The Value of Information on Resilience Decision Making in Repeated Disaster Environments

June 10, 2020

Author Affiliations and Contact Information:

Noah Dormady, Ph.D.
Associate Professor
John Glenn College of Public Affairs
The Ohio State University
1810 College Rd.,
Columbus OH 43210
Dormady.1@osu.edu

Robert Greenbaum, Ph.D.
Professor and Associate Dean
John Glenn College of Public Affairs
The Ohio State University
1810 College Rd.,
Columbus OH 43210
Greenbaum.3@osu.edu

Kim Young, Ph.D.
Senior Lecturer
John Glenn College of Public Affairs
The Ohio State University
1810 College Rd.,
Columbus OH 43210
Young.1807@osu.edu

Abstract: This paper reports on a series of controlled human-subjects experiments on the decision of firms to invest in resilience to mitigate supply-chain disruptions and their willingness to pay for advisory information to improve resilience planning investments. Here we focus specifically on strategic inventories, which have been identified in the supply chain and economic resilience literatures to be a core resilience-building tactic. Of critical importance to organizations like the Department of Homeland Security (DHS) and state and county offices of emergency management, we find that firms are willing to pay for external resilience information when they operate in information-poor environments. We also find that when firms purchase resilience information, they are less susceptible to the decision-making bias known as the gambler's fallacy, which has been shown to adversely affect firms operating in repeated disaster environments. This paper is one of the first of its kind to conduct experimental analysis on a national subject population of CEOs and COOs in the context of resilience. The results inform resilience planning efforts for public- and private-sector firms and organizations, with broad implications for the use of informational policy instruments to build economic resilience.

Keywords: *Economic Resilience; Supply Chain Resilience; Experimental Economics; Strategic Inventories; Decision Analysis*

JEL Classifications: C92; D25; E22; G31; H54; Q54

Introduction

A key element of local communities' and economies' ability to withstand and recover from natural disasters is the preparation and response of the local business community. A resilient enterprise is considered one that can recover quickly in the face of disruption (Sheffi and Rice, 2005). This comports with the more general definition of resilience provided by the National Research Council that we adopt—"the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (2012, p.16). Understanding the micro foundations of community resilience is more important now than ever, as economic losses from natural hazards have been increasing throughout the world for many years, and this pace is projected to increase exponentially. Historically, the physical mechanisms of these events, such as rainfall or wind, have not changed over the long-term (Wong et al., 2014), but economic development and population growth have created greater exposure to them, and vulnerability has increased because mitigation has not kept pace (Hallegatte, Vogt-Schilb, Bangalore, & Rozenberg, 2017; Whitehead & Rose, 2009).

The global COVID-19 pandemic has reinforced the crucial role that individual businesses play in terms of sustaining the economic resilience of individuals and their communities. The pandemic has also reminded everyone of the need for advance planning and the related challenges of making decisions in the face of uncertainty. It is thus imperative that we understand how public policy can effectively induce business leaders to improve their firms' resilience. This includes appropriate levels of investment in building resilience capacity. Unfortunately, given the practical implications to the business and broader community of increasingly costly disasters, academic theory across the many relevant disciplines has not paid sufficient attention to the realities faced by private enterprise. Existing hazards research examining business decision making has focused almost exclusively on the behavior of firms in the context of a single shock/event (see, for example, the comparative assessment provided in Hosseini, Barker, & Ramirez-Marquez, 2016)—as if firms operating in these environments experience only "one off" disasters rather than with greater regularity.

Resilience investment decisions, such as investments in inventories, stockpiles or system redundancy, are fundamentally different when the realities of repeated events are taken into consideration. Resilience decisions of private (and public) enterprises bear a very real cost to the firm in the here and now. These often take the form of inventories or system redundancy involving capital or infrastructure expenditures. These investments involve the active decision to incur a current opportunity cost by foregoing expenditures in currently-profitable labor, plant and equipment to avoid probabilistic business interruption at a future, uncertain date (Pettit, Fiksel, & Croxton, 2010). In this context of repeated disasters, these decisions extend well beyond the classic questions of optimal inventory and should also be informed by considerations brought to bear on these issues from the decision sciences. For example, does a recent disaster provide firms with a rationale for not investing in resilience going forward? In other words, if a major disruption has recently occurred, it must be unlikely to strike again—right? This decision-making bias, known as gambler's fallacy, has been identified in recent resilience research (Dormady, Greenbaum, & Young, 2017). As scholars are learning more about resilience, they are learning that resilience is a process (Rose & Dormady, 2018) that is informed by past events. It is important therefore, that we understand how past events influence resilience decisions.

