Decision Making in Natural Disasters: An Analysis of Firms' Strategic Behavior on Economic Resilience and Influence of Hurricane Intensity Forecasts on Evacuation Decisions

Dissertation

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Abstract

This dissertation is about organizational-level resilience and decision-making in the face of natural hazards. Research on resilience emerged to explain systems' ability to absorb and recover in the midst of adversity and uncertainty from natural disasters, crises, and other disruptive events. While interest in resilience has accelerated, research multiplied, and the number of policies and implementations of resilience to natural hazards have increased over the last several years, mainly at the level of communities and regions, there has been a dearth of empirical work on resilience at the level of the firm. And although different strategies have been proposed in the supply-chain literature, most of these include resilience actions that must be put in place prior to disruptions. These pre-disaster planning actions are often referred to as "mitigation" in the literature. In this dissertation, I will focus on measuring economic resilience at the level of the firm. The biggest difference between supply-chain resilience and economic resilience is that the latter focuses on resilience actions that can be implemented after a disruption begins whereas the former focuses on actions that must be put in place before a shock. This dissertation will make the major contribution of introducing a resilience strategy that I call resource sharing in the context of economic resilience.

This dissertation consists of three main papers. Chapters one and two are studies at the level of the firm. The third chapter is an empirical analysis at the individual level.

The first chapter is a theoretical component that provides propositions, conceptualizations and a theoretical framework to understand the relationships between the sharing of resources, the dependence on critical resources on the external environment, and resilience at the level of the organization. The second chapter uses empirical data and a sample selection model to test some hypotheses posed in the first chapter. The objective is to understand how the sharing of resources among organizations is related to economic resilience. Empirical results that are obtained from a sample of firms affected by Superstorm Sandy and Hurricane Harvey indicate that there is unobserved heterogeneity that explains the strategic behavior of firms in the post-disaster and that those firms that are more likely to resource share are also the ones that exhibit higher economic resilience.

The third chapter is based on a human subjects experiment aimed at testing the effect of hurricane intensity forecasts on evacuation decision-making in a disaster-preparation context. This chapter highlights the role of information and forecasts to public sector managers (e.g., state emergency managers) who have to make evacuation decisions aimed at avoiding potential losses – human lives in this case. In line with the extant literature that posits improved individual judgement accuracy that arises from statistical forecasts and assumes benefits derived from improved hurricane forecasting, I hypothesize that decision-makers with more information (i.e., individuals exposed to hurricane intensity forecasts) and decision-makers with less information (i.e., individuals not exposed to hurricane intensity forecasts) exhibit differences in their decision to evacuate, in the accuracy of their decision (i.e., timing), and in their determination for evacuation location. Results indicate that decision makers with more information in the form of forecasts evacuate more frequently and earlier than decision makers exposed to lower levels of information. The implications of these findings highlight the importance of information provided by hurricane intensity forecasts on the evacuation decision. This chapter has in common with the previous two chapters the analysis of strategic behavior of individual entities (i.e., businesses, emergency management officials) in the context of natural disasters and the study of factors that influence the flow of information in the decision-making process.

Dedication

To my wife Melisa, and my princesses Miranda and Rebeca: the best part of everyday.

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Chapter 1: The Relationship between Resource Sharing and Economic Resilience: A Conceptual Framework from Resource Dependence Theory

"Competition has been shown to be useful up to a certain point and no further, but cooperation, which is the thing we must strive for today, begins where competition leaves off" (Franklin D. Roosevelt, 1912)

1.1 Introduction

This chapter examines the *decision-making* of organizations in the aftermath of natural disasters. More specifically, it aims to outline a theoretical framework about cooperative behavior in disruptive environments by explaining why a firm[1] decides to *share resources* with other organizations after the occurrence of a disturbing event such as a natural disaster and how these interorganizational relationships shape the *economic resilience* of the firm. Although the topic of cooperation among organizations and the study of collaborative strategies used by firms to cope with uncertainties and complexities is not new (e.g., Gray & Wood, 1991, Rosenfeld, 1996, O'Mahony & Bechky, 2008), the literature has recently witnessed a rising academic interest in studying the relationship between a resource sharing strategy and a firm's resilience, particularly from the fields of supply chain management and economics (e.g., Brandon-Jones, Squire, Autry, & Petersen, 2014; Scholten & Schilder, 2015; Gabler, Richey Jr, & Stewart, 2017;

[1] Barnard (1968, p.72) defined an organization as "a system of consciously coordinated personal activities or forces. A firm, on the other hand, is a business organization aimed at maximizing profits by selling its products and/or services (Varian, 1992). Although a firm is a specific type of organization -a business, corporation, or Enterprise- throughout this document and without loss of generality, I will use the words "firm" and "organization" as synonyms to make reference to any type of organization.

Dormady, Rose, Rosoff, & Roa-Henriquez, 2018; Dormady, Roa-Henriquez, & Rose, 2019).

At the organizational level, the concept of resilience emerged to explain a firm's ability to absorb and recover in the midst of adversity and uncertainty from natural disasters, crises, and other disruptions. Some scholars argue that resilience is enhanced when decision-makers comprehend low-probability, high consequence risks (Kunreuther, Meyer, & Michel-Kerjan, 2013). According to this view, which focuses primarily on mitigating and reducing the frequency and impact of disasters, an effective enterprise risk management assessment will be incomplete if firms are unaware of their ability to strengthen property and avoid damage. In fact, this view has been incorporated and broadly adopted by the National Research Council in its definition of resilience as "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (NRC, 2012; p. 16). Other scholars, nonetheless, consider that resilience refers to an embedded capacity of organizations and their individual structures (Van der Vegt, Essens, Wahlström, & George, 2015). They argue that traditional risk management tools do not adequately address hazards not only because decision-makers do not well understand the mechanisms of improbable events causing the disasters but also because many of these events occur simultaneously, which makes it hard for their consequences to be predicted and anticipated[2] (Van der Vegt et al., 2015). This stream of research is more related to the notion of the inherent capacity of firms to

[2] Resilience research – for this reason – has started to incorporate the concept of "anticipative resilience", which refers to preparatory resources developed purposefully to cope with crises and disruptions (see Azadegan and Jayaram, 2018).

cope with shocks after a disaster strikes (Tierney, 2007, Rose, 2007; Cutter, 2016). This chapter goes more in line with this approach to facing disruptions because it acknowledges that resilience is a process[3] and points out not only to the steps that can be taken before the shock but also to the actions and tactics that take place and are implemented after the disaster occurs, which underlies the analysis of economic resilience. Although a more complete definition will be provided in a later section, it is important to mention at this point that the concept of economic resilience does not focus on property damage but on business interruption (BI), for which the impact (in dollars) is typically twice as large as the impact on property damage (Rose & Blomberg, 2010).

The concept of economic resilience has spanned and theoretically supported the advancement of research on resilience in different fields including climate change (e.g., Pelling, 2010), enterprise resilience (e.g., Sanchis & Poler, 2014), community resilience (e.g., Bondonio & Greenbaum, 2018), and supply chains (e.g., Brusset & Teller, 2017). In particular, this chapter helps strengthen the foundation of the supply-chain literature, which overlaps with the study of resilience, though, supply-chain research generally focuses more narrowly on resilience actions that must be put in place prior to shock. These pre-disaster planning actions are often referred to as "mitigation" in the literature (see, e.g., Christopher & Lee, 2004). This is the biggest difference between supply-chain resilience and economic resilience—the latter focuses on resilience actions that can be

[3] The notion of resilience as a "process" relates to putting things in place that can be implemented after a disaster. But it is not about explicit actions before a disaster—which is mitigation. Resilience process pre-disaster is setting things up for what can be done/used after a disaster. For example, buying inventories may be part of the process because they are not utilized for resilience until after a disaster. But, strengthening levees to prevent catastrophe is a form of mitigation because it does not need to be implemented after (see Dormady et al., 2019)

implemented after the shock whereas the former focuses on actions that must be put in place before a shock. It should be clear to see the important contributions of economic resilience given this critical distinction—firms can seldom plan for every contingency in a disaster context and the study of innovation and ingenuity in responding to resource constraints and curtailments is what economics is all about. Whereas the abundance of resilience research has focused on mitigation and hardening by pre-planning, economic resilience is focused almost entirely on what organizations do to respond to the unforeseen or unexpected.

While interest in resilience has accelerated, research multiplied, and the number of policies and implementations of resilience to disruptions (e.g., natural hazards, economic recessions, terrorism) has increased over the last several years, there has been a dearth of work on resilience at the level of the firm (Dormady et al., 2018; 2019). In contrast, much of the current research on resilience has hinged upon developing studies at the level of communities and regions (e.g., Norris, Stevens, Pfefferbaum, Wyche, & Pfefferbaum, 2008; Tierney, 2014; Martin & Sunley, 2014; Wolman, Wial, St. Clair, & Hill, 2017). At the same time, extant literature has identified the need to build and formalize the theory behind the recent proliferation of studies on the topic, which includes numerous definitions, tactics, metrics, and ad hoc formulations with little or no theoretical foundations (Dormady et al., 2019). This is confirmed by a recent editorial note of the *Academy of Management Journal* (Van der Vegt et al., 2015), where editors explicitly call for more research on organizational resilience for managers and decision-makers to be trained with theory-based models and tools that allow for more effective responses to vulnerabilities and external disturbances. This claim highlights the need for resilience to include a managerial perspective and not just as an engineering or sociological construct.

In the spirit of Van der Vegt et al.'s (2015) call, this chapter provides a theoretical framework to aid in conceptualizing the influence of a resource sharing resilience strategy on economic resilience by borrowing from a Resource Dependence Theory (RDT) perspective. This is unique to all resilience literatures (e.g., economic, sociological, supply chain) and is integrated with other theories and concepts and helps to better explain strategic firm behavior, more specifically, the decision of a firm to share resources in the midst of a disruption or after the occurrence of a natural disaster. In this regard, by drawing on RDT, this dissertation addresses the issue of dependency on external resources in a disaster context and suggests that it is important to study the decisions of organizations to share resources as a strategy to avoid dependencies and obtain critical resources that allow them to survive in the post-disaster. The next sections provide a definition of economic resilience, a review of different firm-level actions or strategies that organizations use after the onset of a disaster including a definition of a resource sharing strategy, and different propositions that integrate theories to these definitions. The chapter concludes with some implications for further research.

1.2 Defining Economic Resilience

This chapter follows the definition of economic resilience provided by Rose (2004, 2007, 2017) and formalized by Dormady et al. (2019) in a production theory context. According to this approach, there are two major categories or dimensions of economic resilience. The first dimension is the one that classifies resilience as static or dynamic.

- Static economic resilience refers to the ability of a firm to efficiently continue its operations with remaining resources at a given point in time after the occurrence of a shock and denotes the need to compensate for deficiencies in the availability of production inputs (Rose, 2004; 2007; Dormady et al., 2019).
- Dynamic economic resilience refers to the ability of a firm to recover over time while using resources efficiently and after investing in repair and reconstruction as a means of accelerating and shortening recovery (Rose, 2004; 2007; Dormady et al., 2019).

The concept of static economic resilience is partially derived from Holling's definition (1973) of resilience as the ability of a system to absorb change and maintain functioning after a disturbance. However, unlike Holling´s definition that considers that resilience is a property of the system, the definition of static economic resilience also assumes that resilience can be enhanced before a disruption and also focuses on how the system (i.e., the firm) uses scarce resources efficiently in the post-disaster (Rose, 2004; 2007; Dormady et al., 2019). On the other hand, the definition of dynamic economic resilience is more related to Pimm´s definition (1984) of resilience as the ability and speed of the system to return to pre-disaster conditions.

The second dimension is the one that classifies resilience as inherent or adaptive. Inherent resilience refers to actions that result from the capacity already built into the system whereas adaptive resilience refers to actions that result from ingenuity or extra effort (Rose, 2004; 2007; Dormady et al., 2019). These two dimensions and definitions of resilience are mapped onto one of four cells in Table 1.

Table 1. Definitions and Dimensions of Resilience

	Inherent	Adaptive
Static	Ability of the firm to maintain functioning while using resources efficiently and by using actions that result from the capacity already built into the organization.	Ability of the firm to maintain functioning while using resources efficiently and by using actions that result from ingenuity and/or extra effort.
Dynamic	Ability of the firm to hasten recovery over time while using resources efficiently and by using actions that result from the capacity already built into the organization.	Ability of the firm to hasten recovery over time while using resources efficiently and by using actions that result from ingenuity and/or extra effort.

Unlike other fields such as supply chain (which emphasizes pre-disaster actions) and engineering where resilience is characterized as a property of the system and the attention is on mitigation actions and property damage (which have already taken place) (Rose, 2017; Dormady et al., 2019), the focus on economic resilience is "the reduction in the loss of the flow of goods and services emanating from property, or capital stock" (Dormady et al., 2019, p. 447). That is, it centers on the reduction in the loss of the firm's throughput[4] due to a disruption. In this regard, economic resilience focuses on the reduction of *business interruption* and the analysis of actions that are implemented after a disaster hits. In today's environment, which is characterized by an increase in the

[4] Throughput is the rate at which the system generates its products or services per unit of time (Besanko, Dranove, Shanley, & Schaefer, 2013).

frequency and magnitude of disasters (Wong et al., 2014), it is essential for firms to identify and understand their capabilities and limitations in the use of resources to avoid or reduce business interruption and avoid or decrease losses. This is vitally important to firms and to regional economic health because, as mentioned above, business interruption is typically twice the magnitude (in dollars) of property damage.

The literature on business interruption that lies behind the concept of static economic resilience is closely connected to the literature on business continuity (Sheffi, 2005; Herbane, 2010) as both center on the continued functioning of individual firms and their recovery from disaster. Nonetheless, although the literature on business continuity has some important economic resilience implications (e.g., such as enhancing inherent resilience by designing flexible and redundant systems prior to disasters),[5] it heavily emphasizes on cyber/information technology considerations, which are beyond of the scope, not only of the literature on economic resilience but also of this chapter.

1.3 Firm-level Resilience Actions or Strategies

To improve either static or dynamic resilience, firms may choose to use both intraorganizational and interorganizational strategies. In the context of a disaster, the application of these set of actions is based on the rationale of how organizations react when there is a shortage or disruption in one or more of their inputs. This is formalized in Dormady et al. (2019) who employ a production theory framework to analyze how firms cope with disasters in the absence of a demand shock. These actions or strategies are represented by eleven discrete activities, as provided in Table 2. Building on Rose (2009)

[5] See Rose (2015) for other exceptions.

and Dormady et al. (2018), the table provides a naming convention for each resilience tactic along with definitions and examples that clarify the use of the respective strategy.

Table 2. Common Firm-level Resilience Tactics and Definitions

Resilience Tactic	Definition (Activities Involved)
1-Conservation	*Maintaining intended production or service levels using lower amounts of an input or inputs (e.g., achieving the same level of production using less water, electricity or workers, without substituting other inputs for them).*
2-Resource Isolation	*Modifying a portion of your business operations to run without a critical input (e.g., following the disaster an office building could still be operational without water). This can include the isolation existing before the hurricane or your extra effort to isolate it post event.*
3-Input Substitution	*Replacing a production input in short supply with another (e.g., replacing electricity by natural gas, water provided by pipeline with bottled or trucked water, whole milk with powdered milk, employees for tasks previously performed by machinery).*
4-Inventories	*Continuing business operations even when a critical input is in short supply by using emergency stockpiles and ordinary working supplies of production inputs (e.g., water tanks, canned goods, and stockpiled materials in general).*
5-Excess Capacity	*Using a plant or equipment that was idle before the hurricane in place of a damaged plant and equipment (e.g., bring on line physical assets not previously in use; such assets might include computers, equipment, vehicles, and vacant buildings).*
6-Relocation	*Moving some or all of the business activity to a new location (either temporary or permanent), including shifting data from onsite to "cloud" storage.*
7-Management Effectiveness	*Improving the efficiency of your business in the aftermath of the natural disaster (e.g., allowing for flexibility in business operations/procedures to minimize red tape during recovery, offering flexible working hours, minimizing reporting requirements or monitoring to facilitate more efficient or responsive operations).*
8-Import Substitution	*Importing some of your needed production inputs when you cannot obtain them from your usual local or regional suppliers, including new contractual arrangements (e.g., buying your materials or supplies from other regions or countries).*
9-Technological Change	*Improvising all or part of your production process without requiring a major investment expenditure (e.g., replacing two food preparation kitchens with one, replacing your paper accounting system with an automated one).*
10-Production Recapture	*Making up for lost production by working overtime or extra shifts. This must involve actual production and not include the selling of goods and services that were previously produced but could not be sold because of a slump in demand (e.g., adding an additional shift for employees or having them work additional overtime hours).*
11-Resource Sharing	*Hastening recovery through mechanisms such as bargaining (e.g., renegotiating supply contracts with key suppliers), the selective exchange of certain resources (short term agreements for a defined period of time with other organizations, e.g., the utilization of facilities in exchange for the provision of any service or any other resource), creating new partnerships (e.g., building relationships with other businesses in order to share information and/or expertise), and resource pooling (e.g., joint ventures in order to bid for public contracts).*

Dormady et al. (2018) provide evidence of the use of these tactics based on a 2017 survey that collected primary data from firms affected by Superstorm Sandy in 2012. In this survey, 43% of firms observing business interruption derived from Superstorm Sandy employed technological change, which was the most utilized tactic. Thirty-two percent (32%) of firms used resource sharing, 30% used conservation, 25% used relocation, and the least utilized tactic was import substitution with 16% of firms implementing this strategy. However, not necessarily the most and least utilized tactics were the most and least cost-effective respectively. For instance, for completely recovered firms, Dormady et al. (2018) found that conservation, relocation and resource sharing consistently rank among the most cost-effective tactics in explaining economic resilience.

In this regard, the decision to choose a particular strategy or strategies has been mainly modeled based upon the cost-effectiveness of using a specific action and on inputs' prices, flexibility, and technology of the firm's production function. Dormady et al. (2019), for instance, assume that firms choose post-disaster strategies that optimize their production function and use inherent and/or adaptive tactics that allow them to continue operating efficiently in presence of resource inputs constraints. However, additional to these factors, there are others not yet explored in the literature that explain economic resilience, which are specific of each strategy depending on whether the tactic used is intraorganizational or interorganizational.

Intraorganizational strategies refer to actions that the firm carries out internally (i.e., within the firm). There is no need for the organization to engage with another firm or organization outside of its own. With these actions, which are performed independently without the collaboration of an external partner, organizations are *autonomous* and “seek to seal off their core technologies from environmental influences” (Thompson, 1967, p.19). Intraorganizational strategies include cases in which subsidiaries, branches or franchises are aided by their corporate network (i.e., firm).

Some of these tactics are aimed at absorbing – whether on the input side or on the output side – the changes derived from the external event. That is, the goal is to *buffer* the irregularities in the resource flows and adapt the system to the variabilities that may undermine recovery (Thompson, 1967; Menzar & Nigh, 1995; Bode, Wagner, Petersen, & Ellram, 2011). Examples of these types of actions include *conservation* (e.g., achieving the same level of production using less water, electricity or workers, without substituting other inputs for them), the use of *inventories* or emergency stockpiles and ordinary working supplies of production inputs such as water tanks, canned goods and stockpiled materials in general, and the use of *excess capacity* represented in plant and equipment that was idle before the disaster.

Other tactics involve attempts to level the fluctuations in the operations following the shock. In this case, unlike adaptation, the main objective is to *smooth* the variabilities hindering resilience (Thompson, 1967). Some of these actions involve, among others, *input substitution* (i.e., the use of alternative inputs or substitution to compensate for the scarcity in one of the post-disaster production factors) and *production recapture* (i.e., making up for lost production by working overtime or extra shifts) (Dormady et al., 2019).

Other tactics are aimed at adapting the organization to the external shocks that cannot be buffered or leveled. The main objective of these actions is to monitor the flow of inputs and output and adapt the organization by *forecasting* expected changes (Thompson, 1967). In the context of increasing resilience, these tactics include *technological change* (i.e., improve the efficiency of the organization in the aftermath of a disaster by allowing for flexibility in operations), *resource isolation* (e.g., continue operating in the absence of an input or shifting production to a product line that does not require the curtailed input), and *management effectiveness* (e.g., inducing those who use services or require the goods during peak hours, and by minimizing red tape during recovery) (Dormady et al., 2019).

Last, other actions used by organizations to cope with disasters are related to *rationing* (Thompson, 1967). The main objective of these tactics is to restrain the provision or use of a specific input by limiting the waste of materials or unnecessary resources. To enhance resilience, some organizations resort to a tactic of *conservation* intended to use lower amounts of an input or inputs during the production process. This involves, for instance, achieving the same level of production by using less electricity, water or labor without substituting a production factor by another (Dormady et al., 2019).

1.3.1 A Resource Sharing Strategy

Not all tactics are intraorganizational, and some firms use multiple actions, so they can leverage one another's resources to absorb shocks or improve their static resilience on the one hand and hasten recovery or improve their dynamic resilience on the other (Rose, 2007; Dormady et al., 2018). It is in this sense that organizations resort to using some *interorganizational strategies* that involve ties, alliances and partnerships not only with customers and/or suppliers but also with their peers and similar organizations to strengthen relationships and gain access to critical resources that provide stability to the operations of the firm (Thompson & McEwen, 1958).

Although the rationale of a firm in using intraorganizational strategies may be related to building capacities that increase its inherent resilience so as to have a higher control of resources and reduce the variability in the flow of inputs or production factors (e.g., having more inventories), it is likely that after an external event such as a natural disaster, an organization finds itself with the need of resources that are out of its autonomous domain and are not easily accessible due to the post-disaster conditions. To survive during such a disruption, organizations need to obtain critical resources from the external environment (Pfeffer and Salancick, 2003).

Among the interorganizational actions used by firms, *bargaining* is likely the most common. It involves a review of short-term agreements and periodic negotiation with another organization (Thompson & McEwen, 1958). Following a disaster and in the context of resilience, it is useful to employ bargaining when a firm needs to renegotiate supply contracts with key suppliers or renegotiate agreements with contractors for the provision of a service (Dormady et al., 2019). Also, in many post-disaster situations, organizations may also renegotiate with unions or key employees some future benefits in exchange for the voluntary assistance during the recovery process. Although bargaining goes beyond a market relationship and requires a direct interaction with another entity, at some point it ensures the provision, though limited, of the resource that the organization needs for the continuity of its operations (Tolbert & Hall, 2009).

Another tactic used by managers is *creating ties*, relying on existing ties and using third-party organizations that support the ties. Ties with other organizations allow building relationships with other managers to share information and/or expertise in post-disaster situations. It may be less common to cooperate by creating new ties than relying on those existing in the aftermath of a disaster. Organizations will tend to collaborate with others after they perceive that the type of cooperation they receive create value for the firm (Cheng, 2011). The action of creating ties is derived from the concept of social capital that explains how networks, norms and trust facilitate the coordination and cooperation among organizations for mutual benefit (Putnam, 1993). In turn, social capital is embedded in social relationships in which both the number of ties and the quality of connections, instead of individual managers' attributes, improve the structure of the network (Granovetter, 1973; 1985). The literature supports this notion that ties are important but strong connections are even more. Strong connections to other organizations provide tools, critical resources and information after the onset of a disaster (Aldrich, 2011). Organizations employ this tactic when they need to ensure the flow of resources and consider that having a channel of communication with other firms is a key element in facilitating this exchange (Tolbert & Hall, 2009). For instance, recent research shows how pre-disaster relationships and networking patterns played a vital role in post-disaster rebuilding following Hurricane Katrina (Doerfel, Chewning & Lai, 2013).

Last, a less commonly used set of actions involves the combination and commitment of resources of two or more organizations for a long-term purpose. This tactic is defined as *coalition* (Thompson & McEwen, 1958) and is used when a more effective response to a disaster requires the mutual commitment and developing of joint activities by multiple organizations. For instance, after being hit by different natural disasters, six energy companies launched in 2016 the Grid Assurance, a strategic alliance that would help to improve grid recovery after a shock. Another example involves the creation of a joint venture by two or more firms to bid for public contracts after their operational capacity have been diminished by an external shock. It is not clear, however, what characteristics a good partner should have. From the research on business recovery, although there is a large literature on the role of spatial dependence in firm location decisions with empirical evidence suggesting a strong dependence in decisions by firms to reopen following a disaster (see, e.g., LeSage, Pace, Lam, Campanella, & Liu, 2011), there is no research about the role that nearby firms in a similar location have on one another's resilience. This is a topic that is beyond the scope of this dissertation.

