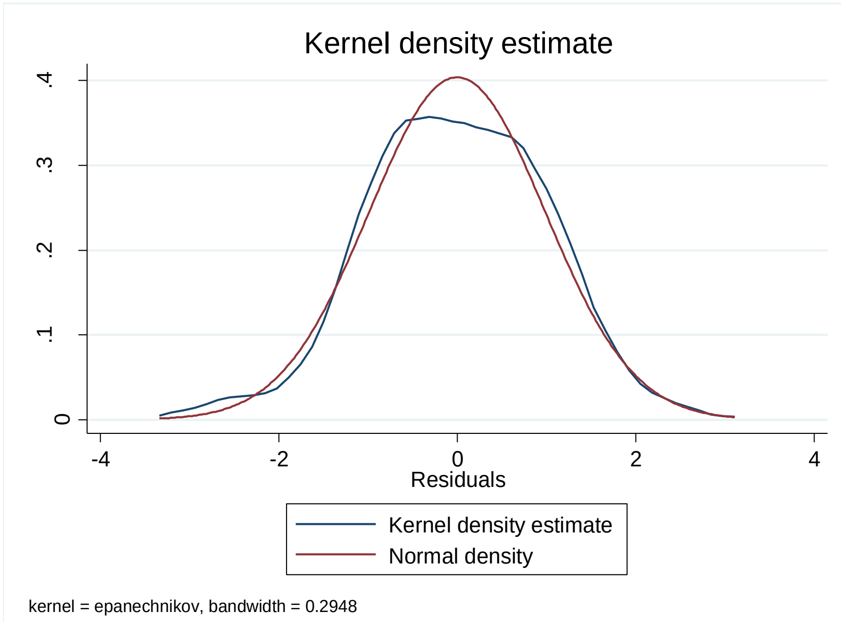

Figure 21 Kernel Density Estimation for Regression on Logged Loan Amount.

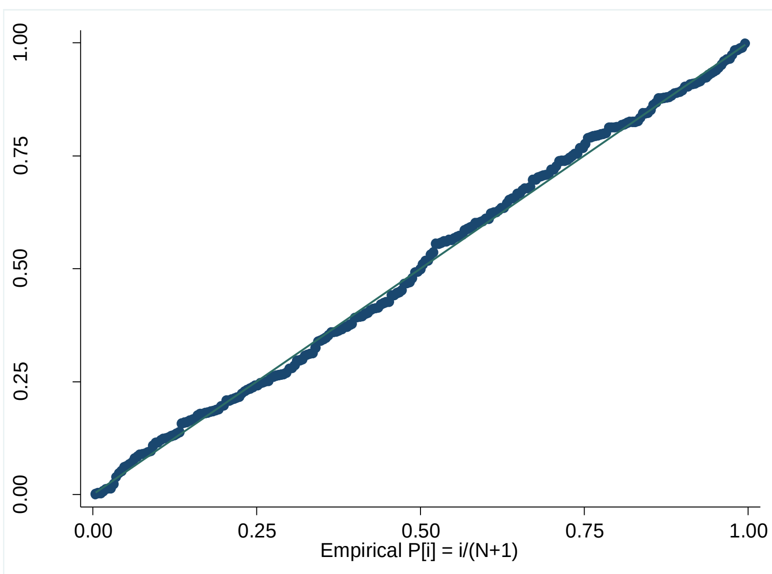

Figure 22 Normal Probability Plot for Regression on Logged Loan Amount.

Table 37 Shapiro-Wilk Test for Regression on Logged Loan Amount.

Variable	Obs.	W	V	z	Prob>z
r	249	0.963	1.018	-0.087	0.535

I again plot the fitted values against the residuals to see if there is heteroskedasticity, as presented in Figure 23. There is a definite visual improvement to the distribution of the residuals in terms of constant variance, as shown in Table 37, the visual evidence indicates that this model is still superior.

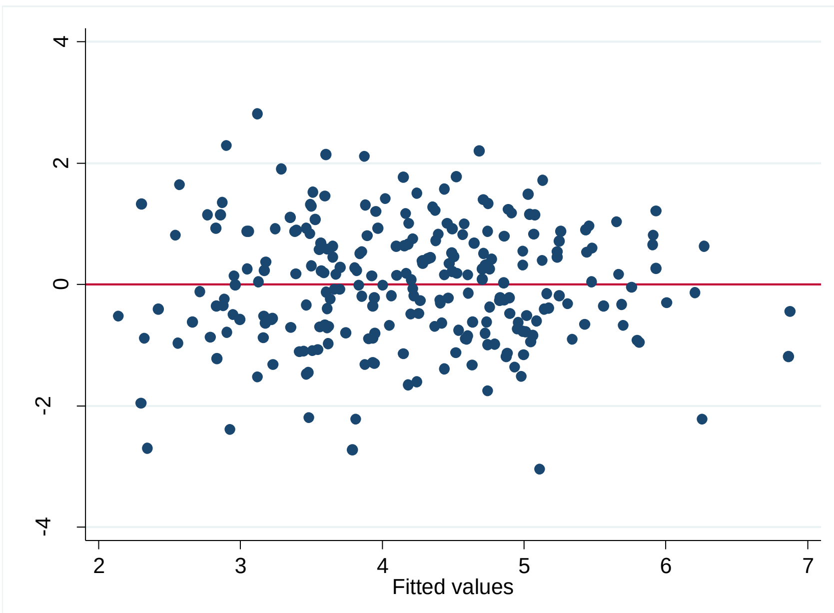

Figure 23 Fitted Versus Residual Values for Regression on Logged Loan Amount.