Importantly, private enterprise is heterogeneous. Resilience investment considerations are fundamentally different for larger firms than for small and medium-sized enterprises (SMEs). Middle market firms (the focus of this empirical analysis)—defined by annual revenues between $10 million and $1 billion—in particular, cannot afford the same degree of process duplication, redundancy, or inventory buffers. Over/under investment in resilience bears a much higher relative opportunity cost for these firms—particularly when the competitive nature of the business climate that they face is taken into consideration. For this reason, these firms will often hire consultants to make up for their own hazard mitigation and resilience decision-making limitations, while the largest firms, with the largest resources, may hire consultants as a matter of course (Orr & Orr, 2012). The decision to engage outside resources can be considered a characteristic of a resilient organization (Lee, Vargo, Seville, 2013). However, decisions that are informed by third parties are also subject to heuristic biases informed by the decision sciences. How

decision makers perceive the credibility of information providers is an important component of the decision on whether to act on the advice (Wu, Greer, and Murphy, 2020). Further, the literature on advice indicates that paying for information leads to greater likelihood of being persuaded by that information—a decision making bias known as sunk cost bias. To date, both the burgeoning economic and supply chain resilience literatures have yet to be informed by these important areas of study that so obviously come to bear on these critical decisions faced by private (and public) enterprise.

Thus, this paper examines the resilience investment decisions of middle market firms in the context of repeated catastrophic events using a controlled experiment. We use an expert subject population of managers (predominantly CEOs and COOs) from mid-sized firms alongside a more standard subject population from a university experimental economics student subject pool. Subjects in the experiment make decisions to strategically invest in inventory buffers to avoid supply chain disruption associated with a probabilistic, repeated catastrophic event. Subjects are randomly assigned into one of two treatment groups—one in which they can hire consultants to provide them with the probability of a disaster and one in which that information is provided free of charge. Econometric analyses of the data provide insights into the learning behavior of firms making strategic resilience investments in the context of both repeated events and consultancy information. In this way, the experiment allows us to control for two of the most vexing and potentially countervailing decision biases—gamblers fallacy and sunk cost bias. The use of an experimental design provides an unrivaled statistical control that is not possible with observational data.

The results inform resilience planning efforts for public- and private-sector firms and organizations, with broad implications for the use of informational policy instruments to build resilience. We find evidence that status quo bias influences resilience decisions, as businesses that purchased consulting information in a previous period were much more likely to do so going forward. This indicates that efforts to encourage the acquisition of information may be more efficiently targeted at businesses that have not previously sought external advice. There is some nuance in this finding, however, as we also find that businesses with less overall information regarding the probability of an impending disaster were more likely to purchase information.

We find that providing businesses information about the probability of a disruptive disaster does indeed lead to more informed decisions and greater likelihood of managers to switch from their initial investment decisions. Interestingly, however, we find a difference in the likelihood to act depending on whether the information was free or purchased. When firms purchase information, the data indicate that they are less susceptible to the gambler's fallacy. We postulate that this is a function of the value they place on purchased information. This challenges current practice among public agencies operating under the assumption that the government should provide more free information.

Next, the paper reviews the relevant literature on the role of information in decision making and related decision-making biases, followed by details on the experimental design.

Background Literature

Building resilience capacity in the face of hazards has been the subject of numerous scholarly endeavors in a broad array of disciplines including supply chain and logistics management (Bode, et al., 2011; Graves & Tomlin, 2003; Pettit, Croxton, & Fiksel, 2013; Tang, 2006; Tomlin, 2006), production economics (Tang & Tomlin, 2008; Dormady, Roa-Henriquez, & Rose, 2019), sociology (Tierney, 2006; Tierney 2014; Tierney 2019), geography (Cutter et al., 2008; Cutter, 2016), and public policy (Dormady & Ellis, 2018; Flynn, 2007; Ganguly, Bhatia, & Flynn, 2018). From Holling's (1973) seminal paper on the resilience of ecosystems, resilience theories (and their pragmatic applications) have informed numerous disciplines in the social and behavioral sciences (Hosseini, Barker, & Ramirez-Marquez, 2016), the natural and environmental sciences (Berkes, Folde, & Colding, 2000), civil and industrial engineering (Hosseini, Barker, & Ramirez-Marquez, 2016; Shafieezadeh & Burden, 2014), and economics and business management (Rose, 2007).