By examining this set of interorganizational actions, this dissertation makes the contribution of elucidating the factors that go into the decision to choose a *resource sharing* strategy in the context of economic resilience. Following Thompson & McEwen, (1958), this dissertation relates resource sharing, which involves cooperation among firms, to the use of the following mechanisms:

1) The selective exchange of certain resources or short-term agreements for a defined period of time with other organizations (e.g., the utilization of facilities in exchange for the provision of any service or any other resource).

2) Bargaining (e.g., renegotiating supply contracts with key suppliers).

3) Creating new partnerships (e.g., building relationships with other businesses in order to share information and/or expertise), and

4) Resource pooling (e.g., joint ventures in order to bid for public contracts). One common characteristic of these cooperative actions is that they involve the combination and commitment of resources of two or more organizations

The role of resource sharing as a form of collaboration and cooperation has been explored in the more narrow supply chain resilience literature; however, research on this tactic in the more expansive context of economic resilience has not been provided. The equivalent actions in the supply chain literature include new alternative sourcing arrangements (Lee and Wolfe, 2003; Tomlin, 2006), collaborative information exchange (Pettit et al., 2013), information-sharing, collaborative communication, mutually created knowledge and joint relationship efforts (Scholten and Schilder, 2015), among others. As previously mentioned, the supply chain literature incorporates some pre-disaster and proactive planning actions that move beyond mitigation toward actually building "anticipative" resilience (Azadegan & Jayaram, 2018) or resilience capacity (i.e., a form of creating inherent capacity in the economic resilience terminology). It is also important to note that the supply chain literature addresses the concept of resilience actions primarily from the planning side (i.e., prior to a disaster) and focuses on mitigating the negative consequences derived from a disruption. This includes common resilient supply chain tactics such as diversification (Chopra & Sodhi, 2004; Kleindorfer & Saad, 2005), information sharing (Cheng, 2011), integration (Frohlich & Westbrook, 2001; Narasimhan & Kim, 2002; Hendricks, Singhal & Zhang, 2009), and supply and demand-side flexibility (Tang and Tomlin, 2008).

In the case of the tactic of resource sharing, the supply chain literature defines it as "the process of leveraging capabilities, resources and assets as well as investing in capabilities, resources and assets with supply chain partners (Cao, Vonderembse, Zhang, & Ragu-Nathan, 2010). Even though this definition highlights the importance of leveraging current and building future capabilities (i.e., a form of inherent resilience because it involves both, capabilities that are naturally embedded and the construction of capabilities in the supply chain structure), the definition does not incorporate the concept of adaptive resilience or how firms use ingenuity, extra effort, or improvisation under stress to respond to unforeseen disruption after it begins (Dormady et al., 2019). The literature on economic resilience acknowledges that resilience is a process and is the product of using tactics that leverage on the natural capacity of the firm (inherent) or that leverage on the natural capacity of the firm and use ingenuity, extra effort, and improvisation (inherent and adaptive) (Dormady et al., 2019).

Intra- and interorganizational actions aim to improve resilience, however, it is likely that firms cannot completely recover by using these tactics alone. The exception would be if firms did not suffer any property damage in the midst of a disaster and the disruptions were only due to a shortage of inputs. Although static economic resilience does accelerate the time path of recovery (aside from investment in repair and reconstruction) , it does not accelerate the duration, which requires restoring capacity to pre-disaster levels and, in turn, prevents any resilience tactic to completely restore capacity to the same levels before the disaster (Rose, 2017). Given that it is likely that no tactic per se will lead to a full recovery, the objective in this chapter is to understand what drives an organization to choose a resource sharing strategy and how this strategy influences economic resilience. It should be totally clear that a resource sharing action is only about interorganizational behavior (e.g., when a firm renegotiates contracts with a supplier) whereas some other managerial actions are typically intraorganizational because a firm is not engaging with another firm or organization outside of its own (e.g., management effectiveness when a firm cuts its own red tape and enhance resilience). In this sense, the appropriate literature explaining why a firm shares resources – a type of cooperative organizational form or strategic behavior – should incorporate interorganizational theories as we see in the next section.

1.4 Resource Dependence Theory in the context of Economic Resilience

The analysis of strategic behavior of firms after disasters is relatively new. The literature offers a few papers that help to explain how firms respond after disasters. Zolin and Kropp (2006) present a conceptual framework that considers how internal and environmental factors shape organizational decisions during and after disasters. Bode et al. (2011) provide a model of intra- and interorganizational responses to supply chain disruptions. Scholten and Schilder (2015) study the role of collaboration in supply chain resilience. And Dormady et al. (2019) use a production theory framework context that provides optimal production decisions of firms for each resilience strategy presented in Table 2.

Resource Dependence Theory (RDT) helps to explain the mechanism that leads firms to share resources after the onset of a disaster. It has not been used to address dependency on resources outside of a disaster context. Its fundamental tenet is that organizations' main goal is to survive and that dependence on "critical" and important resources that are obtained from the external environment influences organizational actions to achieve this goal. However, the fact that organizations depend on the environment to survive is not in itself problematic. If the external environment were a stable source of resources, dependency would not be an issue; however, environments change because some organizations survive and others never recover and fail, which creates instability in the supply of resources (Pfeffer & Salancik, 2003). To cope with this uncertainty, organizations react by using intra- and interorganizational actions that allow stabilizing the internal resource flow. The following propositions derive from RTD and outline why organizations share resources after a disaster occurs.

1.4.1 Organizational Objective after Natural Disasters

> ***Proposition 1**: After the onset of a natural disaster, survival becomes the prime organizational goal, but the attainment of this goal depends on the ability of the firm to increase its static economic resilience, which is obtained by reducing or avoiding business interruption (BI).*

Firms may have different motivations to act and initiate organizational responses following external events. In a supply chain setting, for instance, a disruption may be represented in the form of quality issues from suppliers, delivery failures, plant fires, and natural disasters that significantly threaten or impair the normal operations of a firm. Each of these external events may have a particular organizational response that aims to resume operations at the same level previous to the disruption.

According to the RDT, in a non-disaster context (i.e., external events different from natural disasters), organizations are motivated by the maximization of their autonomy (Thompson & McEwen, 1958) and the stabilization of the access of an uncertain flow of resources (Oliver, 1991) because they are not self-contained or self-sufficient (Pfeffer & Salancik, 2003). The notion of organizational autonomy derives from the rational systems perspective, which argues that efficiency is maximized when the organization controls all elements involved in its operation (Thompson, 1967). The premise of stabilization of access to external resources derives from the open systems perspective, which argues that scarcity in the external environment influences organizational behavior because firms have to compete for external resources (Pfeffer & Salancik, 2003). Bode et al. (2011), for instance, suggest that firms strive to stabilize the flow of resources in their internal and external operations, and this provides the organizational motivation to respond to supply chain disruption affecting a business relationship between a buying firm and one of its suppliers.

However, in a disaster context, the maximization of their autonomy and the stabilization of the access of an uncertain flow of resources may not be organizational motivations per se. Actually, RDT contends that organizations' main motivation is to survive and that "organizations survive to the extent they are effective" (Pfeffer & Salancik, 2003, p.1) and to the extent they have the "ability to acquire and maintain resources” (Pfeffer & Salancik, 2003, p.1). This implies that autonomy and stabilization are necessary but not sufficient conditions for organizational survival. Additionally, other traditional measures such as sales growth, market share, profitability, return on investment, and return on equity are not as important to affected businesses in the post-disaster, and just the question on whether to stay in business and fight for survival becomes relevant (Zolin & Kropp, 2006). In this regard, in a natural disaster, survival is considered the organizational purpose and any strategy implemented in the post-disaster should aim to improve survival chances. It is in this context where resilience is considered a necessary mechanism that maintains viability to the firm after significant environmental challenges (Alesch, Holly, Mittler, & Nagy, 2001).

In terms of what drives organizations to pursue resilience, one of the main tenets of economic resilience theory is that firms implement actions that contribute to the reduction in the loss of the flow of goods and services produced from property or capital stock. This has been defined as business interruption (BI), which is one of the key concepts underlying economic resilience, particularly static economic resilience, and begins at the point when the disaster strikes but continues until the firm has recovered or has achieved an alternative goal (Rose, 2017). Therefore, if resilience is a variable of considerable importance to organizational survival in a post-disaster environment (Alesch et al., 2001), the reduction of BI is essential in the mechanism that maintains operability and, in turn, viability to the firm.

1.4.2 Influence of Resource Sharing on Static Economic Resilience

> ***Proposition 2:*** *After the onset of a natural disaster, a strategy of resource sharing has an influence on organizational survival but its impact is mediated by the ability of the firm to increase its static economic resilience, which is obtained by reducing or avoiding business interruption (BI).*

A typical firm engages in business relationships that are usually reflected through buyer–seller arrangements or long-term contracts with given suppliers. Although these forms of interorganizational relationships guarantee a stable flow of resources, they prevent firms from establishing more advantageous relationships with other suppliers. Some of these transactions create vulnerability "by the extent to which the organization depends on certain types of exchanges for its operation" (Pfeffer & Salancik, 2003, p. 45) and describe a specific form of power relationship, the kind that entails dependency because of the necessity of one party to obtain "something" that the external party can provide (Emerson, 1962).

From an RDT perspective, the only reason why an organization would enter into these contracts is because it needs to obtain from the external environment the required resources that would allow it to survive. To avoid this dependence, firms behave strategically and seek to share resources by engaging in collaborative interorganizational relationships such as joint ventures, alliances and/or short-term agreements (Hillman, Withers, & Collins, 2009), which are "negotiated in an ongoing communicative process, and which relies on neither market not hierarchical mechanisms of control" (Hardy, Phillips, & Lawrence, 2003, p.323). That is, organizations are motivated to collaborate to avoid dependencies and to acquire resources that they cannot develop internally and that are critical to their survival (Powell, Koput, & Smith-Doerr, 1996; Hardy, Phillips, & Lawrence, 2003).

In a supply chain context, empirical evidence indicates that resource sharing has increased resilience to disruptions via improved coordination and response by leveraging and investing in capabilities, resources and assets with supply chain partners (i.e., in the economic resilience language, this implies that resource sharing has allowed the firm to build capacities that improve its inherent resilience). That is, as part of the collaboration "toolbox," resource sharing has been proved to be vital to cope with disturbances because has enabled the development of synergies required to prepare for, respond to, mitigate, and recover from supply chain disruptions (Scholten and Schilder, 2015).

The theoretical framework of economic resilience supports the notion that implementing a resource sharing strategy in the post-disaster will keep operations running (i.e., avoid business interruption) while using resources efficiently, which is what static economic resilience is all about. Its results are product of the capacity already built into the firm (inherent), those that result from ingenuity, extra effort and improvisation (adaptive), or both (inherent and adaptive) (Dormady et al., 2019). As a consequence, the reduction or avoidance of business interruption that results from implementing a resource sharing strategy is essential in the transmission mechanism that maintains viability to the firm in the post-disaster.

1.4.3 The Decision of Sharing Resources

1.4.3.1 Criticality, Dependence on Suppliers, and Uncertainty

> ***Proposition 3a:*** *Firms that depend on critical resources supplied by external parties will be more likely to utilize a resource sharing strategy after the onset of a natural disaster than firms that do not depend on critical resources.*
>
> ***Proposition 3b:*** *Firms that are uncertain in the supply of the critical resource will be more likely to utilize a resource sharing strategy after the onset of a natural disaster than firms that are certain of attaining the supply of the critical resource.*

According to Pfeffer and Salancik (2003), there are two dependent dimensions that measure the importance of a resource exchange, namely the relative magnitude of the exchange and the criticality of the resource. The first dimension is measured in terms of the *proportion* of total inputs or total outputs involved in the exchange. An organization that requires only one essential input for its operations will be more dependent on its supplier(s)[6] than an organization that requires multiple inputs, each in relatively small proportion and from different sources of supply. The second dimension relates to the *criticality* of the resource. Criticality is related to the ability of the organization to continue operations even in the absence of the resource. The extreme case of dependence on critical resources is described when an organization requires one or more primary resource(s) that are supplied by only a *single* source and the absence of any of the resources causes a disruption to the operations. These two dimensions can be thought of, diagrammatically, as the intercept and slope of a demand curve, respectively. Whereas the first dimension influences the overall left-to-right dimension of the curve, the second

[6] I also assume in this chapter that an organization that requires one input and only relies on one supplier is more dependent than an organization that requires one input but relies on multiple suppliers.

dimension influences the slope (or elasticity or need) of the critical resource. In this regard, a firm aims to reduce criticality by making its resource demand curve more responsive, that is, more elastic. At the same time, a firm aims to reduce dependence on its supplier(s) by shifting the demand curve to the left, which decreases the required amount of critical resource(s) needed to operate.

Equally important, beyond demand, supply matters to the firm or organization as well. An additional but related consideration is uncertainty around the supply of the critical resource. It is in this context that firms strive for a stable and reliable flow of resources (Weick, 1969; Katz & Kahn, 1978; Oliver, 1991). These resources come from the external environment in which the firm operates (e.g., its supply chain, natural resource utilization, foreign imports). That is, uncertainty in RDT is seen as problematic because the critical resource is no longer assured when the conditions in the external environment change (e.g., when there is a disruption in the supply chain as a consequence of a natural disaster).

From an RDT perspective, uncertainty is associated with a lack of control and power over the environment but not with a lack of information (Bode et al., 2011). This suggests that firms may have enough information to carry out their operations but need to manage their dependence relationships to gain control over the external environment. Nonetheless, firms are also prone to exchange information. Organizations will engage in information sharing if their current information level does not allow the firm to function deterministically (Bode et al., 2011).

If a firm depends on critical resource(s) that it obtains from external supplier(s) and there is uncertainty about the supply of the resource to continue operations, it is likely that the firm will seek to implement a resource sharing action after the onset of a disaster aimed at facilitating access to the critical resource. These forms of cooperation that may include inherent resilience actions such as contingent agreements, short-term contractual arrangements or accessing suppliers of goods from outside the affected area, are decisions that result from building capacities before the occurrence of the disruptive event. That is, despite being dependent on the external environment, firms can manage uncertainties and reduce dependencies from external parties (e.g., suppliers) by implementing resilience tactics after the disaster hits (Rose, 2017).

A firm may also depend on a critical resource but may not need it from its supplier(s) or another external party following the disaster. This may occur because of resilience actions such as availability of inventories or stockpiles of critical materials, purposeful construction of excess capacity, or back-up equipment (i.e., the firm has possession over the resource, in the language of RDT). Another reason for this is because organizations may have enhanced their inherent resilience before the disruption by creating stable and enduring relationships with other firms that are part of their network (e.g., associations), and these ongoing and informal relationships allow firms to obtain resources to continue operating after the catastrophe (i.e., the firm has access to the resource, in the language of RDT). In this regard, the firm's social capital improves the chances of the organization to have access to critical resources that otherwise would only be sourced after engaging in formal contracts with external parties (Putnam, 1993). Under these circumstances, the firm may decide not to pursue a resource sharing strategy because it has been able to reduce dependencies by building capacities, which has enhanced its inherent resilience (i.e., in the language of the supply chain literature, this is called anticipative resilience).

In short, criticality per se does not lead the firm to share resources in the post-disaster if the firm has managed, increased the access to the resource, and reduced dependencies and do not need from external suppliers to obtain the critical resource. Likewise, the dependence on an external supplier does not necessarily lead a firm to share resources in the post-disaster if the resource is not critical to the firm.

1.4.3.2 Substitutability of the Resource

> ***Proposition 3c:*** *Firms that need critical or non-substitutable resource(s) provided by external supplier(s) will be more likely to engage in a resource sharing strategy after the onset of a natural disaster than firms using substitutable resources.*

Pfeffer and Salancik (2003) contend that one way of diminishing dependence is by developing substitutable resources and/or substitutable exchanges. Whereas the former is contingent upon the current state of knowledge and the flexibility of the firm's production function, the latter depends on the organizational ability to establish relationships to gain access to other sources for the resource and improve their "concentration of resource control" (Pfeffer & Salancik, 2003, p.49). The criticality and control of the resource by a few suppliers do not restrict the organizational objective of reducing dependence on the external environment if the firm may have access to the resource from other sources.

The extent to which a firm can substitute critical resources or gain access to other sources is a key factor in reducing dependence. As a consequence, if firms are able to reduce dependence by developing substitutable resources or having alternative sources of supply, there may be no need for them to engage in a resource sharing strategy in the post-disaster, although this may not always be the case. Dormady et al. (2019), for instance, suggest gains from trade when firms can acquire substitute materials from neighboring firms. This is the case of a firm that is not faced with a water outage and allows neighboring firms and their customers to utilize its restroom facilities so that they do not incur business interruption. The firm may decide to share the use of its facilities in exchange of any other resource that substitutes a critical input. In doing this, the firm is able to broaden the range of resource inputs and reduce the vulnerabilities derived from the dependence on a seemingly "critical" input that becomes less critical once the firm had gained access to a substitute or partially substitute input. This is a situation where it is feasible to engage in resource sharing in presence of substitutable resources. What makes different the decision of a firm to share resources in this case when compared with the previous example in which a firm is able to develop a substitutable resource internally is related to the possession of the resource (Pfeffer and Salancik, 2003). In the first case, the firm owns or develops alternative sources of the "critical" resource internally and in turn decreases the likelihood of sharing resources in the post-disaster. On the other hand, if the firm's production function is not so flexible (see e.g., Dormady et al., 2019) but the organization may gain access to some external and partially substitutable resources after the disaster, it may resort to utilize a resource sharing strategy.

Another scenario where it is feasible for a firm to utilize a resource sharing tactic in presence of substitutable resources is when it develops a partially substitutable resource in the post-disaster but there are complementarities associated to the use of the resource. In this case, although the firm has managed to reduce the dependence on the "critical" resource provided by a current supplier, it has gained dependence on a new "critical" resource provided by a new supplier. In this case, the firm will likely use a resource sharing tactic to reduce the dependence that arises from the new "critical" input.

In short, RDT contends that organizations will try to reduce dependencies by engaging in interorganizational relationships when the critical resource is non-substitutable; however, if the firm needs a resource that is at least partially substitutable then there is less dependence and the chances of using a resource sharing tactic is reduced. Nonetheless, if the resource is substitutable and the firm does not have access to alternative suppliers, it may share resources and exchange any other resource that substitutes one of its "critical" inputs. As a consequence, despite the proposition posed at the beginning of this section, it may occur that a firm that relies on non-critical and substitutable resources and/or substitutable exchanges utilizes a resource sharing tactic in the post-disaster.

1.4.4 Organizational and Environmental Factors

1.4.4.1 Property Damage

> ***Proposition 4a:*** *As the firm's property damage increases, it is more likely for the firm to engage in resource sharing after the onset of a natural disaster.*
>
> ***Proposition 4b:*** *At very high levels of property damage, it is not relevant for the firm to share resources.*

It was previously mentioned that the focus of economic resilience is not on property damage; however, it is an important factor that explains the decision of a firm to engage or not in a resource sharing strategy. Zolin and Kropp (2006) contend that the higher the proportion of property damage or assets that are damaged, the more difficult to resume operations will be. This is also informed by RDT because property damage increases dependence and firms need to use strategies to fight this type of contingency. In this regard, the higher the property damage, the higher the dependence, and the higher the chances to recover by using a resource sharing strategy. However, at very high levels of property damage, it may be irrelevant for a firm to share resources (e.g., firms whose facilities are underwater after a natural disaster will not be able to resume operations even after sharing resources). In terms of inherent and adaptive resilience, a firm may engage in substitution of land and opt for relocation (another well-established tactic) after a disaster, but this depends on the type of property damage (e.g., perishable, capital), the loss of reliable infrastructure and/or damage to their physical plant (Dormady et al., 2019). Firms may also decide to go out of business and not survive as result of such environmental uncertainties as RDT predicts. This implies that at very high levels of property damage, it is more difficult for a firm to resume operations and the less likely that a resource sharing strategy will be implemented in the post-disaster (i.e., it is irrelevant for the firm to resource share).

1.4.4.2 Size

> ***Proposition 4c:*** *Small and medium size firms are more likely to engage in a resource sharing strategy after the onset of a natural disaster than large size firms.*

According to Zolin and Kropp (2006), location of destroyed assets, structural characteristics and the size of the business play an important role in organizational survival. A high-level disruption such as a natural disaster may have a totally different impact on a large firm when compared with a medium or small organization. A small firm has fewer locations or their assets are concentrated in a few places and may have all its assets destroyed when a disaster occurs whereas a large firm may lose only a small proportion of its assets in the aftermath of the disaster. Whereas the location and amount of destroyed assets may be important in determining whether a firm survives or not, small and medium firms may decide to use a resource sharing action that avoids or diminishes business interruption and help in the recovery process. The rationale of this decision is that these firms are embedded in local communities and they are regarded an engine of social capital, civic engagement, high trust and reliability and reciprocity in their associations (Cooke & Wills, 1999). RDT suggests that the size of the firm matters for avoiding resource dependence. That is the case of industries with large investments in well-established industries such as oil, steel or utilities, which are protected in their operations against foreign competition (Pfeffer & Salancik, 2003). In this regard, larger firms leverage their financial resources to exert control and power over other organizations, competition and markets, which implies they do not need to share resources after a disaster because it is likely that they do not need to reduce any dependence. What this implies is that when firms are larger, they are more likely to have their resources "in house" and do not need to share. They are less dependent on external resources by virtue of their size and are more likely to use intraorganizational strategies.

1.4.4.3 Industry

Zolin and Kropp (2006) suggest that the type of industry may play a key role in determining whether a firm engages in a resource sharing strategy in the post-disaster. It is possible that some industries have a greater survival capacity than others and this would encourage firms to implement any resilience strategy that improves that likelihood. RDT contends that industries that will survive are those that begin to demand certain organizational performances. An example of a type of firms with low probabilities to survive after the onset of a disaster includes retail businesses because once their customers evacuate, they may not return. Manufacturing firms are heavily invested in plant and equipment and run the risk of not reopening when there is a large damage to property and assets even if these are insured. However, Dahlhamer and Tierney (1998) found evidence suggesting that the largest proportion of recovered businesses after the Northridge earthquake were in the manufacturing and construction sectors. Dietch and Corey (2011) also found evidence that the manufacturing or construction firms outperform retail/wholesale businesses in the post-disaster as the latter generally report more difficulty in returning to pre-disaster levels given the loss of customers and reduction of sales. As Zolin and Kropp (2006) suggest, although it is likely that the type of industry influences the decision of a firm to share resources, no propositions are made in this chapter related to the type of industry because other variables such as size and property damage seem to be better predictors.

1.5 Implications for Further Research

This discussion has produced several areas for future research as well as important implications for extant research. The first implication is one that has been discussed along this article. It deals with delineating a solid theoretical foundation for one economic resilience strategy – resource sharing– and responding to different authors who contend that the vast majority of research on resilience are characterized by an absence of formal theories, particularly the research related to organizational resilience (Van der Vegt et al., 2015, Dormady et al., 2019). In this regard, this paper fills an important gap and is unique to all resilience literatures (e.g., economic, sociological, supply chain) in the way of explaining strategic firm behavior; more specifically, the decision of a firm to share resources in the midst of a disruption or after the occurrence of a natural disaster. It may provide a framework for explaining the election of other post-disaster tactics from a strategic standpoint

A second implication is related to how the theory and practice help to enhance managers and decision-makers' capabilities to respond more effectively to vulnerabilities and external disturbances. In this regard, this theoretical framework lays the groundwork for the empirical application and testing of some of the propositions posed in this chapter. This particular empirical application will be presented in the next chapter. From the policy side, this chapter provides the fundamentals for policy-makers to foster community development and resilience based on the reduction of economic dependence on critical resources in high exposed-to-disaster areas. For government agencies such as the U.S. Small Business Administration (SBA), this chapter provides the theoretical support to explore practices that may help businesses to be better prepared to cope not only with the predictable but also with the unforeseen. Given that small firms are the ones more likely to utilize interorganizational strategies in the post-disaster, as previously mentioned, the SBA may provide counseling to affected businesses and disseminate information regarding the most applicable resilience tactic(s) based on firms' characteristics. It can also incentivize the creation of partnerships and/or joint ventures, and allocate a percentage of government contracts to highly dependent and exposed firms. By designing specific actions aimed to build capacities in these types of organizations, the SBA will create mechanisms geared to reduce small firms' business interruption, increase their chances of survival, and improve their competitive advantage capabilities in the long run.