Table 38 Breush-Pagan Test of Constant Variance for Regression on Logged Loan Amount.

chi^2	$Prob>chi^2$
4.69	0.030

APPENDIX G

CONTINUOUS VS. FACTOR USE OF THE ORDINAL FLOOD DEPTH VARIABLE

This section justifies the use of a continuous measure of flood depth when the ordinal flood depth data is used (Section 5.2.) using a basic model of number of employees and flood depth on survival.

First, I use the continuous variable in Table:

Table 39 Continuous Use of the Flood Depth Ordinal Variable (M1).

Variable	O.R.	S.E.	p-value
Constant	0.289	0.271	0.103
Flood depth (ft.)	0.045	0.017	0.133
Number of employees	0.032	0.017	0.027 **
$\chi 2$	5.79 (p-value 0.055)		
2 log (L_1)	304.5335		
McFadden's Pseudo R-Squared	0.019		
N	246		

O.R.=Odds ratio; S.E.=Standard error; p=value represents 1-tailed test
* = $p \leq 0.1$; ** = $p \leq 0.05$; *** = $p \leq 0.001$

Then I use the factor variable in Table 39:

Table 40 Factor Use of the Flood Depth Ordinal Variable (M2).

Variable	O.R.	S.E.	p-value
Constant	0.404	0.343	0.120
Flood depth (ft.)			
<2	-0.878	0.670	0.095*
2-4	0.301	0.559	0.295
4-6	-0.103	0.445	0.408
6-8	0.397	0.432	0.179
8-10	0.413	0.469	0.189
>10	-0.257	0.673	0.351
Number of employees	0.033	0.017	0.028**
$\chi 2$	10.45 (p-value 0.165)		
2 log (L_1)	299.8707		
McFadden's Pseudo R-Squared	0.034		
N	246		

O.R.=Odds ratio; S.E.=Standard error; p=value represents 1-tailed test
* = p ≤ 0.1; ** = p ≤ 0.05; *** = p ≤ 0.001

Then I compare the two models using a likelihood ratio test in Table 40:

Table 41 Likelihood Ratio Test M1, M2.

Model	ll(null)	ll(model)	df	AIC	BIC
m1	-155.160	-152.267	3	310.5335	321.0495
m2	-155.160	-149.935	8	315.8707	343.9134
$\chi 2$	4.66 (p-value 0.458)				
N	246				

The results of the likelihood ratio test, BIC test, and AIC test all show that m1 (continuous measure) is superior.

APPENDIX H

FIXED EFFECTS LINEAR PROBABILITY MODEL AS A CONDITIONAL LOGISTIC REGRESSION ALTERNATIVE

One way to avoid excluding groups from the matched analysis is to run a fixed effects linear probability model since the predicted probabilities have more variation within groups. This is similar to the conditional logistic regression in that it looks at differences within groups, but is a linear prediction. The results of running a fixed effect linear probability model with robust standard errors (XTREG FE in STATA grouped by the matching strata) are shown in Table 41.

Table 42 Linear Probability Models for Matched Pairs.

	Approved + Disbursed			Disbursed Only		
Variable	Coef.	S.E.	p-value	Coef.	S.E.	p-value
Constant	0.166	0.365	0.325	0.441	0.422	0.115
Damage						
	-					
Flood depth (ft.)	0.031	0.051	0.276	-0.056	0.061	0.153
Average maximum wind speed (m/s)	0.019	0.012	0.056*	0.014	0.014	0.153
Business Characteristics						
	-					
Number of employees	0.009	0.014	0.263	-0.015	0.015	0.156
Sales volume ($10,000)	0.001	0.001	0.038**	0.001	0.001	0.033**
Treatment Status						
	-					
Loan approved but not disbursed	0.014	0.099	0.443	-	-	-
Loan disbursed	0.169	0.062	0.004**	0.176	0.066	0.005**
Area Characteristics						
	-					
Density (1000 people/mi^2)	0.024	0.015	0.059*	-0.027	0.003	0.068*
Median household income ($1,000)	0.002	0.002	0.150	0.002	0.104	0.231
Adaptation						
Moved	0.204	0.104	0.027**	0.275	0.104	0.005**
F	2.82 (p-value 0.005)			3.25 (p-value 0.003)		
Rho	0.420			0.452		
R-Squared:						
Within	0.102			0.131		
Between	0.022			0.009		
N	280[a]			212[b]		

Coef.=Beta coefficient; S.E.=Robust standard error; p=value represents 1-tailed test

* = p ≤ 0.1; ** = p ≤ 0.05; *** = p ≤ 0.001

[a]107 groups

[b]83 groups

The models use the full set of observations and show disbursal to still be a significant and positive predictor of survival. In the first model, disbursal increased survival probability by 17 percent and by 18 percent in the second model. In addition, density was a marginally significant, negative predictor of survival, decreasing survival probability by 2-3 percent. The significance of moving was also consistent with the conditional logistic regression, increasing survival probability by 20 percent in the first model and 28 percent in the second. Sales also significantly increased survival probability, with each $10,000 increase in sales yielding a .01 percent increase in survival probability. The R^2's of the linear probability models are somewhat lower than the conditional logistic regression. The model with both approved-but-not-disbursed and disbursed businesses has a within-group R^2 of .102 and the disbursed only model has a within-group R^2 of 0.131.

The limitation of running a linear prediction model is that it is not constrained to values between 0 and 1. This is illustrated by the summary of the predicted probabilities for each observation in the models in Table 42.

Table 43 Summary of Linear Predicted Probabilities for All Observations.

	Obs.	Mean	s.d.	Min	Max
Linear prediction (approved + disbursed)	280	0.664	0.249	0.144	2.061
Linear prediction (disbursed only)	212	0.675	0.334	-0.191	2.455

Predicted probabilities ranges from 0.14 to 2.06 in the first model and between -0.19 and 2.45 in the second model.