Chapter 2: The Relationship between Resource Sharing and Economic Resilience: An Empirical Analysis of Firms' Resilience from the Perspective of Resource Dependence Theory

2.1 Introduction

Events like Superstorm Sandy in the Northeastern United States in 2012, Hurricane Harvey in Houston in 2017, and Hurricane Maria in 2017 in Puerto Rico exposed the fragilities and vulnerabilities of firms, mainly small and medium size, to cope with interruptions derived from natural disasters. Despite different actions that organizations have implemented before such disruptive events, typically referred to as *mitigation*, aimed at reducing the frequency and magnitude of property damage, the losses in the flow of goods and services emanating from property and capital stock continue to have a greater impact on the well-being of the citizenry and the economy in general. These losses, in which a firm incurs, known as *business interruption*, begin when the disaster hits and continue until the organization has recovered or has achieved a new equilibrium (Rose, 2017).

For instance, in September 2018, almost one year after Hurricane Maria in Puerto Rico, anecdotal estimates suggested that around 44,000 businesses had not benefited from reconstruction spending and were still struggling against interruptions and were striving to keep the business afloat. Additionally, between 5,000 and 8,000 small businesses had closed permanently, which impaired recovery and, in turn, economic health given that small employers represented around 80% of the private sector workforce (Leiber, 2018). This goes in line with some statistics from the Federal Emergency Management Agency (FEMA) that estimates that roughly 40-60% of small businesses never reopen their doors following a disaster. Despite this, business interruptions can be reduced when firms implement actions or strategies after a disaster begins. Avoiding or reducing business interruption by implementing resilience tactics is a strategic decision given that business interruption losses are usually not eligible for public assistance programs. This has been the case, for example, for Superstorm Sandy and Hurricane Harvey, in which recent evidence outlines the impact of post-disaster actions that allowed businesses to keep their operations running.

From a 2017 survey carried out to gather primary data from recent businesses affected by Sandy, it was found that losses would have been around $340 million for 111 affected firms in the sample if these organizations had not implemented strategies that avoided losses by around $140 million (Dormady et al., 2018). A similar survey, which is used in this dissertation, was carried out in the Houston area following Hurricane Harvey. Figures indicate that losses would have been around $2 billion for 153 affected firms if they had not implemented any post-disaster action. Although mitigation actions have the potential of reducing business interruption, the other way is by implementing post-disaster tactics, as previously mentioned, that aim to increase *economic resilience* and reduce these types of losses. Although a more complete definition is provided in the previous chapter and will be provided in a later section, it is important to mention at this point that the concept of economic resilience does not focus on property damage but on business interruption, whose impact (in dollars) is typically at least twice as large as the impact on property damage (Rose & Blomberg, 2010).

According to the previous arguments, what is important from this dissertation is that, to date, scholars have focused on the drivers of organizational recovery or factors that lead firms to be resilient or accelerate recovery (e.g., Dietch & Corey, 2011; LeSage et al., 2011; Graveline & Gremont, 2017) and little attention has been devoted to strategic decisions of firms after the onset of a natural disaster. Although some research is found in the supply-chain literature (e.g., Bode et al, 2011; Scholten & Schilder, 2015), it focuses on pre-planning actions that may fail when unanticipated circumstances escape the ability of firms to fully prepare for them (Dormady et al., 2019). In this regard, there is a dearth of empirical work related to the strategic behavior of firms or the decisions that firms make following a catastrophe to cope with uncertainties and reduce business interruptions. This chapter fills in that gap in the literature and focuses specifically on providing empirical evidence about the effect of the strategic decision of firms in using a type of interorganizational collaborative tactic – resource sharing – after a disaster hits. The importance of this research is related not only to the generation of new knowledge on the relationship between resource sharing and economic resilience but also on evolving the theory and practice for managers and decision-makers to enhance their capabilities to respond more effectively to vulnerabilities and external disturbances. From the policy side, this chapter provides the fundamentals for policy-makers to foster community development based on the reduction of economic dependence on critical resources in high exposed-to-disaster areas.

In general, the fact that studies on organizational resilience and potential empirical work that results from key strategic decisions in the aftermath of a disaster is scarce seems paradoxical, given past and more recent theoretical efforts intended to provide a comprehensive framework of analysis that contributes to the understanding of how firms actually cope with natural hazards or disruptive events (e.g., Rose, 2004; Rose & Liao, 2005; Rose & Krausmann,, 2013; Dormady et al., 2019). One likely reason for this is related to complications that arise in assessing resilience at the level of the firm given that its measurement relies on the occurrence of an external event to ascertain the differential outcome between the pre- and post-disaster. Maybe, this is one the reasons of why most studies focusing on organizational resilience infer resilience indirectly by measuring recovery via different performance measures. Examples of this include the estimation of effects derived from social and environmental practices on sales growth, improved financial volatility, and survival rates (Ortiz-de-Mandojana & Bansal, 2016), the measurement of vulnerability factors and controllable capability factors to construct a supply chain performance tool (Pettit, Croxton, & Fiksel, 2013), the analysis of the effects on stock prices following external events such as the terrorist attacks of September 11, 2001 (Gittell, Cameron, Lim, & Rivas, 2006) and the financial crisis in 2008 (DesJardine, Bansal, & Yang, 2017).

The implications of this chapter are twofold. On the one hand, there are still many important aspects of how firms cope with disruptive events that have not been empirically explored in the literature. Such gaps include an absence in measuring the effects of strategies (or resilience tactics) that organizations can implement following a shock (e.g., resource sharing is one these unexplored tactics). In this regard, by using a unique dataset derived from two surveys released to gather information about affected firms from Superstorm Sandy and Hurricane Harvey respectively, this dissertation utilizes a direct measure of economic resilience – avoided losses – to assess the effects exerted by the decision of sharing resources in the aftermath of the hurricanes. On the other hand, the empirical evidence provided in this chapter is informed by extending the application of Resource Dependence Theory (RDT) beyond a non-disaster context and by addressing the issue of dependency on external resources by suggesting that firms use a strategy of resource sharing in the post-disaster to avoid dependencies on the external environment and obtain critical resources that reduce or avoid business interruptions and enhance their economic resilience.

The empirical strategy or empirical model used in this chapter is a Heckman-type model, which emerges naturally as the most suitable analytical approach. The reason is that firms are able to self-select the type of tactic they use and choose a post-disaster strategy or strategies that lead to minimize or avoid losses, that is, to enhance its static economic resilience (i.e., the choosing of a strategy is not at random). This will be explored in more detail in the methodological approach. Next sections in this chapter provide a background on the literature with some definitions and hypotheses, a methods section that describes the dataset, the variables and the research model, and concludes with results and research implications. The findings provided in this chapter provide an important contribution to the literature on economic resilience.

2.2 Theoretical Background

2.2.1 Defining Economic Resilience

This chapter follows the definition of economic resilience provided by Rose (2004, 2007, 2017) and formalized by Dormady et al. (2019) in a production theory context. According to this approach, there are two major categories or dimensions of economic resilience. The first dimension is the one that classifies resilience as static or dynamic.

- Static economic resilience refers to the ability of a firm to efficiently continue its operations with remaining resources at a given point in time after the occurrence of a shock and denotes the need to compensate for deficiencies in the availability of production inputs (Rose, 2004; 2007; Dormady et al., 2019).
- Dynamic economic resilience refers to the ability of a firm to recover over time while using resources efficiently and after investing in repair and reconstruction as a means of accelerating and shortening recovery (Rose, 2004; 2007; Dormady et al., 2019).

The concept of static economic resilience is partially derived from Holling's definition (1973) of resilience as the ability of a system to absorb change and maintain functioning after a disturbance. However, unlike Holling´s definition that considers that resilience is a property of the system, the definition of static economic resilience also assumes that resilience can be enhanced before a disruption and also focuses on how the system (i.e., the firm) uses scarce resources efficiently in the post-disaster (Rose, 2004; 2007; Dormady et al., 2019). On the other hand, the definition of dynamic economic resilience is more related to Pimm´s definition (1984) of resilience as the ability and speed of the system to return to pre-disaster conditions.

The second dimension is the one that classifies resilience as inherent or adaptive. Inherent resilience refers to actions that result from the capacity already built into the system, which implies those tactics that exist in the organization or those that can be enhanced relatively inexpensively when the firm aims to build resilience capacity (Rose, 2017). Some examples of inherent resilience include inventories, back-up equipment, the ability to utilize more than one fuel in an electricity generating unit, and established government policy levers (Dormady et al., 2019). Adaptive resilience, on the other hand, refers to actions that result from ingenuity, extra effort, and improvisation under stress. Some examples include technological change that transforms the way goods and services are produced, new contracting arrangements with external suppliers and, in the case of governments, the design of new post-disaster assistance programs (Rose, 2017; Dormady et al., 2019).

This chapter focuses specifically on measuring the influence of a post-disaster tactic[7] on static economic resilience (inherent, adaptive, or both), which pertains to the organizational ability to avoid business interruption, keep the operations of the firm running and use remaining resources efficiently, whose scarcity is intensified under disaster conditions.

[7] This dissertation makes reference to the words tactic and strategy as synonyms, without any distinction. However, a tactic or strategy may be composed by one or multiple actions.

2.2.2 Defining Resource Sharing

As just mentioned, this chapter is centered on the empirical analysis of one static economic resilience tactic – resource sharing. As any other static economic resilience strategy, resource sharing is also oriented to the reduction of business interruption losses following a disaster. However, there is a distinction between a resource sharing tactic and other types of economic resilience tactics: some post-disaster actions are performed within the organization (i.e., intraorganizational), internally, without engaging with another firm or organization outside of its own (e.g., when a firm uses its inventories or when cuts its own red tape); however, resource sharing is only about interorganizational behavior (e.g., when a firm renegotiates contracts with a supplier). In this sense, the appropriate literature explaining why a firm shares resources – a type of cooperative organizational form or strategic behavior – should incorporate interorganizational theories such as Resource Dependence Theory (RDT).

Firms resort to utilize some interorganizational actions such as alliances and partnerships not only with customers and/or suppliers but also with their peers and similar organizations to strengthen relationships and gain access to resources that provide stability to the operations of the firm (Thompson & McEwen, 1958). In this regard, although the rationale of a firm in using intraorganizational strategies is related to building capacities that increase its inherent resilience so as to have a higher control of resources and reduce the variability in the flow of inputs or production factors (e.g., having more inventories), it is likely that after an external event such as a natural disaster, an organization finds itself with the need of resources that are out of its autonomous domain and are not easily accessible due to the post-disaster conditions. To survive during such a disruption, organizations need to obtain resources from the external environment (Pfeffer and Salancick, 2003).

Following Thompson & McEwen, (1958), this chapter relates the interorganizational strategy of *resource sharing* to the use of the following mechanisms:

1) The selective exchange of certain resources or short-term agreements for a defined period of time with other organizations (e.g., the utilization of facilities in exchange for the provision of any service or any other resource).

2) Bargaining (e.g., renegotiating supply contracts with key suppliers).

3) Creating new partnerships (e.g., building relationships with other businesses in order to share information and/or expertise), and

4) Resource pooling (e.g., joint ventures in order to bid for public contracts). One common characteristic of these cooperative actions is that they involve the combination and commitment of resources of two or more organizations

Bargaining is the most common interorganizational action involved in a resource sharing strategy used by firms because it involves short-term agreements and periodic negotiation with another organization (Thompson & McEwen, 1958). Following a disaster and in the context of resilience, it is useful to employ bargaining when a firm needs to renegotiate supply contracts with key suppliers or renegotiate agreements with contractors for the provision of a service (Dormady et al., 2019). Also, in many post-disaster situations, organizations may also renegotiate with unions or key employees some future benefits in exchange for the voluntary assistance during the recovery process.

Another action used by managers is *creating ties*, relying on existing ties and using third-party organizations that support the ties. Ties with other organizations allow building relationships and partnerships with other managers to share information and/or expertise in post-disaster situations. The concept of social capital plays a key role in the decision of creating ties by explaining how networks, norms and trust facilitate the coordination and cooperation among organizations for mutual benefit (Putnam, 1993). Social capital is embedded in social relationships in which both the number of ties and the quality of connections, instead of individual managers' attributes, improve the structure of the network (Granovetter, 1973; 1985). Ties are important but strong connections are even more. Strong connections to other organizations provide tools, critical resources and information after the onset of a disaster (Aldrich, 2011).

Last, a less commonly used set of actions involves the combination and commitment of resources of two or more organizations for a long-term purpose. This tactic is defined as *coalition* (Thompson & McEwen, 1958) or *resource pooling* in this dissertation and is used when a more effective response to a disaster requires the mutual commitment and developing of joint activities by multiple organizations. For instance, after being hit by different natural disasters, six energy companies launched in 2016 the Grid Assurance, a strategic alliance that would help to improve grid recovery after a shock. Another example involves the creation of a joint venture by two or more firms to bid for public contracts after their operational capacity have been diminished by an external shock.

2.2.3 Unobserved Heterogeneity, Resource Sharing, and Static Economic Resilience

An important contribution in this chapter is related to the analysis of how a strategy of resource sharing influences the economic resilience of the firm, more specifically, the static component. As mentioned in the introductory section, this has been an issue in the resilience literature in general, which has focused on the drivers of organizational recovery, and little work has been done on the strategic behavior of firms in the aftermath of disruptions, with a few exceptions mainly from the supply chain resilience literature (e.g., Bode et al, 2011; Scholten & Schilder, 2015).

The fact that firms may decide to utilize any post-disaster strategy suggests that the value of employing, for instance, a resource sharing tactic is contingent upon assumptions related to the nature of the resources used in the exchange, as well as some characteristics or attributes of the subject firm and the type of industry in which the firm operates. In this regard, the most important contribution of this chapter is that it provides empirical evidence of the transmission mechanism that links underlying factors explaining the choosing of a particular post-disaster strategy to static economic resilience. The current literature only specifies the effects of some resilience tactics in terms of their business interruption reduction capabilities. These actions involve, among others, conservation of scarce inputs, input substitution, build-up of inventories, use of back-up electricity generators, relocation and production rescheduling (e.g., Rose, Oladosu & Liao, 2007; Kajitani & Tatano, 2009; Rose & Wei, 2013). However, these direct measurements are appropriate only if the decision to use a specific strategy or just a particular action does not depend on the type of the resource, input, or raw material, and it is not influenced by other characteristics at the level of the firm. However, the proposition supporting the notion that the decision to use a specific post-disaster strategy is not dependent on industry-, firm- and resource-level characteristics is flawed. If that proposition were true, there would not be differences in the decision among firms and the choosing of a particular tactic or set of tactics would be the same. In reality, what it is observed is a type of strategic behavior and heterogeneity in the type and the number of tactics chosen by each firm to cope with disasters after the disruption begins. This can be confirmed in Table 3, where we can observe the percentage of tactics after Superstorm Sandy and Hurricane Harvey that were used by a sample of firms. These percentages are based on recent surveys released to collect information about the use of tactics by firms (see e.g., Dormady et al., 2018). Although the next section describes in detail the survey and data collection, it is important to mention that percentages presented in Table 3 are derived from a survey question that asks firms to select the tactics they utilized in the post-disaster.

Table 3 provides evidence of the level of heterogeneity among tactics[8] used. Also notable is the difference not only among tactics but also between natural events. For instance, whereas the tactic of Excess Capacity was used by the 23% of firms in the sample after Superstorm Sandy, only 10% of firms used the same tactic following Hurricane Harvey. Something similar happened with Technological Change where 43%

[8] For a complete definition of each tactic, see the previous chapter, Rose (2017), or Dormady et al. (2018).

of firms utilized the tactic after Sandy whereas 24% of firms utilized it after Harvey. Also, a higher percentage of firms did not use any tactic after Harvey in comparison to post-Sandy (6.54% vs 3.60%). This indicates that there is some unobserved heterogeneity that influences the decision of a firm to utilize a specific action or set of actions instead of other(s) tactics in the aftermath of a disaster, a topic that has not been explored in the literature and that contributes not only to the literature on economic resilience but the resilience literature in general.

Table 3. Percentage of Firms using Tactics

Resilience Tactic	Percentage of Firms using the Tactic after Sandy	Percentage of Firms using the Tactic after Harvey
1-Conservation	*29.73%*	*23.53%*
2-Resource Isolation	*22.52%*	*24.18%*
3-Input Substitution	*20.72%*	*20.26%*
4-Inventories	*37.84%*	*35.29%*
5-Excess Capacity	*23.42%*	*9.80%*
6-Relocation	*25.22%*	*23.53%*
7-Management Effectiveness	*42.34%*	*45.75%*
8-Import Substitution	*16.22%*	*14.38%*
9-Technological Change	*43.24%*	*24.18%*
10-Production Recapture	*32.43%*	*29.41%*
11-Resource Sharing	*31.53%*	*33.99%*
12-None	*3.60%*	*6.54%*

Number of firms in the sample for Sandy = 111
Number of firms in the sample for Harvey = 153

By the same token, it is also likely that some of the industry-, firm-, and resource-level characteristics influence not only the decision of choosing a particular strategy but also the level of resilience, that is, the static economic resilience of the firm. For instance, it is likely that firms will choose a particular post-disaster strategy after observing their level of property damage; however, Rose (2017) suggested that property damage may lead to business interruption, at least partially. It is also the case that the size of the firm plays a key role in the utilization of interorganizational strategies (Pfeffer & Salancik, 2003). However, research has found that size also affects the resilience and adaptation of organizations to disasters because small and medium sized firms tend to underinvest on resilience when compared with large firms (Wedawatta & Ingirige, 2012). If there are unobserved attributes that lead to both the decision of sharing resources and static economic resilience of the firm, then, there is a problem of self-selection that is present in the analysis and any implication drawn from the empirical estimates will be biased (e.g., Heckman, 1979; Maddala, 1983, Masten, 1993; Leiblein, Reuer, & Dalsace, 2002). Given that firms do not make decisions at random but based on their own maximizing analysis (see e.g., Varian, 1992), they select tactics that are available options to them based on the idea that their implementation will reduce or avoid business interruption (i.e., firms select a post-disaster strategy that keeps operations running while using resources efficiently). If we fail to consider this in the analysis, we might be underestimating the effect of resource sharing if there is actually a transmission mechanism that explains the choosing of this tactic and vice versa. Based on this line of reasoning, the next hypothesis is posed:

> ***Hypothesis 1:*** *Unobserved characteristics underlying a firm's decision to share resources after the onset of a disaster influence its static economic resilience.*

2.2.4 Resource Dependence Theory (RDT), Resource Sharing, and Static Economic Resilience

To cope with the self-selection problem derived from the multiple unobserved industry-, firm-, and resource-level characteristics, it is important to identify the factors that explain the decision to share resources in the post-disaster. Resource Dependence Theory (RDT) provides the theoretical foundation that identifies the transmission mechanism and the causal relationships of specific resource-level characteristics that lead to static economic resilience.

A fundamental tenet of resource dependence theory is that organizational survival depends on the ability of a firm to acquire and maintain critical resources that are obtained from the external environment. However, the fact that organizations depend on the environment to survive is not in itself problematic. If the external environment were a stable source of resources, dependency would not be an issue; however, environments change because some organizations survive and others never recover and fail, which creates instability and uncertainty in the supply of resources (Pfeffer & Salancik, 2003). To cope with this uncertainty, organizations react by using intra- and interorganizational tactics that allow stabilizing the internal resource flow. In the post-disaster, these tactics aim to reduce business interruption and to enhance static economic resilience (Rose, 2017). The implementation of these tactics depend on the capacity already built into the firm (inherent), on ingenuity, extra effort and improvisation (adaptive), or both (inherent and adaptive) (Dormady et al., 2019). Based on this argument, it follows that resilience is considered a necessary mechanism that keeps the operations of the firm running after significant environmental challenges (Alesch et al., 2001). That is, the capacity of a firm to survive in the aftermath of a disaster is mediated by its ability to achieve static economic resilience, which can be obtained by reducing or avoiding business interruption.

Resource sharing is one of the interorganizational tactics that lead firms to reduce dependence from the external environment. Among the factors that explain the sharing of resources after the onset of a disaster, this chapter focuses on the *resource importance* variable. According to Pfeffer and Salancik (2003), there are two dependent dimensions that measure the importance of a resource exchange, namely the relative magnitude of the exchange and the criticality of the resource. The first dimension is measured in terms of the *proportion* of total inputs or total outputs involved in the exchange. An organization that requires only one essential input for its operations will be more dependent on its supplier(s)[9] than an organization that requires multiple inputs, each in relatively small proportion and from different sources of supply. The second dimension relates to the *criticality* of the resource. Criticality is related to the ability of the organization to continue operations even in the absence of the resource. The extreme case of dependence on critical resources is described when an organization requires one or more primary resource(s) that are supplied by only a *single* source and the absence of any of the resources causes a disruption to the operations. These two dimensions can be thought of, diagrammatically, as the intercept and slope of a demand curve, respectively. Whereas the first dimension influences the overall left-to-right dimension of the curve, the second dimension influences the slope (or elasticity or need) of the critical resource. In this

[9] I also assume in this chapter that an organization that requires one input and only relies on one supplier is more dependent than an organization that requires one input but relies on multiple suppliers.

regard, a firm aims to reduce criticality by making its resource demand curve more responsive, that is, more elastic. At the same time, a firm aims to reduce dependence on its supplier(s) by shifting the demand curve to the left, which decreases the required amount of critical resource(s) needed to operate.

One way of diminishing dependence is by developing substitutable resources and/or substitutable exchanges. Whereas the former is contingent upon the current state of knowledge and the flexibility of the firm's production function, the latter depends on the organizational ability to establish relationships to gain access to other sources for the resource and improve their "concentration of resource control" (Pfeffer & Salancik, 2003, p.49). The criticality and control of the resource by a few suppliers do not restrict the organizational objective of reducing dependence on the external environment if the firm may have access to the resource from other sources. The extent to which a firm can substitute critical resources or gain access to other sources is a key factor in reducing dependence. As a consequence, if firms are able to reduce dependence by developing substitutable resources or having alternative sources of supply, there may be no need for them to engage in a resource sharing strategy in the post-disaster. Based on the previous arguments, the following hypotheses are posed:

> ***Hypothesis 2:*** *Firms that depend on critical resources supplied by external parties will be more likely to utilize a resource sharing strategy after the onset of a natural disaster than firms that do not rely on critical resources.*
>
> ***Hypothesis 3:*** *Firms that depend on non-substitutable resource(s) will be more likely to engage in a resource sharing strategy after the onset of a natural disaster than firms using non-critical or substitutable resources.*

2.3 Methodology

2.3.1 Data

To test the previous hypotheses, this chapter relies on two surveys. The first survey was conducted in the New Jersey and New York areas to firms affected by Superstorm Sandy in 2012. The second survey was conducted in the Houston area to firms affected by Hurricane Harvey in 2017. Dormady et al. (2018) provide detailed information about the sampling methodology and the instrument development for the first survey released in 2017 in the New Jersey and New York areas. The second survey, the one released in 2018 in the Houston area, has not yet been used in any formal research. Nonetheless, the sampling methodology and the questions developed in both surveys are the same so, for the purpose of this dissertation, both surveys have been combined into one to obtain a total sample size of 264 firms represented by 111 firms affected by Superstorm Sandy and 153 firms affected by Hurricane Harvey. However, the actual number of observations that is used in the analysis is slightly lower – 245 observations – given unreported values in the dependent variable associated to 19 firms that belong to the sample. As will be detailed in a next section, this occurs in the survey when a firm responds not having using any post-disaster tactic.

To collect the data, the survey research began with a GIS and satellite imaging assessment of storm inundation areas and areas based on FEMA's definition of levels of disaster to ascertain sampling areas for firms likely to have incurred either property damage, business interruption (BI), or both. In order to qualify for the study, potential participants had to respond pre-screening questions describing 1) the level of responsibility for financial decisions in the company (only respondents who were responsible, were actively involved, or shared responsibility in financial decision were allowed to continue with the survey), 2) if the respondent was still working in the affected business prior to the event (only respondents who said they were still in the same business were allowed to continue with the survey), 3) if the firm had experienced business interruption (only respondents who said their business experienced business interruption were allowed to continue with the survey), and 4) the extent that the affected business had recovered the ability to produce at pre-disaster levels (the survey includes firms that said had recovered partially, to the same levels, and levels better than before the hurricane. The only groups that were eliminated were firms that said were not in business when the disaster hit or were no longer in business at the time of the survey).

The survey instrument was motivated by a formal microeconomic analysis on the resilience of the firm (Dormady et al., 2019) and included questions related to the implementation of eleven post-disaster resilience tactics, which were specified previously in Table 3 and that firms can use to improve their resilience and respond to disruptions of critical inputs caused by major disasters. The survey also included several contextual questions pertaining to firms' recovery, level of damages, and relevant controls such as industrial classification and firm size. The surveys were conducted by a leading and professional business survey firm, RTi Research.

2.3.2 Measures

2.3.2.1 Static Economic Resilience

The next step is to translate all previous definitions into something that can be measured. Given that the focus of static economic resilience is "the reduction in the loss of the flow of goods and services emanating from property, or capital stock" (Dormady et al., 2019, p. 447), it actually measures the reduction in the loss of the firm's throughput[10] due to a disruption. In this regard, the measure of static economic resilience used in this chapter is a function of business interruption (BI). That is, following Rose (2004, 2017), for static economic resilience, the metric is the amount of BI prevented by the implementation of a given resilience tactic or set of actions comprising a resilience strategy – resource sharing, in this case. A natural way to compute the reduction of business interruption is by measuring a firm´s avoided losses, which are losses in sales revenue that a firm did not incur because it was resilient – because it avoided some business interruption.

In the surveys, the variable *Avoided Losses*[11] is a continuous variable that takes a value equal or greater than zero for those firms that reported having used one of the tactics identified in Table 3. From 264 firms in the sample, 19 firms responded not having utilized any post-disaster tactic. This implies that the number of firms in the sample that reported having used any tactic was 245. The variable was measured by including the following question in the surveys:

---

[10] Throughput is the rate at which the system generates its products or services per unit of time (Besanko, Dranove, Shanley, & Schaefer, 2013).
[11] This variable is measured by using midpoint numbers from survey response bins.

By using the tactics listed below, your affected business avoided some potential losses in Sales Revenue. Please provide your best estimate of the Sales Revenue your business would have lost HAD YOU NOT USED the selected resilience tactics.

As this variable is in levels, it is appropriate to make a transformation and use it in logarithmic form. In this case, the transformation is given by *log(1 + Avoided Losses)* and the dependent variable is redefined as the *natural logarithm of avoided losses.*[12]

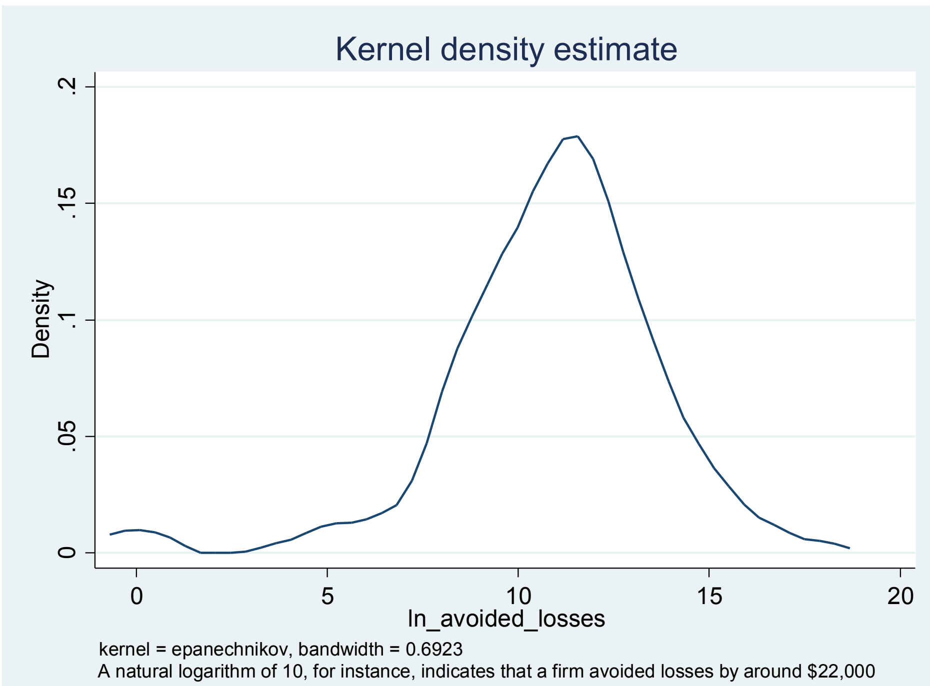

Figure 1. Statistical behavior of *natural logarithm of avoided losses*

[12] In cases where the variable is nonnegative as in this particular situation, the *log(1 + variable)* is advised to be used. Models using the dependent variable in logarithmic form usually satisfy more closely the assumptions of the classical linear model (CLM) than models using the dependent variable in original form (i.e., values equal or greater than zero); in particular, the logarithmic form helps to mitigate heteroskedastic and skewed conditional distributions (Wooldridge, 2013). This is even more appropriate given the type of model specification used in this chapter – a sample selection model – that is structured in two stages where both stages are heavily dependent on the assumption of normality of errors.

Figure 1 above presents the statistical behavior of natural logarithm of avoided losses, which follows approximately a normal distribution as can be observed from the graphic.[13]

2.3.2.2 Explanatory Variables

A sample selection model always involves two equations, namely the regression or main equation and the selection equation, which is modeled under the assumption of existence of a sample selection process. The primary argument in this chapter is that static economic resilience – represented by its two measures of *natural logarithm of avoided losses* and *resilience index* in the main equation – is influenced by the decision of firms to utilize a resource sharing strategy after a disaster. To test this hypothesis, this chapter utilizes the selection equation to estimate the most likely value (i.e., propensity) for the decision of a firm to use a resource sharing strategy by using the following probit model (see, e.g., Guo & Fraser, 2015):

$$\text{Prob}\left(w_i = 1 \mid z_i\right) = \phi\left(z_i \gamma\right) \tag{1}$$

In equation 1, w_i represents the decision to share resources for the ith firm, z_i is a vector of exogenous variables determining the selection process of w_i, γ is a vector of estimated coefficients for these variables, and $\phi(\bullet)$ is the standard normal cumulative distribution function.

The variables or vector of characteristics used to estimate the level of resource sharing in the first stage probit model include resource-level measures related to the

[13] Technically, *log(1 + Avoided Losses)* cannot be normally distributed; however, it might be less heteroskedastic than Avoided Losses (see, Wooldridge, 2013)

resource importance such as criticality of the resource and reliance on suppliers. It also includes a variable that specifies whether the resource is *substitutable* or not. This model also incorporates some controls at the level of the firm and industry such as level of property damage, firm size, and type of industry. These control variables will be detailed in the next section.

To measure the *resource importance* variable, I relied on the following item in the surveys:

> *Does your business rely on any Critical Raw Materials and Intermediate Inputs (e.g., processed materials, and parts and components, as opposed to final goods and services)? Critical refers to raw materials your business REQUIRES to produce its main products/services. Please do not consider utilities such as water, gas, electricity and telecommunication, as Critical Raw Materials or Intermediate Inputs.*

This is a binary variable that takes the value of 1 if the respondent said the business relies on critical materials and 0 otherwise. In the survey, if the respondent answers yes, the question is followed by this related question:

> *Which of the following best describes your suppliers of Critical Raw Materials and Intermediate Inputs (e.g., processed materials, and parts and components, as opposed to final goods and services) during your business's RECOVERY period?*

This is a nominal categorical variable that takes the value of 1 if the response was "Our business uses only one Critical Raw Material or Intermediate Input supplied by a large variety of competing suppliers," the value of 2 for "Our business has only one Critical Raw Material or Intermediate Input supplied by a small number of suppliers (or a single supplier) ," the value of 3 for "Our business has multiple Critical Raw Materials and/or Intermediate Inputs supplied by a large variety of competing suppliers," and the value of 4 if the response was "Our business has multiple Critical Raw Materials and/or Intermediate Inputs supplied by a small number of suppliers (or a single supplier)". Table 4 presents a contingency table that counts the number of cases in which each of these options was chosen and classifies the responses depending on whether firms decided to share resources or not.

Table 4. Contingency Table: Suppliers of Critical Resources – Resource Sharing

Resource Sharing	Describe the suppliers of Critical Raw Materials during Recovery				Total
	1	**2**	**3**	**4**	
No = 0	17	20	16	5	58
Yes = 1	17	12	10	4	43
Total	34	32	26	9	101

As can be observed in Table 4, there are a small number of cases in category 4 for both categories of the resource sharing variable. Given that few cases in a cell may lead to a model being unstable or cause the inability to fully estimate a model, the literature provides a rule of thumb in which it is suggested that 10 cases per cell is a good number to find statistical differences between categories, although each situation is different and also depends on the data availability (see, e.g., Long, 1997; Hosmer & Lemeshow, 2000).

For this particular situation, a new variable was created in which categories 3 and 4 were collapsed into one. Additionally, the category related to the number of firms responding that they do not rely on any critical resource in the previous question was also incorporated into this new variable. This new variable identified as *resource importance* is presented in Table 5 in a contingency table against the decision to share resources:

Table 5. Contingency Table: Resource Importance – Resource Sharing

Resource Sharing	**Resource Importance during Recovery**				Total
	0	**1**	**2**	**3**	
No = 0	103	17	20	21	161
Yes = 1	41	17	12	14	84
Total	144	34	32	35	245

In this regard, the definition of each category for the newly created explanatory variable defined as *resource importance* is the following: 0 if the firm does not depend on a critical resource (i.e., resource is not important), 1 if the firm uses only one Critical Raw Material or Intermediate Input supplied by a large variety of competing suppliers, 2 if the firm has only one Critical Raw Material or Intermediate Input supplied by a small number of suppliers (or a single supplier), and 3 if the firm has multiple Critical Raw Materials and/or Intermediate Inputs supplied by a large variety of competing suppliers, a small number of suppliers, or a single supplier.

To measure the *resource substitutability* variable, I relied on the following item in the surveys:

> *Which of the following best describes your supply of Critical Raw Materials and Intermediate Inputs (e.g., processed materials, and parts and components, as*

opposed to final goods and services) during your business's RECOVERY period?

This is also a nominal categorical variable that takes the value of 1 if the response was "The Critical Raw Material(s) and Intermediate Input(s) can be substituted (i.e., if not available, you could use some other readily available raw material)", and the value of 2 if the response was "The Critical Raw Material(s) and Intermediate Input(s) cannot be substituted". As in the previous measure, another variable was created in which the category of firms not depending on critical resources is incorporated. The new variable that is used into the analysis is defined as *non-substitutable resource.* Table 6 presents this variable in a contingency table against the decision to share resources. The new categories of the explanatory variable identified as *non-substitutable resource* are the following: 0 if the firm does not depend on a critical resource or the resource is substitutable or partially substitutable, 1 if the firm depends on a non-substitutable resource.

Unlike the previous measured variable, in which it was possible to adjust and collapse categories to obtain a minimum number of cases per cell (i.e., it is suggested to have at least 10 cases per cell), there are 9 cases in a cell in the Contingency Table 6 representing those firms that reported having non-substitutable critical resources and decided to share resources. Although this is a seemingly situation where the research is constrained by the data availability, the large number of cases in the other cells may offset this issue and help to find statistical differences between categories.

Table 6. Contingency Table: Non-substitutability – Resource Sharing

Resource Sharing	Non-substitutable Resource		Total
	0	1	
No = 0	140	21	161
Yes = 1	75	9	84
Total	215	30	245

2.3.2.3 Control Variables

Given that the main goal in this chapter is to test that firms that are more likely to use a post-disaster resource sharing tactic are also the ones with higher static economic resilience as posed in hypothesis 1, it is important to develop a model that considers firm- and industry- level characteristics in the estimation process. For instance, based on a rigorous literature review, Webb, Tierney, and Dahlhamer (2002) provide a comprehensive list of those factors they consider should include a statistical model to predict long-term business recovery from disasters. These factors include firm-level characteristics such as size (e.g., full-time employees prior to disaster), business age, if the building where the business was located when the natural disaster occurred was owned or leased, and the level of property damage after the disaster. At the industry level, they also consider economic sector. In another research aimed at testing how surviving businesses respond during and after a major disaster, Zolin and Kropp (2006) incorporated industry characteristics such as business activity as well as organizational factors such as size and percentage of business assets destroyed. Dietch and Corey (2011) incorporate variables such as industry sector, size, supply-line problems, and perceived quality of managerial decision-making to predict long-term business recovery four years after Hurricane Katrina. Wedawatta and Ingirige (2012) also analyzed resilience and adaptations of small and medium-sized enterprises to flood risks and considered in their research some firm- and industry-level factors such as number of employees, age of business, property ownership, and main business activity. All the previous literature implies there are more or less of a consensus of those factors that should be included as control variables when estimating the impact on business resilience and/or business recovery.

For the analysis of this chapter, this study will incorporate several controls in the selection equation and the main equation. Based on the literature that supports the inclusion of those factors potentially affecting the decision of sharing resources, the selection equation includes variables related to *property damage, firm's size*, and *business sector*. Property damage is originally a continuous variable that is incorporated in logarithmic form in the model. As it occurs with the *Avoided Losses* original variable, this is also a variable that is expressed in levels (i.e., dollars) and takes nonnegative values (i.e., zero for those firms that did not suffer property damage and values greater than zero for those firms that suffered any property damage).

As the literature supports the notion that at higher levels of property damage more difficult will be for a firm to resume operations (see, e.g., Zolin & Kropp, 2006), this chapter also explores the possibility of nonlinearities associated to the influence of property damage on the decision to share resources. It is based on the idea that a firm might decide not to share resources until reaching a tipping point after which it chooses to share resources, and after reaching another tipping point at which it abandons the idea to continue with the tactic. In this regard, another type of model is estimated by using the property damage variable as categorical. Table 7 presents a contingency table between the different categories associated to property damage and resource sharing.

Table 7. Contingency Table: Property Damage – Resource Sharing

Resource Sharing	Property Damage						Total
	0	1	2	3	4	5	
No = 0	71	24	18	17	14	17	161
Yes = 1	15	15	13	10	20	11	84
Total	86	39	31	27	34	28	245

The definitions of the different categories are the following: 0 if the firm did not experience property damage, 1 if property damage was between \$1 and \$10,000, 2 if property damage was between \$10,001 and \$50,000, 3 if property damage was between \$50,001 and \$150,000, 4 if property damage was between \$150,001 and \$999,999, and 5 if property damage was equal or greater than \$1,000,000.

The variable that is defined as *firm's size* is incorporated in the model in terms of the number of employees prior to the disaster. The original variable ranges from 1 employee to 90,000 employees. In this regard, total number of employees is also prone to be transformed in logarithmic form given its internal feature of taking small to large integer values.[14] Unlike the previously defined logarithmic variables of *Avoided Losses* and *Property Damage*, the transformation of total number of employees prior to disaster into logarithmic form does not require to add 1 to the original variable given that the lowest value taking this variable is precisely 1 employee.

[14] See Wooldridge (2013)

The last control to be incorporated in the selection equation is *industry sector*. Table 8 presents a contingency table between the different categories associated to firm's sector and resource sharing.

Table 8. Contingency Table: Industry Sector – Resource Sharing

Resource Sharing	Industry Sector					Total
	1	2	3	4	5	
No = 0	24	27	36	15	59	161
Yes = 1	16	14	11	16	27	84
Total	40	41	47	31	86	245

The definitions of the different categories for the original variable are based on the NAICS code and are collapsed into the following categories defined in Table 8: 1 if the firm belongs to the construction or manufacturing sectors, 2 if the firm belongs to the wholesale or retail sectors, 3 if it operates in the utilities or transportation or information or finance or real estate sectors, 4 if it operates in the professional, scientific and technical sectors, and 5 if it operates in a sector other than those previously defined. The rationale for this classification is based on extant literature supporting the hypothesis that firms operating in the manufacturing and construction sector performs better in the post-disaster compared to those in retail or service sectors (Dietch & Corey, 2011).

Other variables to be included are those to which resource dependence theory refers may help to avoid dependencies. These variables are expressed in the form of other tactics such as *inventories* and *resource isolation*, which are aimed at reducing the problem of overreliance on suppliers in the post-disaster by buffering the organization against uncertainties and instabilities (Pfeffer and Salancik, 2003).

The main equation also requires the use of control variables. As previously mentioned, the variables used as control should include *time in business, number of locations, property ownership, business proprietorship, firm's size, property damage, and firm's sector or business activity*

2.3.3 Descriptive Statistics

Table 9 provides a summary on descriptive statistics for the variables included in the model for the selection equation. The decision to share resources serves the purpose of the dependent variable in the first stage probit model.

Table 9. Descriptive Statistics of Variables included in the Selection Equation

Variable	Category	Definition of Category	Summary Statistics
resource sharing	0	firm did not use tactic	65.71% (n = 161)
	1	firm used tactic	34.29% (n = 84)
resource importance	0	non critical resources	58.78% (n = 144)
	1	one critical resource - many suppliers	13.88% (n = 34)
	2	one critical resource - one or few suppliers	13.06% (n = 32)
	3	various critical resources - one or many suppliers	14.29% (n = 35)
resource non-substitutability	0	non critical or partially substitutable resource	87.76% (n = 215)
	1	non substitutable resource	12.24% (n = 30)
property damage categories	0	$0	35.10% (n = 86)
	1	$1 - $10,000	15.92% (n = 39)
	2	$10,001 - $50,000	12.65% (n = 31)
	3	$50,001 - $150,000	11.02% (n = 27)
	4	$150,001 - $999,999	13.88% (n = 34)
	5	Above $1,000,000	11.43% (n = 28)
property damage	Continuous variable		mean = 879697, median=10000, min = 0, max = 25000000
ln property damage	Continuous variable		mean = 7.28, median=9.2103, min = 0, max = 17.03
employees prior disaster	Continuous variable		mean =2895.47, median=40 min = 0, max = 90000
ln employees prior disaster	Continuous variable		mean = 4.16, median=3.69 min = 0, max = 11.41

Variable	Category	Definition of Category	Summary Statistics
industry sector	1	manufacturing or construction	16.33% (n = 40)
	2	wholesale or retail	16.73% (n = 41)
	3	utilities, transportation, information, finance	19.18% (n = 47)
	4	professional, scientific, technical	12.65% (n = 31)
	5	Others	35.10% (n = 86)
tactic inventories	0	firm did not use tactic	61.22% (n = 150)
	1	firm used tactic	38.78% (n = 95)
tactic resource isolation	0	firm did not use tactic	75.10% (n = 184)
	1	firm used tactic	24.90% (n = 61)

N = 245 observations in the first stage probit model.

Table 10 provides a summary on descriptive statistics for the variables included in the model for the main equation. The dependent variable in the second stage OLS model is the natural logarithm of avoided losses. On the other hand, some of the variables that are incorporated as controls in the second stage equation were already defined in the selection equation. These include property damage (natural logarithm of property damage), firm's size (natural logarithm of number of employees prior to disasters), and industry sector. The tactic of resource sharing is also included in the second stage along with a correction factor, the inverse Mills ratio that accounts for sample selection bias. Next section will provide details about the model specification and the Heckman modeling approach.

Table 10. Descriptive Statistics of Variables included in the Main Equation

Variable	Category	Definition of Category	Summary Statistics
avoided losses	Continuous variable		mean = 959074, median=74000, min = 0, max = 65000000
ln avoided losses	Continuous variable		mean = 10.89, median=11.21, min = 0, max = 17.99
time in business	1	Less than 5 years	3.67% (n = 9)
	2	5 to 10 years	20.00% (n = 49)

Variable	Category	Definition of Category	Summary Statistics
	3	11 to 15 years	15.92% (n = 39)
	4	16 to 20 years	17.14% (n = 42)
	5	20 to 25 years	17.96% (n = 44)
	6	26 to 50 years	15.92% (n = 39)
	7	51 to 100 years or more than 100 years	9.39% (n = 23)
single location	0	more than one location	40.00% (n = 98)
	1	single location	60.00% (n = 147)
owns the building	0	renting or leasing building	42.45% (n = 104)
	1	owns building	57.55% (n = 141)
sole proprietorship	0	different from sole proprietorship	63.67% (n = 156)
	1	sole proprietorship	36.33% (n = 89)
Hurricane Harvey	0	superstorm sandy	43.67% (n = 107)
	1	hurricane Harvey	56.33% (n = 138)

N = 245 observations in the second stage OLS equation.
Variables related to property damage, firm's size, industry sector, and the tactics of inventories, resource isolation and resource sharing are also included and have already been defined.

2.3.4 Empirical Strategy and Model Specification

As the main goal in this chapter is to analyze the influence of a resource sharing strategy on static economic resilience, a Heckman-type model emerges as the most suitable analytical approach. The reason is that firms are able to choose a post-disaster strategy or strategies that lead to minimize or avoid losses, that is, to enhance its static economic resilience (i.e., the choosing of a strategy is not at random). In this regard, firms are able to self-select the post-disaster strategic choice that is observed based on unobserved factors that will, ultimately, affect the decision and in turn firm's resilience.

To correct for this selection bias, this chapter employs a Heckman-type model that is derived from the literature on labor economics and that aims to estimate the average wage of women using data from a population of women in which those who are not in the sample are excluded by self-selection, that is, women who decide not to work (Heckman, 1978, 1979). The novelty of Heckman's work gave the possibility to be extended to the evaluation of treatment effectiveness (Maddala, 1983). This chapter certainly applies the treatment effect model, which differences from Heckman's model in two aspects: 1) a dummy variable indicating the treatment condition w_i (i.e., $w_i = 1$ if firm i decides to utilize a resource sharing strategy in the post-disaster, and $w_i = 0$ otherwise) is directly entered into the main equation and 2) the outcome variable y_i (i.e., natural logarithm of avoided losses) of the OLS regression equation is observed for both $w_i = 1$ and $w_i = 0$ (Guo & Fraser, 2015). The treatment effect model is represented by the following equations:

Regression Equation: $y_i = x_i\beta + w_i\delta + \varepsilon_i$ (2)

Selection Equation: $w_i^* = z_i\gamma + \mu_i$ where $w_i = 1$ if $w_i^* > 0$ and $w_i = 0$ otherwise (3)

$$\text{Prob}\left(w_i = 1 \mid z_i\right) = \phi\left(z_i\gamma\right) \text{ and } \text{Prob}\left(w_i = 0 \mid z_i\right) = 1 - \phi\left(z_i\gamma\right)$$

The estimation of the treatment effect model is based on a two-stage process to correct sample-induced endogeneity. The first stage in this process uses a probit model (Equation 3) in which z represents a vector of variables that determine the likelihood of a firm entering the sample (i.e., resource importance, substitutability, property damage, firm's size, and industry sector), and u represents the errors that are independent and identically distributed with a mean of 0. The second stage uses an OLS regression (Equation 2) to predict static economic resilience. To account for the potential biases that may result from self-selection (i.e., nonrandomness), the treatment effect model uses Equation 3 to create a selection parameter, the inverse Mills ratio (IMR), which is included in the regression or main equation as control variable aimed at adjusting the treatment effect (i.e., Equation 2). Usually, the IMR coefficient is referred to as lambda and is computed by multiplying sigma and rho, where sigma represents the standard deviation of the residuals in the second-stage equation, and rho is the correlation between error terms in the first- and second-stage equations (Certo, Busenbark, Woo, & Semadeni, 2016).

In the context of this dissertation, the problem arises because of the firms' decision to utilize a resource sharing strategy, or other type of strategy, or no strategy at all and they make this decision based on unobserved characteristics associated with the firm, resource, and or type of industry. If this selection process is not explicitly considered, the effects may be erroneously attributed to the decision per se when there are unobserved attributes that influenced the strategic choice.

Heckman models should include at least one variable in the first stage that does not appear in the second stage (Sartori, 2003). In the context of resource sharing and static economic resilience, these variables are the ones related to *resource importance and non-substitutability*. This chapter also explores if the inclusion of variables in the first stage depends on the timing of the decision. That is the case of property damage that might affect the decision to choose a particular strategy because the level of damage is observed first and then the firm decides to act accordingly. If that is the case, property damage might affect the strategic choice directly but its effect on resilience is indirect. The variables that appear in the selection equation but not in the regression equation are known as exclusion restrictions because they influence the probability of a firm appearing in the sample, but do not influence the static economic resilience in the second-stage OLS model (Certo et al., 2016).

In general, the literature suggests there are two necessary conditions for sample selection bias, namely 1) the selection equation in the first stage must include significant predictors, and 2) the error terms in the regression and selection equations, e and u respectively, must be correlated. This occurs because an omitted variable creates a correlation between the two error terms. Empirically, it is possible to examine the correlation between e and u and report the significance of the IMR (Wooldridge, 2010). Additionally, Certo et al., (2016) provide clear explanations on how Heckman-type models differentiate with instrumental variables in two-stages least squares by suggesting that exclusion restrictions that appear in a selection equation are exogenous variables intended to predict whether or not an observation appears in a sample; in this case, the propensity of a firm to share resources. On the other hand, instrumental variables are exogenous variables intended to represent endogenous independent variables. Additionally, Heckman-type models include an adjustment factor (i.e., IMR) that is included in the regression equation (i.e., second stage) but is derived from the selection equation (i.e., first stage). The only similarity is that the variables chosen (whether an instrument or exclusion restriction) should not correlate with the error term associated with the dependent variable in the second stage (see, e.g., Guo & Fraser, 2015)

2.4 Results

2.4.1 First-stage Estimates of Post-disaster Resource Sharing Strategy

Table 11 presents the results from four potential post-disaster resource-sharing strategic choice models developed in a first-stage (i.e., selection equation). The probit model estimated in the first step utilizes 245 observations and discriminates those firms that shared resources from those that did not share resources in the post-disaster.

Table 11. First-stage Estimates of Post-disaster Resource Sharing Strategy

VARIABLES	(Probit Model 1)[a]	(Probit Model 2)[b]	(Probit Model 3)[c]	(Probit Model 4)[d]
resource_importance – one critical resource; many suppliers			0.512*	0.506*
			(0.282)	(0.288)
resource_importance – one critical resource; one or few suppliers			0.180	0.103
			(0.292)	(0.295)
resource_importance – various critical resources; one, few or many suppliers			0.361	0.303
			(0.285)	(0.287)
non_substitutable_resource – non substitutable resource			-0.296	-0.266
			(0.308)	(0.310)
ln_property_damage	0.0618***			
	(0.016)			
property_damage – $1 - $10,000		0.583**	0.414	0.344
		(0.266)	(0.288)	(0.294)
property_damage – $10,001 - $50,000		0.733**	0.691**	0.690**
		(0.288)	(0.291)	(0.298)
property_damage – $50,001 - $150,000		0.643**	0.604*	0.513*
		(0.305)	(0.309)	(0.315)
property_damage – $150,001 - $999,999		1.128***	1.081***	1.023***
		(0.278)	(0.281)	(0.286)
property_damage – Above $1,000,000		0.564*	0.493	0.482
		(0.317)	(0.319)	(0.327)

VARIABLES	(Probit Model 1)[a]	(Probit Model 2)[b]	(Probit Model 3)[c]	(Probit Model 4)[d]
ln_employees_prior_hurricane – firm's size	0.0552	0.0686*	0.0670*	0.363***
	(0.035)	(0.037)	(0.038)	(0.130)
ln_employees_prior_hurric_squared – firm's size				-0.029**
				(0.0121)
industry_sector – wholesale or retail	0.127	0.139	0.262	0.366
	(0.301)	(0.303)	(0.318)	(0.325)
industry_sector – utilities, transportation, information, finance	-0.334	-0.323	-0.257	-0.120
	(0.296)	(0.298)	(0.309)	(0.314)
industry_sector – professional, scientific, technical	0.640**	0.601*	0.641*	0.649*
	(0.322)	(0.325)	(0.341)	(0.344)
industry_sector – other	0.0144	0.0195	0.106	0.158
	(0.260)	(0.262)	(0.273)	(0.273)
Tactic – Inventories				0.00730
				(0.186)
Tactic – Resource Isolation				0.00299
				(0.218)
Constant	-1.176***	-1.268***	-1.393***	-1.969***
	(0.305)	(0.318)	(0.342)	(0.434)
Likelihood Ratio		34.02***	38.15***	44.34***

[a] Probit Model 1 includes control variables and property damage as continuous variable, [b] Probit Model 2 includes control variables and property damage as categorical variable, [c] Probit Model 3 includes variables from Model 2 plus variables related to resource dependence, [d] Probit Model 4 includes variables from Model 3 plus the tactics of inventories and resource isolation

N = 245 observations

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model 1 is a baseline model that incorporates an intercept term and control variables of property damage, firm's size, and industry sector. Model 2 includes the same variables from Model 1 but instead of using property damage as continuous variable, it includes property damage as categorical variable. Model 3 includes the same variables used in Model 2 plus those variables aimed at testing the importance of critical resources and dependence on suppliers as well as the substitutability of the resource. Finally, Model 4 includes those variables incorporated in Model 3 plus the tactics of inventories and resource isolation, which according to resource dependence theory buffer the organization against uncertainties and instabilities and may prevent the use of interorganizational strategies (Pfeffer and Salancik, 2003).

Results from the first-stage probit models in Table 11 are novel and have not been tested before in the literature. For the first variable, resource importance, coefficients have expected signs according to what theory says, although not all of the coefficients on the categories are statistically significant. This coefficient is tested in models 3 and 4. The reference or comparison category (i.e., counterfactual) is associated to firms' responses that report not depending on any critical resource. In this regard, businesses in the first category – firms that rely on a critical resource supplied by many supplier – are more likely to utilize a post-disaster resource sharing strategy than firm that do not rely on critical resource ($p<0.1$). For the other two categories – firms that rely on a critical resource supplied by one or few suppliers and firms that rely on several critical resources supplied by one, few or many suppliers – there is no statistical evidence supporting the hypothesis that those firms that are found in these categories are more likely to use a resource sharing tactic after a disaster than firms with no critical resources. However, as previously mentioned, the direction of the coefficients are the expected according to what is found in the theory.

For the second variable, non-substitutability of the resource, results are non-statistically significant and the direction of the estimates may appear contradictory. This coefficient is also tested in models 3 and 4. The reference category is associated to firms' responses that report not depending on any critical resource or depending on a substitutable resource, at least partially. In general, resource dependence theory says that one way to reduce dependencies is by developing substitutable resources, which is contingent upon the production function of the firm and its ability to use interorganizational strategies to acquire resourced from the environment. In this regard, it would be expected that firms with non-substitutable resources would be more likely to utilize a resource sharing tactic after a disaster than firms with non-critical and substitutable resources or at least partially substitutable. However, the negative sign indicates the opposite. It is important to say that this might occur because when firms develop, for instance, partially substitutable resources, there may emerge complementarities associated to the use of the resource. If this is the case, firms that are able to substitute an important resource may exhibit dependence on other(s) suppliers, which increase their chances to resource share in order to reduce those dependencies.

The model also includes control variables. The first variable is property damage, which is introduced in the model in two forms: as natural logarithm and as categorical variable. The natural log of property damage is included in model 1 in linear form. It is statistically significant ($p<0.01$) and its coefficient has the expected sign, which indicates the following: the larger the property damage of a firm, the more likely is for that firm to resource share after a disaster. However, in considering that there may be nonlinearities associated to property damage that are not captured by its natural logarithm, this chapter also explores nonlinear effects by using a categorical version of this variable. Models 2, 3, ad 4 include the variable of property damage in categorical form. All coefficients of the different categories in model 2 have the expected signs, indicating that it is more likely that firms share resources when they suffer property damage than when they do not suffer any property damage. However, after controlling for different variables and including possible confounders, models 3 and 4 are particularly suggestive. They indicate that at low levels of property damage – $1 to $10,000 – the statistical evidence says that firms are not more likely to resource share than those firms not suffering property damage. However, after reaching a tipping point, the statistical evidence says that firms are more likely to resource share. And at very high levels of property damage – above $1,000,000 – firms again are not more likely to share resources than firms suffering any property damage.

Another control included in the model is the firm's size. The natural logarithm of the employees_prior_disaster variable is included in linear form in models 1, 2, and 3. The evidence says there is statistical support for the hypothesis indicating that the larger a firm is, the more likely is for the firm to resource share ($p<0.1$). However, based on the literature on RDT saying that smaller firms may be more in the need to use interorganizational strategies to avoid dependencies, model 4 includes a non-linear component of the natural logarithm of the variable. The estimate of the linear term of this variable in model 4 is also positive and statistically significant ($p<0.01$). Additionally, the estimate of the non-linear term of this variable (i.e., the quadratic component) indicates that the likelihood of a firm sharing resources decreases as firms become larger (i.e., the coefficient term is negative and statistically significant with $p<0.05$). This suggests that small and medium firms will be more like to resource share than large firms as larger firms leverage their resources and resort to intraorganizational tactics, as the theory predicts.

Other control variable, business sector, is included in the model given prior theoretical findings related to higher probabilities of survival among manufacturing and construction firms. These higher probabilities, as previously mentioned may be due to the use of post-disaster tactics such as resource sharing. The results support previous findings because none of the firms involved in other categories are more likely to share resources than those firm in the manufacturing and construction sector. The exception is for firms in the professional, scientific and technical sector ($p<0.1$).

The last variables included to control for some effect are inventories and resource isolation, given RDT's claim that these types of actions may reduce the problem of overreliance on suppliers in the post-disaster by buffering the organization against uncertainties and instabilities. After controlling for these variables, model 4 did not find any statistical effect on the likelihood to use a resource sharing tactic.

After running some likelihood ratio tests, it is possible to conclude that model 3 is not better than model 2, but model 4 is statistically significant better than model 2 and 3. This is particularly true when the variables related to inventories and resource isolation, which are non-statistically significant and their magnitude is non-substantial (i.e., estimate coefficients are 0.00730 and 0.00299 for inventories and resource isolation, respectively) are dropped from the analysis.

2.4.1 Second-stage Estimates of Static Economic Resilience

Table 12 provides the results of the second-stage selection bias models that consider static economic resilience as the dependent variable, which is operationalized by the natural logarithm of avoided losses as its performance measure. These models incorporate different control variables defined previously in Table 10. The main objective of the second stage is to analyze the effect of the resource sharing tactic while controlling for a self-selection factor – the inverse Mills ratio, which is usually represented as lambda. The idea is to analyze how the inverse Mills ratio influences the estimate of resource sharing in the second-stage.

Model 3 corresponds to the second stage of the same model identified in the first stage in Table 11. Model 4 also identifies the second stage of the same model estimated in the first stage that is presented in Table 11. It is important to remember that model 4, unlike model 3, incorporates a non-linear form of firm's size in the first stage. Finally, there is another model that is estimated and presented in Table 12 and corresponds to model 5, which does not include a first-stage probit model in Table 11 but only the OLS estimation in Table 12. This model aims to compare how the effect of the resource sharing tactic may be underestimated when not controlling for the selection bias factor, the inverse Mills ratio in this case. The intuition behind not incorporating the selection bias factor implies assuming that firms choose strategies at random and that any difference that we observe between both groups (i.e., the groups of firms that shared vs the group of firms who did not share), after controlling for other factors, does not depend on which firm is most suitable to use the tactic. In the following paragraphs, I will refer explicitly to results from models 3 and 4. I will refer to model 5 at the end this section.

Table 12. Second-stage Estimates of Static Economic Resilience (Natural Log of Avoided Losses)

VARIABLES	(OLS Model 3)[c]	(OLS Model 4)[d]	(OLS Model 5)[e]
Hurricane_Harvey	0.750**	0.752**	0.733**
	(0.342)	(0.341)	(0.354)
industry_sector – wholesale or retail	-1.189*	-1.217*	-1.163**
	(0.621)	(0.639)	(0.586)
industry_sector – utilities, transportation, information, finance	-0.87	-0.844	-1.174**
	(0.609)	(0.622)	(0.556)
industry_sector – professional, scientific, technical	-0.575	-0.658	-0.107
	(0.701)	(0.716)	(0.629)
industry_sector – other	-1.079**	-1.098**	-1.093**
	(0.540)	(0.555)	(0.509)
ln_employees_prior_hurricane – firm's size	0.241***	0.234***	0.322***
	(0.086)	(0.085)	(0.0738)
sole_proprietorship	-0.353	-0.305	-0.172
	(0.374)	(0.371)	(0.377)
single_location	-0.629*	-0.512	-0.823**
	(0.357)	(0.362)	(0.362)
owns_the_building	0.229	0.155	0.290
	(0.335)	(0.338)	(0.346)
age_of_business - Less than 5 years	0.151	0.151	0.125
	(0.927)	(0.932)	(0.960)
age_of_business - 5 to 10 years	0.321	0.298	0.352
	(0.530)	(0.528)	(0.551)
age_of_business - 16 to 20 years	0.0255	-0.00285	0.0244
	(0.548)	(0.546)	(0.571)
age_of_business - 20 to 25 years	0.980*	0.946*	0.933*
	(0.536)	(0.535)	(0.560)
age_of_business - 26 to 50 years	0.0231	0.0539	-0.0663
	(0.561)	(0.560)	(0.582)

VARIABLES	**(OLS Model 3)[c]**	**(OLS Model 4)[d]**	**(OLS Model 5)[e]**
age_of_business - 51 to 100 years or more than 100 years	-1.018	-0.949	-1.088
	(0.673)	(0.669)	(0.704)
resource_sharing	3.189**	3.579***	0.677*
	(1.239)	(1.175)	(0.357)
Constant	9.404***	9.276***	9.975***
	(0.814)	(0.825)	(0.755)
λ Inverse Mills Ratio	-1.631**	-1.919***	N.A
	(0.760)	(0.724)	N.A

[c] OLS Model 3 corresponds to the second stage of first-stage Model 3, [d] OLS Model 4 corresponds to the second stage of first-stage Model 4, [e] OLS Model 5 does not have a counterpart in the first stage

N = 245 Observations

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The most important analysis that is carried out in models 3 and 4 is the test of the effect of the resource sharing tactic on static economic resilience. The analysis is based on the idea that unobserved characteristics underlying a firm's decision to share resources after the onset of a disaster may affect its capacity to avoid losses derived from business interruption. This hypothesis is supported by examining the inverse Mills ratio in models 3 and 4. It is statistically significant, which means there is a process or transmission mechanism that helps to explain the choosing of resource sharing. The negative sign of the inverse Mills ratio indicates that the greater the firm's propensity to share resources based on its unobserved characteristics, the higher its static economic resilience (see Dolton and Makepeace, 1987, for the interpretation on the lambda term). The lambda term is statistically significant (p<0.01 in model 4). In this regard, the effect of the resource sharing tactic in the second stage has been adjusted by including the self-selection term. The effect of the resource sharing tactic is also statistically significant (p<0.01). Its interpretation says that among firms that would be likely to use the resource sharing strategy (from the first-stage prediction), those that used it had, on average, approximately 35 times greater avoided in losses (i.e., %Δ Avoided Losses = 100[exp(3.579) – 1] = 3484%). It is important to mention that this apparently large number includes only those firms with a propensity to resource share.

The first control variable, type of hurricane, appears to be an important control as there is statistical evidence that supports the notion that, on average, firms affected by hurricane Harvey had higher levels of static economic resilience, that is, they were able to avoid more losses than firms affected by superstorm Sandy (p<0.05). The results of the second control variable – business sector – are consistent with previous findings that support the idea that firms in the wholesale or retail sector are less likely to recover. In this case, the statistical evidence says that wholesalers or retailers that belong to the sample did not avoid as much losses as firms in the manufacturing or construction sectors (p<0.1). As previously mentioned, the literature predicts this result as a consequence of customers abandoning the area after a disaster hits.

Another important control variable is size, which is represented by the number of employees prior the disaster. The evidence indicates that larger firms seem to have a higher level of static economic resilience, that is, are able to avoid more losses (p<0.01). This result is expected and is explained because larger firms are able to leverage their financial resources to enhance their resilience capacity. The coefficient of the variable *sole_proprietorship* is not statistically significant but it has the expected sign. That is, sole proprietorship firms are usually smaller firms and their owners, many times, do not have the financial resources or the necessary support beyond the one offered by local communities to enhance their resilience. A related variable to *sole_proprietorship* is the number of locations. There is a negative relationship between the variable named *single_location* and static economic resilience, indicating that firms with just one location were less able to avoid losses than firms with multiple locations ($p<0.1$). Another variable with the expected sign but no statistical support is the one related to businesses that own their buildings vs those that lease it or rent it.

The last control variable utilized in this model is age or time in business. The reference category is the one related to firms that have between 10 and15 years in the market. None of the categories was statistically significant except for the one related to firms that have between 20 and 25 years in the market, indicating that firms included in this last category have higher levels of static economic resilience represented by higher avoided losses.

Last, model 5 is a simple OLS regression that does not incorporate the lambda correction factor. It assumes there is no any process behind a firm's choosing of a resource sharing tactic in the post-disaster and that the election of the implementation of the resource sharing strategy occurs at random. In this case, the estimated coefficient of resource sharing is 0.677 ($p<0.1$), indicating that for every dollar avoided in losses by a firm that did not use a resource sharing tactic in the post-disaster, around \$100 (i.e., $\%\Delta$ Avoided Losses = $100[\exp(0.677) - 1] = 97\%$) were avoided in losses by a firm that did use it. It is obvious that the lack of the adjustment factor underestimates the effect of the tactic. However, this effect would be unbiased if the election of the tactic occurred at random, something that contradicts what theory says.

2.5 Discussion

Three main hypotheses were posed in this chapter. The first hypothesis is empirically supported, that is, there are unobserved characteristics underlying a firm's decision to share resources after the onset of a disaster that influence its static economic resilience. This indicates that there is a transmission mechanism that explains the conditions underlying a firm's decision to share resources. This also indicates that firms may select strategies based on the assumption they recognize those characteristics that potentially impact that election. In this regard, while several industry-, firm- and resource-level characteristics may influence the decision of firms to select a strategy that optimizes their avoided losses, resource dependence theory (RDT) provides some explanations behind the resource-level characteristics that lead a firm to resource share in the aftermath of a natural disaster. Two of those resource-level characteristics were empirically tested in this chapter with mixed results. The first resource-level characteristic corresponds to the second hypothesis. Empirical results indicated that firms that use one critical resource and depend on different suppliers are more likely, on average, to use a strategy of resource sharing than those firms not relying on critical resources. The second resource-level characteristic corresponds to the third hypothesis. In this case, the empirical results did not support the idea that firms using non-substitutable resources are more likely to resource share than firms using non-critical or substitutable resources. Additionally, the sign of the estimated coefficient in the third hypothesis was different from what theory predicts. The emergence of complementarities may clarify this divergence as explained before.

As it occurs with all research, the one carried out in this chapter may also be subject to some difficulties, particularly the ones related to the data. Given that individuals suffer from recall bias, information provided by individuals after the occurrence of a traumatic event as a disaster may pose a challenge. Additionally when asked about avoided losses, individuals may be prone to inflate these figures and attribute them to their own skills without recognizing how different factors conjugate and interplay in the final results. This is also associated to the difficulties in the study of complementarities among tactics, a topic that is explored by Dormady et al. (2018).

Another complication that arises from this study deals with the sample representativeness. Dormady et al. (2018) note the challenges that emerge when doing firm-level survey research. One of the strategies that was implemented to collect the data used in this chapter and that helps to overcome these complications included partnering with a professional survey firm that has existing relationships with a sample of firms and business associations and is able to target businesses in each economic sector so as to ensure the representativeness of the sample (i.e., RTi Research, in this case). Additionally, it should be noted that although the sample of firms used in this chapter is small in comparison to the thousands of firms affected by Superstorm Sandy and Hurricane Harvey, it is one of the largest samples used in resilience research at the firm-level.[15] Nonetheless, it is important to say that this chapter illustrates one possible way to

[15] See for instance Graveline and Gremont (2017) who use a sample of 108 individual businesses.

measure economic resilience that had not been explored in the literature and that the empirical results should be read cautiously as the final results are limited by the small sample size. As previously mentioned, the sample of firms in the data do not include firms that went out of business and, potentially, implemented the resource sharing tactic or were good candidates to implement it.

Despite all challenges that this research poses, it provides interesting results and explores new methods that may help governments to predict the behavior of firms after disasters. In this way, policy makers are provided tools to foster community development and business recovery based on the reduction of economic dependence on critical resources in high exposed-to-disaster areas. This chapter also supports the idea of creating mechanisms and incentives for firms to improve their post-disaster resilience and provides a structure to allocate funds and public assistance programs to those firms that have engaged in efforts to enhance their post-disaster resilience. This is also a topic that deserves further research.

Chapter 3: Effects of Hurricane Intensity Forecasts on Evacuation Decision – Making

3.1 Introduction

Hurricanes are among the most serious natural hazards potentially transforming into natural disasters, bringing about not only property damage and interruption to business operations but also large losses of life. According to the National Hurricane Center (n.d.), a hurricane is a tropical cyclone in which the maximum sustained surface wind is 64 kt (74 mph or 119 km/hr) or more (using the U.S. 1-minute average).

The intensity of a hurricane is classified by meteorologists using the Saffir-Simpson Hurricane Scale (SSHS) that rates hurricanes on a discrete scale of 1 to 5 based on some hurricane characteristics including center pressures, sustained wind speeds and storm surge, which provide a rough estimate of a hurricane's potential for property damage upon landfall. Despite suggestions of some scholars for replacing the SSHS due to the categorization associated to each of the continuous properties involved in the scale and the confusion these categories may create to the public and decision-makers (see, e.g., Kantha, 2006),[16] the SSHS continues to be one of the most important tools used by

[16] Some scholars believe that public and decision-makers may misperceive the threat of the hurricane because of the rather discrete and arbitrary Saffir-Simpson Hurricane Scale (Kantha, 2006). Appendix A presents the SSHS. Category 2 hurricanes, for instance, can have sustained wind speeds that range between 96 to 110 mph indicating that extremely dangerous wind will cause extensive damage. The table also indicates that a change of one unit in maximum wind speed leads to a change in the hurricane category (e.g., a Category 2 hurricane is downgraded to Category 1 if the maximum sustained wind speed decreases

emergency managers to cope with hurricane emergency response decisions. In fact, in recent years, the improvements in hurricane intensity forecasting have been a priority to both, researchers and forecasters, and substantial R&D resources from both public and private sources have been invested to develop new and more accurate models aimed at improving public safety and reducing property loss (Gall et al., 2013; Na, McBride, Zhang, & Duan, 2018). However, despite all these investments geared to enhance forecast skill development, there is a dearth of empirical research that helps in the comprehension of how public decision-makers use the information from these models and systems. To date, it is not clear whether all these resources utilized in developing models and technology aimed at providing more accurate information have actually improved the capacity of emergency managers to make better evacuation decisions.

This chapter is intended to study the effects of hurricane intensity forecasts on evacuation decision-making. As previously mentioned, a key variable included in the SSHS that categorizes the intensity of a hurricane is its maximum sustained wind speed (Kantha, 2006). This refers to the highest one-minute average wind (at an elevation of 10 meters with an unobstructed exposure) at a particular point in time (National Hurricane Center, n.d.). Na et al. (2018) detail different studies that describe the attempts to improve hurricane intensity forecasting through advanced numerical methods, in situ and remote sensing observations, and statistical forecast models. Obviously, if the evacuation decision making process is improved, all efforts aimed to increase hurricane intensity

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from 96 to 95 mph, which, according to the SSHS, would indicate that potential damage has changed from "extensive" to "some").

forecast capabilities are more than compensated not only by the cost reduction in the preparation for hurricanes, evacuation of people, and the moving of assets, but also by the reduction in costs of false alarm evacuations (Regnier, 2008).

The purpose of this research is to evaluate the effect of hurricane intensity forecasts on evacuation decision-making in a disaster-preparation context. In line with the extant literature that posits some improved individual judgement accuracy that arises from statistical forecasts (Goodwin & Fildes, 1999) and assumes benefits derived from improved hurricane forecasting (Lazo, Waldman, Morrow, & Thacher, 2010), I hypothesize that decision-makers with more information (i.e., individuals exposed to hurricane intensity forecasts) will make better evacuation decisions in terms of their decision to evacuate, in the accuracy of their decision (i.e., timing), and in their determination for evacuation location than decision-makers with less information (i.e., individuals not exposed to hurricane intensity forecasts). To examine these hypotheses, I utilize controlled experiments with a subject pool of professional emergency managers and replicate the same experiment with undergraduate experimental economics subject pool students. Also, I use historical/archival data from the National Oceanic and Atmospheric Association's (NOAA) National Hurricane Center (NHC) for Hurricane Rita (2005), which provides information for the counterfactual. Participants are not expected to know that the specific track and hurricane conditions actually correspond to Hurricane Rita. The experiment is set up in two stages and is characterized by a dynamic setting where participants receive updated information in nine (9) different rounds in the first stage in the form of "advisories" reflecting new hurricane conditions. The “advisories” received by participants in the treatment group to be assessed in this chapter also include hurricane intensity forecast information that is described by a forecast measure of the maximum sustained wind speed for the following 24 hours. The dynamic aspect of this experiment is an important contribution to the literature because research on evacuation decision-making has focused on the determinants of evacuation or better ways to communicate forecasts for individuals to evacuate, but the isolated effect of hurricane intensity forecasts in a dynamic setting has not been explored.

Next, the paper reviews the relevant literature on the role of information and forecasts on decision making in different scenarios including hurricane evacuation scenarios, followed by an explanation of the controlled experiment, results and implications. In general, given the particularities and the context of this research that relies on the historical archives of Hurricane Rita as counterfactual, the overall findings of this experiment support the conclusion that the proportion of participants who make the decision to evacuate when having available higher levels of information in the form of maximum sustained wind speed forecasts is higher than the proportion of participants making the same decision with less information. Another important finding is that, in terms of hurricane evacuations, participants with more information evacuate, on average, earlier than those participants with less information. Last, another finding in this experiment is that participants with more information are able to reduce the number of exposed-to-risk individuals when deciding the population to be evacuated. In general, these findings inform more about the importance of hurricane intensity forecasts in the evacuation decision-making process. Sometimes more people die from evacuations done poorly than from the actual hurricanes (e.g., Hurricane Rita is an example of this assertion). In this regard, this research provides a systemic understanding of the influence of one of the informational levels on which disaster and emergency managers rely upon the most.

3.2 Background Literature

A forecast is a calculation or estimation of the future value of a variable whose realization depends inherently on the probability of occurrence of that particular event. In terms of the role of probabilities and forecasts on evacuation decision making, the literature informs some interesting findings, particularly in contexts other than tropical cyclones. In a national security context, for instance, results indicate that specialists responding to precise probability assessments are less willing to support risky actions and more receptive to gathering additional information. That is, in a national security situation, decision-makers are more prone to delay decisions when they are provided quantitative probabilities of different scenarios (i.e., they are provided probabilities and forecasts). At the same time, the research finds that when respondents estimate probabilities themselves, the quantification of probabilities amplifies overconfidence, particularly among low-performing decision-makers (Friedman et al., 2017). In a context of extreme weather conditions, Savelli & Joslyn (2013) suggest benefits in providing non-expert users probabilities of particular adverse weather events (e.g. freezing temperatures, precipitation, high winds) and percentiles (10th, 50th, 90th) of the predictive distribution of continuous weather variables of interest (e.g. temperature, amount of precipitation, wind speed). The research suggests that individuals make better precautionary decisions when they are provided this type of information than when they are not provided probabilities of adverse weather events.

In the context of hurricanes, Petrolia, Bhattacharjee, and Hanson (2010) investigates the variation in the effects of crucial storm forecast factors on hypothetical evacuation decisions made by residents living in the areas of Alabama, northwest Florida, southeast Louisiana, and Mississippi, and concludes that wind speed and landfall time are the only two significant storm forecast attributes that influence the evacuation decision. In this research, Petrolia, Bhattacharjee, and Hanson (2010) explored the impact of wind speed forecasts as one potential factor affecting evacuation decisions and centered on how individual residents choose to evacuate when they face different wind speed scenarios without considering how the hurricane evolves over time. Also, the research did not control for statistical literacy or individuals' understanding of probabilities (Gigerenzer and Edwards, 2003) despite participants being non-specialists (i.e., individual residents). Another recent research paper in the context of hurricanes focused on how to communicate forecasts to individuals for them to make evacuation decisions, for instance, by exploring how different types of forecast and warning messages that include information about storm surge height and impacts influence the decision to evacuate (Morss et al., 2016).

In terms of research on evacuation decision making made by elected officials and/or specialists (e.g., emergency managers), the literature is limited given that most of the research focuses on evacuation decisions made by households and/or individual residents as opposed to evacuation decisions made by experts. According to research, these decision-makers, who rely on different sources of information such as the ones provided by the National Oceanic and Atmospheric Administration (NOAA), experts and advisors, may be prone to make biased decisions when facing the following situations: 1) when they are exposed to receiving too much information. The overload of information in the form of more detailed and more complex data and forecasts has been associated with low quality decisions (Iselin, 1993); 2) when they are exposed to stressful decisions. Stress, which has been associated with how people weigh risk and reward, is considered a main factor in a decision-making process such as evacuation decisions (Mather & Lighthall, 2012); and 3) as a result of natural hazards intensity forecast errors. This is the case of Tropical Cyclones that present a negative correlation between official forecast errors and intensity change, suggesting a significant bias in error such that less intensifying storms are associated with overforecast (positive errors) whereas more intensifying storms are associated with underforecast (negative errors) (Na, McBride, Zhang, & Duan, 2018).

In general, it is vital that decision-makers in charge of issuing evacuation recommendations (e.g., emergency managers) have the most updated information in hand to make "informed" evacuation choices within risky environments. However, the updated or most recent information decision-makers receive is imperfect and based on probabilistic distributions that translate into forecasts that may lead a decision-maker to select alternatives based on false positives (Regnier, 2008). In the controlled experiment I present below, I provide the experimental subjects with information about the forecast of the maximum sustained wind speed and compare this treatment with others not explicitly containing this type of information. Comparing between treatments informs whether decision-makers are willing to delay the decision and wait to collect more information or if there is any influence of the forecast in the decision-making process.

3.3 Experimental Design

I draw on a controlled experiment to test the effect of hurricane intensity forecasts (i.e., maximum sustained wind speed) in the context, or decision-making role, of a high-level disaster risk manager who is providing guidance, advice and/or recommendation to a state governor on the critical evacuation decision for a large-scale coastal community. Participants were asked to make a large scale evacuation decision of a major metro area (in this case, the governor of Texas and the Houston-Galveston metro area). Below, I provide information about how the experiment was designed.

Using historical/archival data from the National Oceanic and Atmospheric Association's (NOAA) National Hurricane Center (NHC) for Hurricane Rita (2005), I use that storm's real-time historical storm forecast information that was given to decision-makers as the storm occurred as the base case control group. This information provides the counterfactual. The specific storm (i.e., Rita) is never disclosed to subjects and they only observe all of the historical forecast information (and historical forecast error). In fact, the name of the hurricane in the experiment is changed from Rita to Rebeca. The critical decision participants are asked to make is whether evacuation should take place and where.

3.3.1 Experiment Operation and Sample Selection

The experiment is designed as an online experimental survey that is part of a current NSF project focused on evaluating the effect of increased informational modeling capabilities (e.g., advanced engineering forecasting models) on decision-making accuracy in a disaster-preparation context. The main goal of the NSF project is testing how more detailed forecasts influence the decision-making process in a disaster risk management environment, mainly whether evacuation should take place and where.

The experiment's participant subjects are sampled from three pools: 1) State employees attending the Public Safety Leadership Academy, which is a leadership certificate program offered by Ohio State's John Glenn College of Public Affairs in partnership with the Ohio Department of Public Safety. Respondents attending this program are law enforcement leaders from across ~~the state of~~ Ohio and include the State Highway Patrol, officers from local police departments, county sheriffs, and other public safety-related positions. 2) Professional emergency managers from other states including Florida, Georgia, North Carolina, South Carolina, Louisiana, and Alabama, were also invited to participate. These two populations of participants most closely mimic the public safety populations that would be providing real-time informational guidance on emergency management to a governor in a major evacuation scenario. 3) Undergraduate and graduate subjects enrolled in the Experimental Economics Laboratory Subject Pool at Ohio State University. This pool consists of approximately 12,000 undergraduate and graduate students, one of the largest university pools in the U.S.

3.3.2 Numeracy Test

Before being assigned to treatments, participants take a short question numeracy test. The numeracy test serves two purposes. First, it provides a baseline control of the participant's ability to make accurate assessments with probabilities. Second, it serves as an endowment generator. Participants earn points that translate to monetary earnings for their completion of the numeracy test. However, it is important to say that although participants do not earn more points for performing better on the test (i.e., all participants receive the same endowment without considering their answer to the short question numeracy test), this variable is included as a control in the empirical estimations. The endowment is then utilized as the loss aversion instrument in the decision-making scenarios (Kahneman, Knetsch & Thaler, 1991; Kagel & Roth, 1995). The number of points earned by a participant after taking the numeracy test is two hundred points (200).

The question used in the numeracy test is drawn from the Berlin Numeracy Test, which has been found to be the strongest predictor of interpreting forecasts, doubling the predictive power of other instruments (see Cokely et al., 2012). The numeracy test question used in the experiment is provided in Appendix B.

3.3.3 Decision Making Scenarios

In the experiment, respondents are provided scenarios (i.e., they are provided videos) and have to make decisions at two different stages (see the text of the videos or vignettes in Appendix C). In the first stage, participants take on the role of a generalized high-level disaster risk or emergency manager who is providing guidance to the governor of Texas on the critical evacuation decision for coastal and low-lying areas (i.e., the state director of the Office of Emergency Management). In this first stage, participants are asked to make a decision at the beginning of each of nine (9) rounds in which they must decide whether to advise the governor to issue a *voluntary* evacuation for specific coastal and low-lying areas facing potential inundation generated by infrastructure failure as a result of a hurricane.[17] Participants do not know beforehand the number of rounds and may decide to evacuate early (i.e., in the first round) or late (i.e., in the ninth round). As previously mentioned, this experiment uses historical information for Hurricane Rita (2005), which provides the counterfactual in terms of the evacuation recommendation (i.e., the right choice is to issue a *voluntary* evacuation recommendation). In this stage, participants are compensated based on their performance by considering not only if they made a right choice but also the timing of the decision (i.e., the experiment will reflect the fact that evacuation decisions may be too tardy, which places a large burden on the community). Table 13 provides information about how the hurricane intensity forecast measures change across the 9 advisories.[18] Details about compensation on round-by round decisions and evacuation zones are presented in the next section.

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[17] The Federal Emergency Management Agency (FEMA) has provided definitions for different types of evacuation including voluntary and mandatory (see the Guide for All-Hazard Emergency Operations Planning, FEMA, 1996). However, the first-stage decision in this research project only considers the decision to evacuate voluntarily.

[18] Numbers corresponding to maximum sustained wind speeds are the real numbers that were provided individuals during Hurricane Rita. In this regard, participants are not required in this experiment to assess the quality of the forecast but only to make an evacuation recommendation without considering if the forecast is correct or incorrect.

Table 13. Hurricane Intensity Forecasts across Advisories

Round	Actual date and time of the storm's current location	Maximum Sustained Wind Speed Forecast *mph* (Next 24 hours)
Advisory 1	11 am EDT, Tuesday, September 20 2005	*100*
Advisory 2	2 pm EDT, Tuesday, September 20 2005	*120*
Advisory 3	5 pm EDT, Tuesday, September 20 2005	*130*
Advisory 4	11 pm EDT, Tuesday, September 20 2005	*140*
Advisory 5	5 am EDT, Wednesday, September 21 2005	*145*
Advisory 6	10 am CDT, Wednesday, September 21 2005	*155*
Advisory 7	4 pm CDT, Wednesday, September 21 2005	*165*
Advisory 8	10 pm CDT, Wednesday, September 21 2005	*180*
Advisory 9	4 am CDT, Thursday, September 22 2005	*175*

In a second stage, after making the first-stage decision, participants are asked to make a *mandatory* evacuation or an evacuation location determination, even if they decided not to evacuate in the first stage (i.e., which communities should be evacuated). This consists of the zones of the coastal area to be evacuated or, more specifically, participants get to decide where evacuation precisely takes place. In this stage, participants are given additional information in which they see a map of the coastal area divided by zones. These zones directly correspond to evacuation planning zones currently utilized by the Houston-Galveston Area Planning Council. These are known areas based on regional identification, demarcated by zip code. Residents of the area are introduced to the "Know Your Zones" program[19] so that they can easily be identified if their zone is called for evacuation.

Participants have to choose the zones to be evacuated after assessing the probability of infrastructure failure, which is provided through three different scenarios; identified as low, medium, and high. After their choice, participants see which zones

[19] See the Disaster Preparedness Guide (2016) for more information.

suffered inundation and, in turn, should have been previously evacuated. As a result, participants' payout not only considers the timing of their decision but also reflects the fact that their technical advice or recommendation was consistent with the success or failure of the infrastructure. In this case, payout is a function of actual historic affected population in each of the zones.

3.3.4 Decision payoffs

As previously mentioned, each participant has an initial endowment of 200 points. One hundred points are assigned to the first stage and 100 points are assigned to the second. The payment in the first stage is based on the accuracy and timing of the evacuation recommendation. Below is presented the information that participants receive when they are informed about how they are compensated in the experiment. After taking the first stage, participants are compensated according to the following rules:

- If you make an inaccurate decision—meaning that you recommend evacuation and the storm ends up turning away from the Houston Area, OR you do not recommend evacuation and the storm does affect Houston—you will lose 100 points.
- If you do not recommend evacuation and the storm turns away and never affects the Houston Area, you will not lose any points.
- If the storm does affect the Houston Area and you do recommend evacuation, there will still be property damage and you will only lose 50 points. HOWEVER—you can improve your payment if you give people more time to evacuate. For every additional hour that you give people to evacuate before a Hurricane Warning is issued, you will get back one point. For example, if you recommend evacuation and a Hurricane Warning is issued 30 hours later, you will only lose 20 points [50 get back 30].

It is important to note that the information provided to participants says that the maximum number of points they will lose is 50 points even after recommending evacuation. This occurs because each participant has up to 50 hours to recommend a voluntary evacuation after which a hurricane warning is issued and a mandatory evacuation takes place. The compensation rules are summarized in Table 14. It presents, horizontally, the choice to be made by each participant. After each subject makes a decision, a state of nature occurs (two states of nature associated to this stage). It is important to note that historical data shows that Hurricane Rita hit north of the Houston-Galveston region in late September 2005, causing very minor ancillary damage to the metro area. Most of the damage was located in the coastal and low-lying areas.

Table 14. Payout Schedule for the First-Stage Evacuation Decision

	Hurricane Track	
Decision	*Hurricane affects*	*Hurricane does not affect*
Evacuation	*f(t)*	*-100*
No Evacuation	*-100*	*0*

In Table 14, *f(t)* is a function that represents the number of points reduced from a participant's endowment depending on the round in which the decision was made. The values that *f(t)* can take are represented in the last column in Table 15, which provides the reduction in a participant's endowment after each round or advisory. Table 15 can be read in the following way: If a participant chose not to voluntarily evacuate the coastal and low-lying areas after the last round (i.e., 9th round of information), the participant observes the result on the screen indicating that the hurricane adversely affected the coastal and low-lying areas. As a consequence, the participant loses 100 points from his/her endowment because the decision was not consistent with the state of nature. Although the second state of nature, "Hurricane does not affect," will never occur, it is of the utmost relevance to provide this hypothetical state in order to achieve the expected results of the experiment. In this regard, the payout structure should convey the required incentives for the participant to make an evacuation choice only after considering that the information provided is consistent with the state of nature.

For the first state of nature, “Hurricane affects,” if a participant chose to voluntarily evacuate the coastal and low-lying areas, the participant sees the result on the screen after the last round (i.e., 9th round of information) indicating that the hurricane did actually adversely affected coastal and low-lying areas. However, this payout depends on the round in which the decision was made, as it is important to give people the greatest amount of time possible to prepare for evacuation. In this case, every additional hour is precious time that could have been used to prepare for evacuation. Table 15 provides information about the payout in each round, in terms of points.

Table 15. Reduction in Endowment for the Decision to Evacuate and State of Nature “Hurricane affects”

Round	Actual date and time of the storm's current location	Time until Landfall (hours)	Time until issuing a Warning	Reduced Points from Endowment
Advisory 1	11 am EDT, Tuesday, September 20 2005	*71*	*47*	*3*
Advisory 2	2 pm EDT, Tuesday, September 20 2005	*68*	*44*	*6*
Advisory 3	5 pm EDT, Tuesday, September 20 2005	*65*	*41*	*9*
Advisory 4	11 pm EDT, Tuesday, September 20 2005	*59*	*35*	*15*
Advisory 5	5 am EDT, Wednesday, September 21 2005	*53*	*29*	*21*
Advisory 6	10 am CDT, Wednesday, September 21 2005	*48*	*24*	*26*
Advisory 7	4 pm CDT, Wednesday, September 21 2005	*42*	*18*	*32*
Advisory 8	10 pm CDT, Wednesday, September 21 2005	*36*	*12*	*38*
Advisory 9	4 am CDT, Thursday, September 22 2005	*30*	*6*	*44*

The table indicates, for instance, that if a participant decided to issue a voluntary evacuation after advisory 8, 38 points would be reduced from the total endowment of 200 points. This means that after the first stage, the participant would have 162 points. It is important to note that an emergency manager was compensated with $0.15 for each remainder point at the end of the experiment. In the case of a student, the compensation was $0.06.

Only following the voluntary evacuation decision and not before or in parallel, participants have to go through a second decision-making stage in the experiment. In this stage, participants are provided a new video in which the instructor explains that now that time has passed to call for a voluntary evacuation, they get to decide whether they will call for a mandatory evacuation, which implies where evacuation will specifically take place. The decision to be made in this stage is related to specific zones to be evacuated. In this stage, participants also stand to risk to lose some of their endowment for evacuating a zone not suffering any inundation. Also, they lose some of their endowment if they do not evacuate a subsequently inundated zone. These rules are incorporated in the payout structure of the experiment as follows:

- For every 25,000 persons evacuated from zones that do not get flooded, 1 point will be removed from your endowment.
- For every 25,000 persons not evacuated from zones that do get flooded, 2 points will be removed from your endowment.

These rules are based on the idea that if flooding occurs in a zone that is not evacuated, there can be loss of life. However, if people are evacuated from a zone and flooding never occurs, some loss of life can occur due to the process of evacuation. There can also be negative social and political consequences for the Governor if people are forced to leave an area that ended up not being in danger.

The payout after the two stages is computed by subtracting any lost point after taking stage 1 and 2 from the initial endowment (i.e., 200 points). The compensation is computed by multiplying the number of points by $0.15 in the case of emergency managers and the number of points by $0.06 in the case of students.

3.3.5 Treatment Conditions

In stage 1, participants receive information that varies according to each treatment. The first stage contains a control group and 3 treatments. In the *Control Group*, participants are not provided any forecast but only the current center location of the hurricane and historic storm track. In *Treatment 1*, participants receive partial hurricane forecasts as they are not provided a cone of uncertainty or track area. In *Treatment 2*, participants receive complete hurricane information including, among others, advised wind speeds, a hurricane central position of six-hour forecast and a cone of uncertainty or track area of about 1-3 days directly corresponding to storm track modeling information provided by the NHC at NOAA. In *Treatment 3*, participants receive the same amount of information than the one received by participants in Treatment 2; nonetheless, besides receiving information about current wind speeds, participants also receive information about forecast wind speeds for the next 24 hours. (See Appendix D and E for an example and definitions of terms used). The additional information in Treatment 3 that varies across advisories was presented previously in Table 13.

In general, for participants who decided to evacuate in any of the rounds provided in the first decision-making stage, they are asked to make a second-stage evacuation location decision as shown in Figure 2. The map presented in Figure 2 describes the evacuation zones demarcated by the Houston-Galveston Area Council and is presented to participants only in Stage 2 (i.e., in Stage 2, participants are required to make a mandatory evacuation decision, which indicates that some damage will occur in any of the zones demarcated in the map). The participants who decided not to call for a voluntary evacuation after the last round in the first stage are also required to make a mandatory evacuation recommendation in the second stage. The location determination refers to different zones that are included in the experiment and presented in the map shown below. These zones refer to Coastal (purple), Zone A (yellow), Zone B (green), and Zone C (orange). These are the actual evacuation zones used by the Houston-Galveston area planning council.

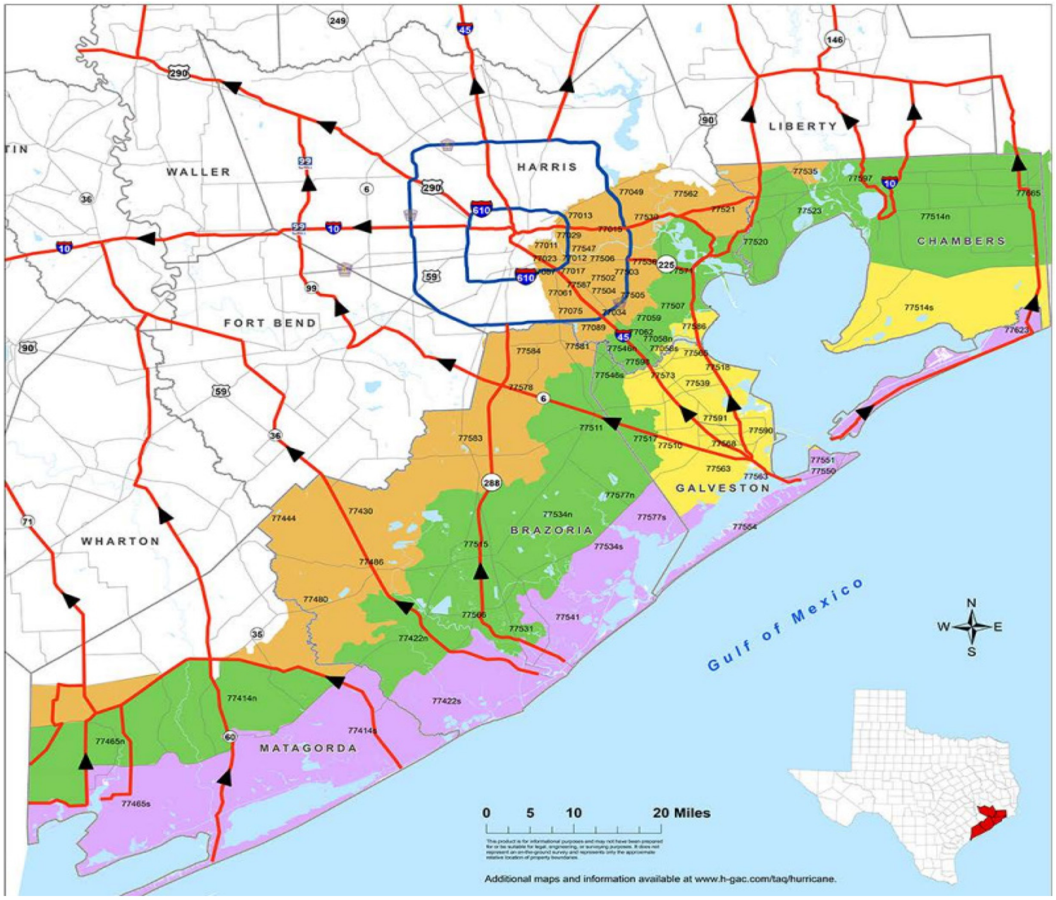

Figure 2. Evacuation Zones Demarcated by the Houston-Galveston Area Planning Council

To identify the inundated zones, which provide the counterfactual in the second stage, I use the map presented in Figure 3. This map was developed by one of the research team members and it contains inundation areas or inundated zones based on the development of racklines from GIS and aerial imagery (i.e., these are identified with green dots) in the Houston-Galveston metro area and allowed to identify actual inundation map that did not previously exist. Figure 3 indicates that the correct zone to evacuate is just the purple (i.e., the Coastal Zone).

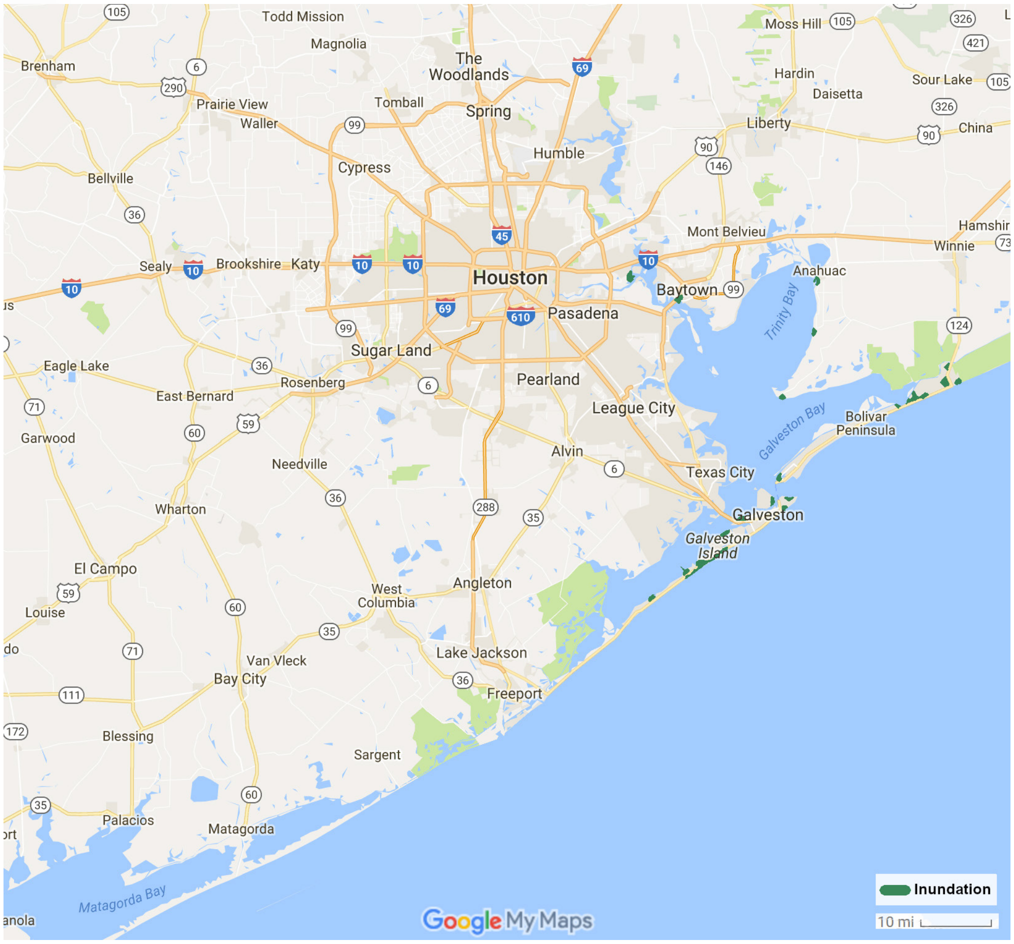

Figure 3. Inundation Map of Houston-Galveston After Hurricane Rita

3.4 Methods and Data

Subjects in the three pools described in section 3.3.1 are randomly assigned into treatment groups through the survey software. The algorithm assigns subjects randomly using a probability distribution to provide for approximately twice as many subjects in the third and fourth treatment groups, as these are the groups that contain the highest levels of information. The experiment was conducted in the summer of 2019 and includes 185 subjects in total, 115 student subjects and 70 professional emergency managers. Four separate treatment groups described below include 24, 25, 69 and 67 subjects, respectively. Table 16 provides descriptive statistics and the breakdown of student and emergency manager counts by treatment group.

Table 16. Treatment Summary Statistics

Treatment	N (subjects)	% Subjects in each Treatment	Mean Number of Rounds in Stage 1 (out of 9 rounds)
Control *(Current Center Location & Historic Storm Track)*	24 (15 students; 9 managers)	12.97% (8.10% students; 4.87% managers)	7.75 rounds
Treatment 1 *(Forecast Center Positions & Historic Storm Track)*	25 (7 students; 18 managers)	13.51% (3.78% students; 9.73% managers)	7.68 rounds
Treatment 2 *(Forecast Center Positions + Cone of Uncertainty & Historic Storm Track)*	69 (44 students; 25 managers)	37.30% (23.78% students; 13.52% managers)	6.55 rounds
Treatment 3 *(Hurricane Intensity Forecast + Forecast Center Positions + Cone of Uncertainty & Historic Storm Track)*	67 (49 students; 18 managers)	36.22% (26.49% students; 9.73% managers)	5.97 rounds

Table 16 indicates that the average number of rounds utilized by participants in the control group before recommending a voluntary evacuation or not recommending evacuation at all was 7.75 rounds. The average number of rounds for participants in Treatment 1 is 7.68 rounds. For participants in Treatment 2, the mean number of rounds is 6.55 and is 5.97 rounds for participants in Treatment 3.

As mentioned in the introduction, the main hypothesis in this chapter is that decision-makers with more information (i.e., individuals exposed to hurricane intensity forecasts) will make better decisions in terms of their decision to evacuate, in the accuracy of their decision (i.e., timing), and in their determination for evacuation location than decision-makers with less information (i.e., individuals not exposed to hurricane intensity forecasts). These hypotheses are tested by comparing mean differences because the experimental subjects are randomly selected and randomly assigned into groups, which implies that differences in means present a reliable test to assess between-group differences such as with hurricane intensity forecast.

3.5 Results

Analysis of behavior of student subjects and manager subjects in the first stage is presented in Tables 17 and 18. Table 17 presents Mann-Whitney test results that examine any difference in the mean or proportion of participants that recommended voluntary evacuation vs those participants who decided not to recommend any voluntary evacuation.

Table 17. Mann-Whitney Test Results: Proportion of Participants who Decided to Evacuate in the First-Stage

Row	Null Hypothesis	Mean 1	Mean 2	(1) - (2)	p-value
1	Mean Evacuation Control = Mean Evacuation Treatment 3	0.42	0.76	-0.34	0.0022
2	Mean Evacuation Treatment 1 = Mean Evacuation Treatment 3	0.48	0.76	-0.28	0.0102
3	Mean Evacuation Treatment 2 = Mean Evacuation Treatment 3	0.68	0.76	-0.08	0.3002
4	Mean Evacuation Student (C) = Mean Evacuation Student (T3)	0.52	0.78	-0.26	0.0701
5	Mean Evacuation Student (T1) = Mean Evacuation Student (T3)	0.29	0.78	-0.49	0.0078
6	Mean Evacuation Student (T2) = Mean Evacuation Student (T3)	0.75	0.78	-0.03	0.7738
7	Mean Evacuation Manager (C) = Mean Evacuation Manager (T3)	0.22	0.72	-0.50	0.0156
8	Mean Evacuation Manager (T1) = Mean Evacuation Manager (T3)	0.56	0.72	-0.16	0.3047
9	Mean Evacuation Manager (T2) = Mean Evacuation Manager (T3)	0.56	0.72	-0.16	0.2833
10	Mean Evacuation Students (T3) = Mean Evacuation Managers (T3)	0.72	0.78	0.06	0.6527

The first three rows in Table 17 compare treatment 3 (i.e., the one that is being tested and contains information about hurricane intensity forecast) against the control group and treatments 1 and 2, respectively. These first three tests incorporate the entire sample, that is, the sample of managers and students. For instance, the test in row 1 suggests statistical differences between the mean or proportion of participants in treatment 3 who decided to evacuate in the first stage when compared with those individuals in the sample who were randomly assigned to the control group (p=0.0022). There are also statistical differences between treatment 3 and treatment 1 (p=0.0102) but there are not statistical differences between treatment 3 and treatment 2 (p=0.3002) despite the higher proportion of participants in treatment 3 who decided to evacuate (76%) vs those participants in treatment 2 who recommended evacuation (68%).

Similar results to the entire sample are obtained when these comparisons are carried out only within the sample of students. However, when the tests only consider the sample of emergency managers, results suggest that there is not statistical difference between treatments 3 and 1 (p=0.3047). This means that there is not much difference for managers to make a voluntary evacuation recommendation if they are provided a cone of uncertainty plus information about hurricane intensity forecast.

Also, test in row 10 provides a comparison between the group of managers and the group of students. Results indicate that there are not statistical differences between the mean or proportion of managers who decided to evacuate vs the proportion of students who recommended evacuation (p=0.6527). However, the results suggest that, on average, students exhibited more risky behavior than managers. On average, a student would evacuate 72% (72 out of 100 times) of the time whereas a manager would evacuate 78% (78 out of 100 times) of the time. Given the context of Hurricane Rita, the decision to evacuate in the experiment is a better choice than the decision of no evacuation. In this regard, students behaved riskier than managers as there is a higher percentage of students who did not recommend voluntary evacuation and delayed his decision until a mandatory evacuation was issued.

Table 18 only provides mean values or proportions of evacuation, that is, it only informs if students or emergency managers in a particular treatment decided to evacuate or not. In this regard, Table 18 provides statistical results associated to the accuracy of the evacuation decision, that is, how so soon was the decision made.

Table 18. Mann-Whitney Test Results: First-Stage Evacuation Decision Accuracy

Row	Null Hypothesis	Mean 1	Mean 2	(1) - (2)	p-value
1	Mean # Rounds Control = Mean # Rounds Treatment 3	7.75	5.97	1.78	0.0005
2	Mean # Rounds Treatment 1 = Mean # Rounds Treatment 3	7.68	5.97	1.71	0.0010
3	Mean # Rounds Treatment 2 = Mean # Rounds Treatment 3	6.55	5.97	0.58	0.1210
4	Mean # Rounds Student (C) = Mean # Rounds Student (T3)	7.00	5.59	1.41	0.0422
5	Mean # Rounds Student (T1) = Mean # Rounds Student (T3)	7.57	5.59	1.98	0.0434
6	Mean # Rounds Student (T2) = Mean # Rounds Student (T3)	5.95	5.59	0.36	0.4477
7	Mean # Rounds Manager (C) = Mean # Rounds Manager (T3)	9.00	7.00	2.00	0.0021
8	Mean # Rounds Manager (T1) = Mean # Rounds Manager (T3)	7.72	7.00	0.72	0.0853
9	Mean # Rounds Manager (T2) = Mean # Rounds Manager (T3)	7.60	7.00	0.60	0.1918
10	Mean # Rounds Students (T3) = Mean # Rounds Managers (T3)	5.59	7.00	-1.41	0.0891

Results in the first three rows in Table 18 indicate that, on average, participants in treatment 3 made an evacuation recommendation in fewer rounds than those utilized by participants in the control group and treatments 1 and 2. However, statistical results suggest that there is no difference between the number of rounds utilized by participants in group 2 vs the number of rounds used by participants in group 3 ($p=0.1210$). Results are similar when the sample of students and the sample of emergency managers are considered separately. When both groups (i.e., students and managers) are compared, the results suggest statistical difference between the average number of rounds used by students vs those used by managers. That is, managers used 7.00 rounds, on average, before making an evacuation recommendation vs 5.59 rounds used by students before committing to a decision. Results are statistically significant, which indicates that the occurrence of these values is not different from randomness.

The most important conclusion from this stage is that managers are more likely to recommend a voluntary evacuation (i.e., students behaved riskier than managers). However, managers take longer, on average, before committing to a decision. This conclusion seems to be consistent with the results observed from the study with national security specialists who prefer to delay a decision until gathering more information. This conclusion is supported by using a Kaplan-Meir curve and some hazard models.

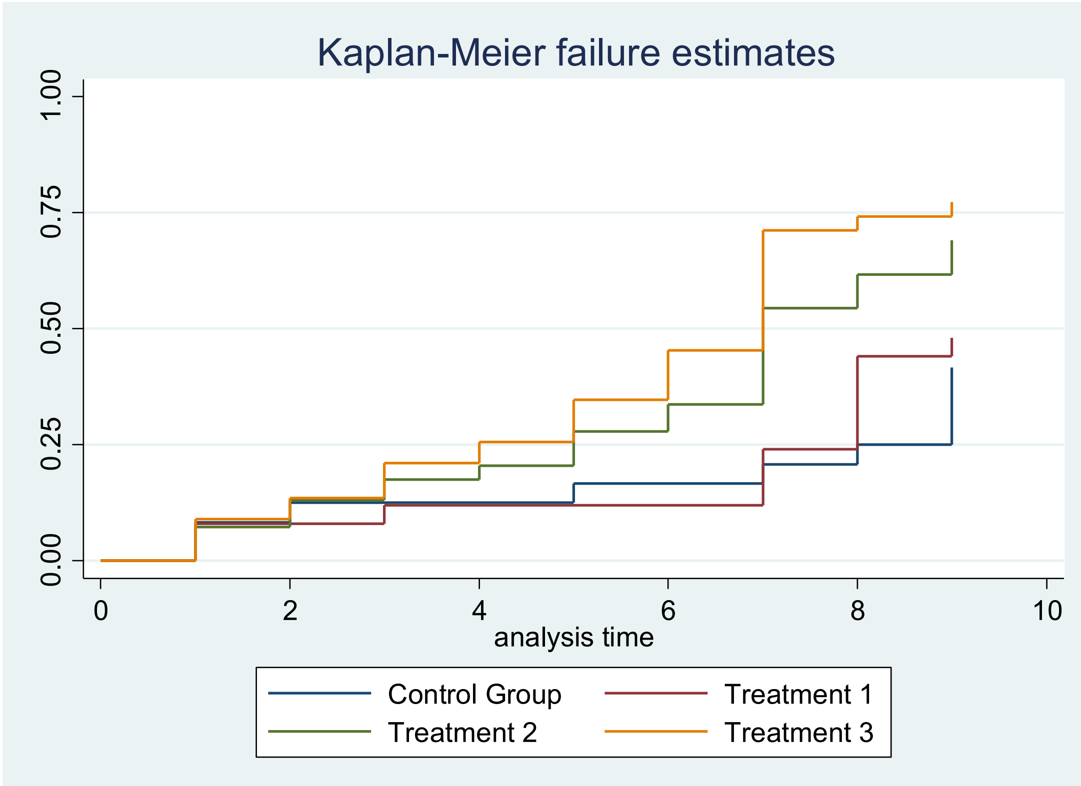

Figure 4. Kaplan-Meier Evacuation Estimates: Probabilities of Observing Evacuation after each Round per Treatment Condition

Treatment differences can be observed in Figure 4 above, which provides the Kaplan-Meier estimates, or the probabilities of observing evacuation in each round (i.e., after each advisory) per treatment condition. This analysis may overcome the fact that there are differences in how the sample of participants is weighted among treatments (around 13% for the Control Group and Treatment 1 and 37% for Treatments 2 and 3). For instance, there is a probability of observing evacuation after the seventh advisory in Treatment 3's participants that is near to 0.75, whereas is close 0.55 for participants in Treatment 2, around 0.25 for participants in Treatment 1 and 0.20 for participants in the Control Group.

To test these types of differences among treatment conditions, I provide some hazard models that are presented in Table 19 below.

Table 19. Hazard Models: First Stage Evacuation Decision - Time to Evacuation

VARIABLES	Model 1	Model 2	Model 3
Control Group		0.729	0.433**
		(0.301)	(0.143)
Treatment 1	1.372		0.594
	(0.567)		(0.195)
Treatment 2	2.308**	1.683	
	(0.763)	(0.552)	
Treatment 3	2.872***	2.094**	1.244
	(0.961)	(0.256)	(0.263)
Numeracy Test	1.185	1.185	1.185
	(0.256)	(0.256)	(0.256)
Observations	185	185	185

Prob > chi2 = 0.0110
Coefficients are Hazard Ratios Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Models 1, 2 and 3 are, in general, the same model with different reference categories. The models incorporate the variable related to statistical literacy that controls participant's understanding about forecasts and probabilities. Model 1 compares each treatment against the Control Group. In general, it says that participants in Treatment 3 were, on average, 2.87 times more at risk to evacuate than participants in the Control Group (i.e., participants in Treatment 3 were more likely to evacuate than those in the reference group). The coefficient is statistically significant. It is also significant in Model 2 when the reference category is Treatment 1, which indicates that those participants in Treatment 3 were more than 2 times at risk of evacuating than participants in Treatment

1. In Model 3, although the coefficient is larger than 1 indicating than participants in Treatment 3 had a higher probability of evacuating than participants in the Treatment 2, the coefficient is not statistically significant.

The last decision that participants are required to make is related to *mandatory* evacuation. As previously mentioned, the stage 2 scenario is presented to all participants, who receive the set of images that are included in Appendix F. In this stage, participants choose to mandatorily evacuate between seven (7) possibilities including the no evacuation of any area in the map. The dependent variable in this stage is categorical and identifies the population that is located in each zones and that is potentially to be evacuated. From the historical records of Hurricane Rita, the optimal decision would have been to evacuate only the Coastal Area with an estimated population of 50,000 people (i.e., this is the choice that leads neither to under-evacuation or over-evacuation). Because of the few cases in the dependent variable category in comparison with each of the Treatment conditions (see Appendix G), I collapsed different categories of the dependent variable as follows: Any possibility that considers evacuating more than 50,000 people is defined as 1, and the evacuation of 50,000 people or less (i.e., Coastal or none) is defined as 0. Additionally, I collapsed the Control Group and Treatment 1 categories of the Treatment variable into just one category.

Table 20 presents the results of the logistic regressions of the dependent variable called *overevacuation* against treatment conditions, the numeracy test and the number of the inundation map[20] used by a participant. Table 20 provides three different models.

Table 20. Logistic Regression Models: Second Stage Evacuation Decision - Mandatory Evacuation

VARIABLES	Model 1	Model 2	Model 3
Treatment 2	-0.211	-0.211	-0.174
	(0.470)	(0.470)	(0.474)
Treatment 3	-0.0676	-0.0663	-0.0669
	(0.481)	(0.485)	(0.486)
Numeracy Test		-0.00801	-0.0110
		(0.376)	(0.377)
Inundation Map – Left			0.246
			(0.394)
Constant	1.492***	1.495***	1.395***
	(0.369)	(0.394)	(0.423)
Observations	185	185	185

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 1 include only Treatment conditions 2 and 3, which are tested against the reference category (i.e., Control Group or Treatment 1). The results indicate that more information does not lead to over-evacuation. For instance, the information related to hurricane intensity forecast did not influence the decision of participants in Treatment 3 to overevacuate in comparison to those participants in the Control Group or Treatment 1 who received less information. In fact, Treatment conditions 2 and 3 are not statistically

[20] These inundation maps are presented in Appendix F (page 141). Because of the few cases, I redefined the variable as follows: inundation map to the left is defined as 1, the inundation map to the right or center is defined as 0).

significant in any of the models included in this second stage decision. Model 2 controls for the numeracy test and Model 3 controls for both, the numeracy test and the type of inundation map used. Neither of these two variables is significant in Models 2 and 3. In general, given these results, it is possible to argue that more information does not lead to an over-evacuation decision.

3.6 Discussion

The main findings of this experiment can be summarized as follows: When presented with more information in the form of hurricane intensity forecasts, participants are willing to recommend evacuation more frequently and earlier than participants exposed to lower levels of information. Table 19 provides quantification for these differences by suggesting that decision-makers in Treatment 3 are more than twice more likely to evacuate than decision-makers in the Control Group and Treatment 1. This also occurs when the comparison is against participants in Treatment 2, although these differences are not statistically significant. Also, experts are willing to recommend a *voluntary* evacuation more frequently than non-experts; however, they take longer, on average, in committing to an evacuation recommendation. This is an important finding and seems to be consistent with other scenarios. In a national security context, for instance, experts with more information usually delay their decision when they are provided forecasts or probability assessments (Friedman, Lerner, & Zeckhauser, 2017). The second main finding is that participants with more information did not overevacuate in comparison to participants who received less information. This might be expected given some literature that argues that the overload of information in the form of more detailed and more complex data and forecasts has been associated with low quality decisions (Iselin, 1993). In this regard, participants with more information did not experience, on average, any over-evacuation decision in comparison to participants who were in the Control Group or Treatment 1.

As expressed in the introduction, these findings are novel in the emergency management literature given that we are testing the interplay of informational complexity in a temporal and spatial setting that has not been teste before. These findings allow knowing more about the importance of hurricane intensity forecasts in the evacuation decision-making process. As a consequence, this research provides a systemic understanding of the influence of one of the informational levels on which disaster and emergency managers rely upon the most.

Finally, this study is limited in some clearly defined characteristics. The first factor is related to the utility function. In terms of this factor, the utility function in the first stage depends on the remaining time that a participant has to make an evacuation recommendation. The second stage, on the other hand, depends on the population exposed to make a decision of evacuation location determination. However, there might be other factors that these utility functions are not considering such as those conditions involved in the process of evacuation (e.g., transportation) that may equally influence these types of elections. Second, although an experiment tries to mimic real-world conditions, there are some contextual factors that are not being incorporated in this analysis such as the stress and anxiety to which decision-makers are exposed when making real-life evacuation decisions. Nonetheless these limitations, this analysis provides a novel perspective of how hurricane intensity forecasts affect the evacuation decision-making process.

Chapter 4: Conclusion

The main topic throughout this dissertation has been decision-making in the face of natural hazards, strategic behavior of individual entities (i.e., businesses, emergency management officials) in the context of natural disasters and the study of factors that influence the flow of information in the decision-making process.

The first two chapters aimed at explaining the conditions under which a firm decides to resource share in the post-disaster. This has been a topic recently explored in the resilience supply chain literature but unexplored in the economic resilience literature. In today´s environment, characterized by an increase in the frequency and magnitude of disasters (Wong et al., 2014), the question about the factors that lead to different organizational outcomes such as survival, recovery and resilience[21] is more relevant than ever. Nonetheless, it is even more relevant to inquire about the type of strategic behavior[22] that firms employ in the aftermath of disruptions. If firms understand and know their capabilities to respond to the unforeseen, they will be better equipped to face

[21] Although the concepts of recovery and resilience are often used as synonyms, this is not always the case. For instance, whereas some management scholars treat resilience as a multidimensional construct (see, e.g., DesJardine et al., 2017, who define resilience in terms of time to recovery and severity of loss), some supply-chain scholars treat the concept of resilience as a characteristic of firms that continue to deliver its products and services to the customer in the midst of disruptions (e.g., Pettit et al., 2013). In this case, supply-chain resilience is not necessarily about recovery, it is about creating capabilities that allow the organization to maintain functioning after a disruption.

[22] This study follows the definition of Strategy provided by Rumelt (2011) as "a coherent set of analyses, concepts, policies, arguments, and actions that respond to a high-stakes challenge".

disruptions, increase survival chances and improve its long-term success (Pfeffer & Salancik, 2003; Bode et al., 2011). Although these questions are not new, there has been a surge and proliferation of studies throughout recent years that have mainly focused on the resilience of firms to disruptive events.

This dissertation is the first effort known in the literature that explores the effect of post-disaster resilience tactics in an environment that is considered strategic for firms. That is, firms do not act in isolation and they need from the external environment to operate and survive (Peffer and Salancik, 2003). That is also the case in a post-disaster setting where firms need to make decisions after assessing their damages and evaluating the possibility to continue running their business operations. Failing to consider the strategic component in the effects of a firm's resilience may lead to biased results and inaccurate understanding of the transmission mechanism that explains how a firm behaves or elects one tactic instead of another. In this regard, the application of a self-selection model on the decision to choose a post-disaster resource sharing tactic is appropriate and novel in the resilience literature and provides a new path on the future estimation of the effects of other resilience tactics. In general, the conclusion of the first and second chapter involve the following: 1) there are unobservables that explain the decision to choose a post-disaster resource sharing tactic, 2) firms that are more likely to use a resource sharing tactic have higher levels of static economic resilience, that is, have the capacity to avoid more losses that derive from business interruption (i.e., from the empirical results, the findings indicate that among firms that would be likely to use the resource sharing strategy, those that used it had, on average, approximately 35 times greater avoided in losses).

As previously expressed, these conclusions have important implication for policy-makers. If governments are able to reduce information asymmetries by providing recommendations, counseling and guidance to affected firms based on theoretical and empirical support that informs about those characteristics potentially improving their economic resilience, policy-makers might help organizations to reduce business interruption and avoid losses. This is the case of a government agency such as the U.S. Small Business Administration (SBA) that provides counseling to small firms, which are precisely the most likely organizations to use interorganizational tactics in the post-disaster. By disseminating this type of information, incentivizing the creation of partnerships and/or joint ventures among small firms, and allocating government contracts to affected businesses in disaster areas, the SBA will be creating mechanisms geared to reduce their business interruption, increase their chances of survival, and improve their competitive advantage capabilities in the long run.

In terms of other types of decision, *voluntary* and *mandatory* evacuation, chapter 3 explores the influence of hurricane intensity forecasts on these decisions. Empirical results corroborate the hypotheses posed in the chapter, that is, there are differences between the decisions made by participants exposed to forecasts of maximum sustained wind speeds and the decisions made by participants not exposed to this type of information. Although it is hard to generalize these findings beyond the context of Hurricane Rita that was used in the experiment as a counterfactual, the empirical findings are novel and support the notion that decision-makers are willing to evacuate more frequently and earlier when exposed to hurricane intensity forecasts. However, from an empirical perspective, there is no influence of maximum sustained wind speeds forecasts on evacuation location determination. This research sheds light and provides some support for arguing that the development of models and technology aimed at providing more accurate information have actually improved the capacity of emergency managers to make consistent evacuation decisions, which is at least what is observed when the experimental results are compared with the data obtained from the historical archives of Hurricane Rita. Although this topic deserves further research, the analysis carried out the third chapter of this dissertation serves as a methodological standard that may be used to assess these same decisions in other hurricane contexts.

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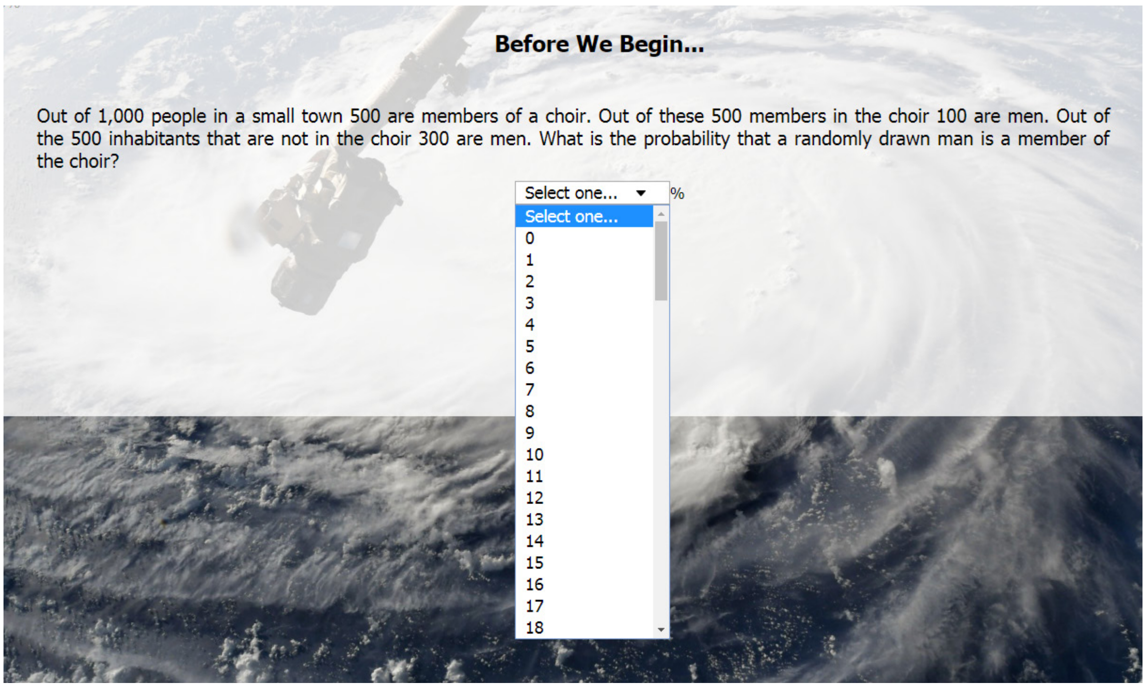
Appendix A. Saffir-Simpson Hurricane Scale

Type	Maximum Sustained Wind Speed Vmax in mph	Damage
Tropical Depression	< 39	
Tropical Storm	39 – 73	
Category 1	74 – 95	Very dangerous winds will produce some damage
Category 2	96 – 110	Extremely dangerous wind will cause extensive damage
Category 3	111 – 129	Devastating damage will occur
Category 4	130 – 156	Catastrophic damage will occur
Category 5	> 156	Catastrophic damage will occur

Appendix B. Numeracy Test



Appendix C. Scenarios or Vignettes

- ***Stage 1 for Treatment 3***

By participating in today's experiment, you will be playing an important role in helping emergency managers make more informed disaster evacuation decisions.

In this experiment, you will be taking on the role of a Senior Advisor at the Texas Office of Emergency Management (OEM). Your job will be to advise the Governor of Texas on his decision to evacuate the Houston-Galveston Metropolitan area—one of the largest metro areas in the country, in the context of a hurricane.

Evacuation orders are an important emergency management function. If populations remain in areas devastated by seawater inundation or storm surge, there can be a high volume of human casualties—unnecessary loss of life. High winds can devastate homes and structures, airborne or waterborne debris can lead to death and injury, and flooding and power outages can curtail access to police, fire and emergency response units.

At the same time, the process of evacuation can devastate communities. Roads and highways can be crowded leaving stranded passengers on roadsides. There can be shortages of gasoline, food and other necessary commodities. There can be looting in abandoned areas.

Elected officials, such as the Governor, can pay a heavy price politically if the process of evacuation is administered poorly. This can be an even greater concern if communities are evacuated and the storm ends up turning away and not having any real effect on evacuated communities. You will have unnecessarily evacuated thousands, or hundreds of thousands of people. It is critically-important that you get this decision right.

In a few moments, we will start the experiment. You will be given a simulated hurricane scenario and asked to make an evacuation recommendation. A tropical cyclone in the eastern Gulf of Mexico has just made the critical transition to a full hurricane. It is currently off the coast of Florida and it is heading west toward the Mexico-Texas border. It may turn upward toward Houston.

Every five to six hours, new information about the hurricane will become available from the National Hurricane Center (NHC) at the National Oceanic and Atmospheric Administration, or NOAA. These are called 'Advisories.' In this experiment, each advisory will be a different round that will last about a minute or so for you. In each of these rounds, you will be asked to make a recommendation to the Governor about whether or not he should call for a *voluntary* evacuation of the coastal and low-lying areas. These communities are at the greatest risk of seawater inundation and storm surge. A *voluntary* evacuation is not mandatory, persons can decide to stay behind and shelter in place.

Keep in mind that a hurricane that is near Florida will take about three days to get to Texas. So, you do not need to make an evacuation recommendation immediately. You will have multiple advisories, or rounds, to make your decision. This is important because hurricanes often turn and go a different direction. Many hurricanes in the past have entered the Gulf and then turned up to Louisiana or Mississippi, not presenting any danger to Texas. So, it is important that you think critically about the information that you are given and make the best decision possible.

If the hurricane approaches the Houston Metro Area, and does not turn and go somewhere else, the last possible opportunity you will have to call for voluntary evacuation will be when the NHC issues a *Hurricane Warning*, which means that death or injury from high winds is imminent within approximately 24 hours. By that point, it will be too late for a voluntary evacuation, and mandatory evacuations may be issued. So, if the hurricane approaches Houston, your time to make this decision runs out when a Hurricane Warning is issued.

Your *payment* will be based on the accuracy and timing of your evacuation recommendation.

Finally, it is important to remember that evacuations are only issued once. So, if you make an evacuation decision too soon, you will not be able to later wait to see how the storm plays out, and later change your decision. You only get one shot at this. Before you are asked to make an actual evacuation recommendation, I am going to show you an example of the type of information you will be getting from a previous hurricane, from Hurricane Ophelia back in 2005.

- ***Stage 2***

The storm is now 36 hours from landfall and the National Hurricane Center has issued a Hurricane Warning for the Houston-Galveston Metro Area. This means that sustained winds of 74 MPH or higher are expected in the area. The National Hurricane Center issues these warnings 36 hours in advance of the storm's expected onset to give the population time to prepare for landfall. Voluntary evacuation orders have also been issued for coastal and low-lying areas.

Now, you will be asked to make another advisory recommendation to the Governor. You will be asked to make a recommendation for the areas that should receive mandatory evacuation orders. A mandatory evacuation is a warning to persons within the designated area that an imminent threat to life and property exists and individuals MUST evacuate in accordance with the instructions of local officials.

The Houston-Galveston Metro Area has pre-identified possible evacuation locations into these four zones. A high resolution version of this image will be available to you after this video to help you make your decision.

You will be making a recommendation regarding which zones should be mandatorily evacuated. Residents are all expected to know their evacuation zones, which are based on zip codes that have been identified by the Houston-Galveston Area Planning Council. The four zones look like this map you are viewing now. These refer to coastal and low laying areas (in purple), zone A (in yellow), zone B (in green), and zone C (in orange).

To assist you in making this important decision, the National Hurricane Center's scientists have used the best available storm surge forecasting models to predict potential inundation, or flooding that could occur. They have given you three scenarios—best, worst and medium case scenarios. These scenarios are based on possible forecasts, or tracks, of the storm's path over the next 36 hours. These show the Houston-Galveston Metro Area—blue areas indicate flooding.

The best-case scenario represents potential flooding if the storm veers to the right and makes landfall to the northeast of the population center.
The middle case scenario represents potential flooding if the storm stays on its current path, not turning to the left or the right.
The worst-case scenario represents potential flooding if the storm veers to the left and makes landfall directly at the Houston-Galveston area.

After this video, high-resolution versions of these scenario maps will also be available to you.

Your payment will be tied directly to the population exposed to flooding and storm surge. After this video you will get details on how you will be paid.

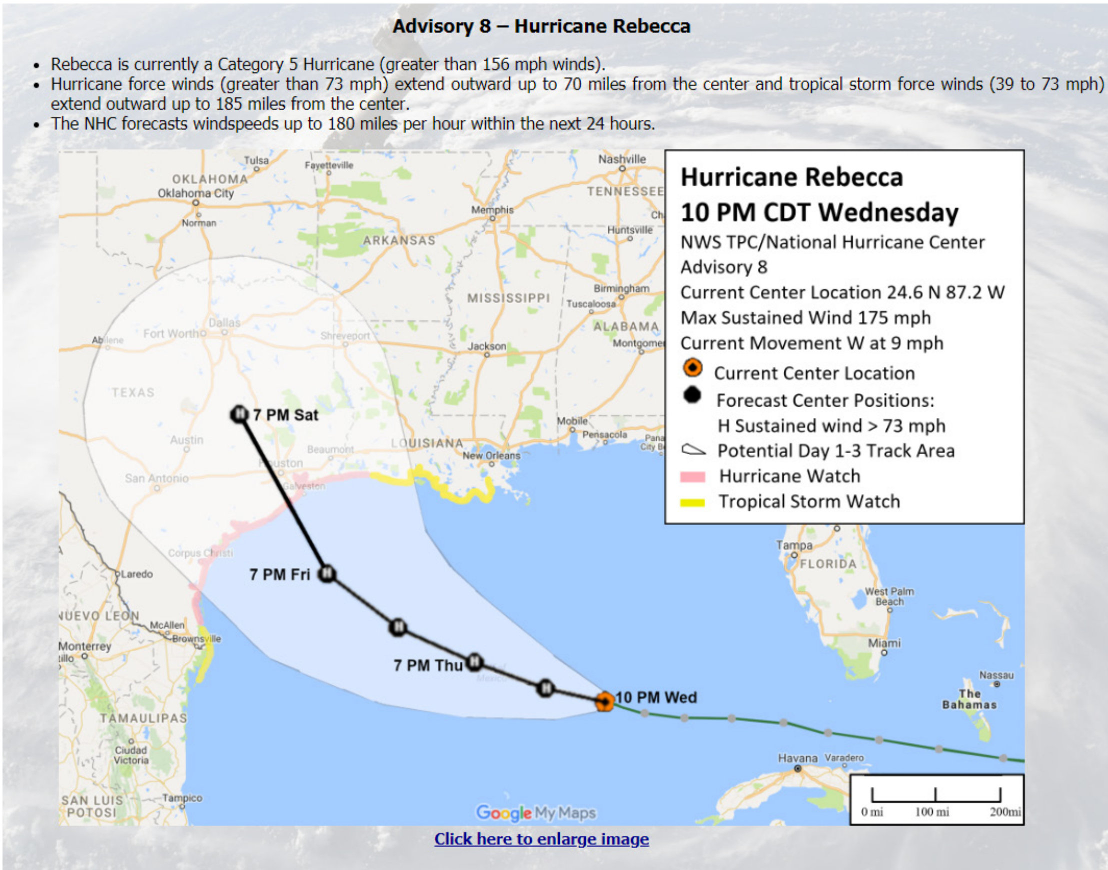
To assist you in making this important decision, the National Hurricane Center's scientists have used the best available storm surge forecasting models to predict potential inundation, or flooding that could occur. They have given you three scenarios—best, worst and medium case scenarios. These scenarios are based on possible forecasts, or tracks, of the storm's path over the next 36 hours. These show the Houston-Galveston Metro Area—blue areas indicate flooding.

- The best-case scenario represents potential flooding if the storm veers to the right and makes landfall to the northeast of the population center.
- The middle case scenario represents potential flooding if the storm stays on its current path, not turning to the left or the right.
- The worst-case scenario represents potential flooding if the storm veers to the left and makes landfall directly at the Houston-Galveston area.

After this video, high-resolution versions of these scenario maps will also be available to you.

After looking at these possible inundation scenarios and evacuation zones, the decision for a subject to make is: which zones to evacuate?

Appendix D. Example of Advisory for Treatment 3 used in the Experiment



Appendix E. Definitions of Terms used in the Advisories for Treatment 3

- The orange circle represents the current location of the storm

- Black circles ahead of the current location represent forecast center positions. The letters on the black circles stand for Hurricane (H) and Storm (S). A hurricane implies sustained winds greater than 73 mph. A storm implies sustained winds between 39 – 73 mph.

- The green line is a track of past positions of the storm.

- The red area along the coast is a hurricane warning. This means that hurricane conditions (sustained winds of 74 mph or higher) are expected.

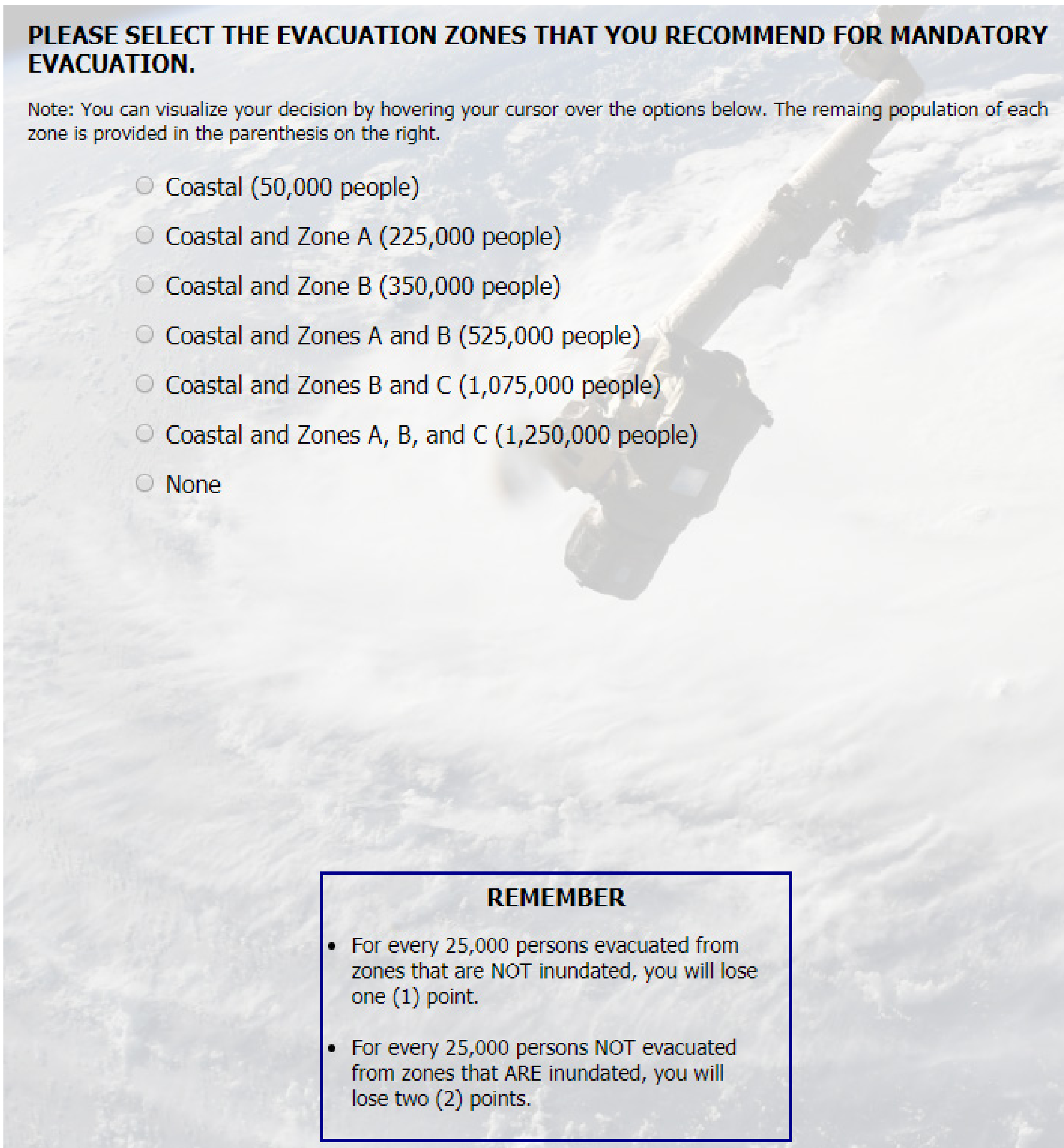
- The pink area is a hurricane watch. This means that hurricane conditions (sustained winds of 74 mph or higher) are possible within the specified area. A hurricane watch is issued 48 hours in advance of the anticipated onset of tropical-storm-force winds in an area.

- The yellow area is a tropical storm watch. This indicates a chance of a tropical storm, with winds from 39 to 73 miles per hour, hitting a specified area within 48 hours.

- The blue area is a tropical storm warning. This indicates a chance of a tropical storm, with winds from 39 to 73 miles per hour, hitting a specified area within 36 hours or less.

- The white region is called a “track area” or "cone of uncertainty." This cone represents a probable track, or direction of the storm. This area of uncertainty grows wider as the forecast track of the storm increases, as it is more difficult to predict the storm's future location beyond 24 and 36 hours. You can consider this white area to represent scientific consensus regarding the possible future locations of the storm.

Appendix F. Images Received by Participants in the Second Stage Decision



PLEASE SELECT THE EVACUATION ZONES THAT YOU RECOMMEND FOR MANDATORY EVACUATION.

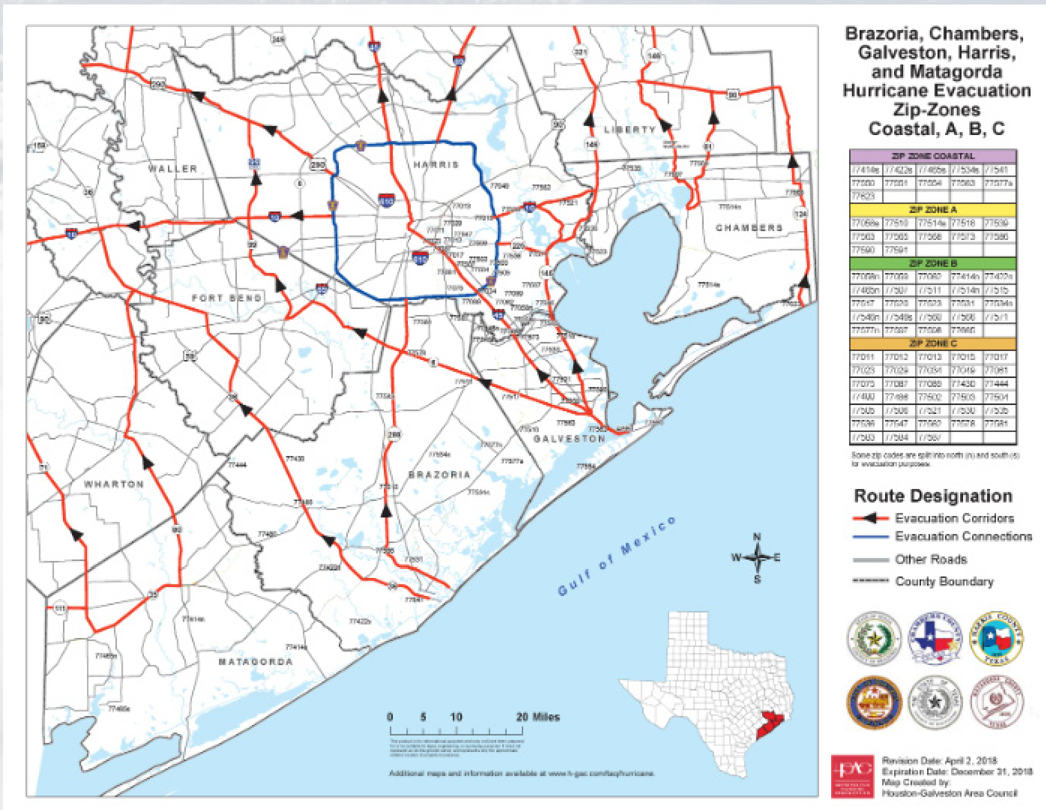
Note: You can visualize your decision by hovering your cursor over the options below. The remaing population of each zone is provided in the parenthesis on the right.

- Coastal (50,000 people)
- Coastal and Zone A (225,000 people)
- Coastal and Zone B (350,000 people)
- Coastal and Zones A and B (525,000 people)
- Coastal and Zones B and C (1,075,000 people)
- Coastal and Zones A, B, and C (1,250,000 people)
- None

REMEMBER

- For every 25,000 persons evacuated from zones that are NOT inundated, you will lose one (1) point.
- For every 25,000 persons NOT evacuated from zones that ARE inundated, you will lose two (2) points.

Appendix F. Images Received by Participants in the Second Stage Decision



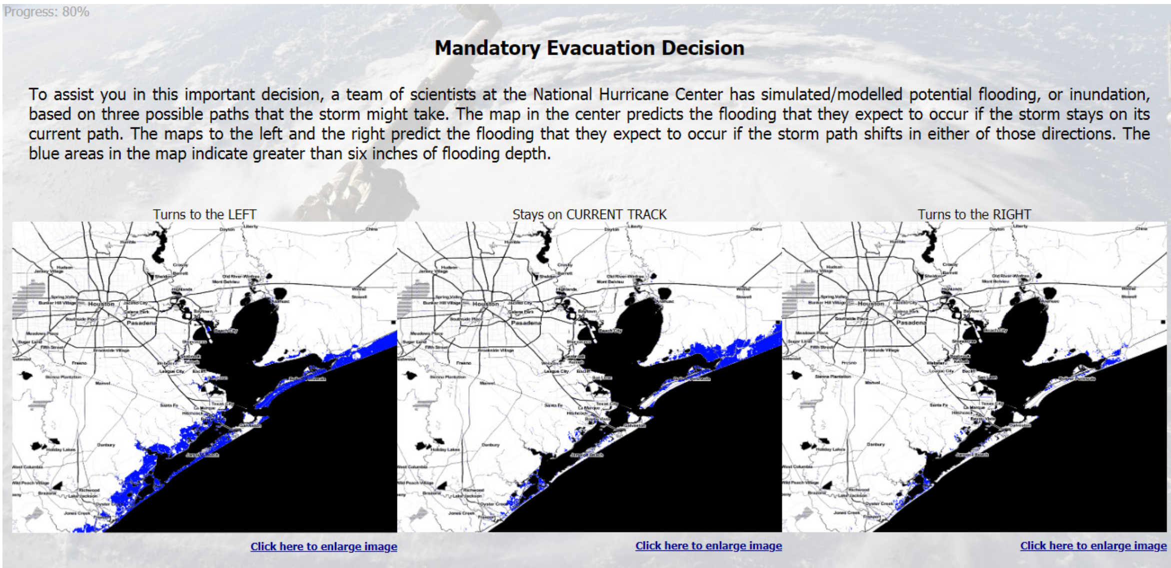
Click here to enlarge image

Click here to view a transcript of the video instructions you just reviewed.

Click here to watch the video shown to you on the previous page.

Click here to see current advisory (Advisory 10)

Appendix F. Images Received by Participants in the Second Stage Decision



Appendix G. Contingency Table of Number of Cases between Evacuated Population and Treatment Conditions

Population Evacuated	Resource Importance during Recovery				Total
	1	2	3	4	
0	0	0	3	3	6
50,000	3	6	12	10	31
225,000	14	6	34	35	89
350,000	0	1	4	3	8
525,000	6	12	14	14	46
1,075,000	0	0	0	1	1
1,250,000	1	0	2	1	4
Total	24	25	69	67	185