A key aspect in building such resilience is the use of economic information to reduce uncertainty and as a tool for making optimal decisions (Pindyck & Rubinfeld, 2013; Repo, 1989). Information deficits can hamper post-disaster recovery (Arneson, Deniz, Javernick-Will, Liel, & Dashti, 2017). Information has

value when inclusion or exclusion would influence a particular decision (Williamson, 1982). Because the acquisition costs of some decision-influencing information may be greater than the expected value added, investments in information should be subject to cost benefit analysis, as are other commodity investment decisions (Leviakangas, 2009; Williamson, 1982). This cost-benefit analysis is particularly relevant under conditions of uncertainty, such as decisions involving disaster preparedness and response. For example, in their study of the decision to purchase flood insurance, Arnal et al (2016) find that probabilistic meteorological forecasts provide increased economic value compared to deterministic forecasts because the quantification of uncertainty is useful to decision-makers with varying risk attitudes. Individuals subsequently use a probabilistic forecast to calculate the potential for flood risk, which is a function of both probability and consequence (potential gain or loss). It suggests that better disaster information may lead to improved private and public sector resilience decisions related to flood protection or hydroelectric power management, among other applications, because decision makers actually incorporate the information.

Willingness to pay for information may be assessed through a variety of approaches. The contingent valuation method (CV or CVM) uses a hypothetical scenario to survey consumers' willingness to pay for products or services (Lee & Hatcher, 2001). An experimental auction (EA) simulates market decision making by assessing exchanges involving real goods and real money. True valuation is revealed through repeated participation in these "markets." The hedonic approach estimates the relationship between the price of a good or service and the characteristics as predictor variables (Lee & Hatcher, 2001). Each of these methods has advantages and disadvantages, which are discussed at length in the literature. Most attempt to elicit individuals' reservation prices.

Some information products and services exemplify characteristics of public goods and governments are vital to both the production and distribution of this information, such as information transmitted from the National Weather Service (Repo, 1989). Other hazard-related information is transacted through market exchange. In either case, the value of information in disaster management and other contexts may be approached from two different angles: measured as the worth to an individual making a decision (perceived value) or as the measured difference in outcomes associated with a behavior change prompted

by information use, realistic value (Leviakangas, 2009). Worth to the decision-maker is a speculative assessment and falls under the category of research examining decision making under uncertainty. The second angle, realistic value, is empirical but may only be measured post-hoc (Leviakangas, 2009).

Investment decisions related to resilience may bridge both information value angles. Information procurement may be prompted by speculation of improved outcomes resulting from information use (realistic value) as assessed by decision-maker before an event occurs (perceived value). Specifically, the decision to hire a consultant or purchase information about the likelihood of a disaster event will be based on the perceived value that new or additional information may provide while informing actions that shield the organization from loss associated with a potential catastrophe.

The role of information in disaster-preparedness decision-making has been documented in a variety of contexts. New Zealand's emergency management and community resilience reform initiative identified technical information and expertise as a core principle of the hazard risk reduction effort (Britton & Clark, 2000). The national legislation crafted to formalize the hazard and risk mitigation efforts included not only the establishment of information systems but the ongoing staff and resources to maintain the systems (Britton & Clark, 2000). In Japan, with roughly half of the population living in close proximity to floodplains, frequent floods have caused devastating life and property loss (Zhai, Sato, Fukuzono, Ikeda, & Yoshida, 2006). At the same time, the persistent severe recession led to reduced investment in "hard" flood countermeasures such as dikes and dams. Contingent valuation analysis has revealed a positive relationship between willingness to pay (WTP) for flood risk reduction and level of risk reduction, but information about environmental impact reduces willingness to pay (Zhai et al., 2006).

Other research has identified the need for improved access to climate information to improve the resilience management of water resources in Brazil and the United States (Kirchhoff, Lemos, & Engle, 2013). In Brazil, the risk attitude of water resource managers is an influential factor in the uptake (use) of information for decisions related to the resilience of water systems threatened by climate change, population growth and competing demands (Kirchhoff, Lemos, & Engle, 2013). When managers lack information about water availability, they tend to rely on a highly conservative water allocation strategy. Yet,

government agencies that serve as boundary organizations to help validate information such as that provided in seasonal climate forecasts can help mitigate managers' risk aversion to act on that advice (Kirchhoff, Lemos, & Engle, 2013). Finally, recent research on flood mitigation in Florida shows that an information-related issue, perceiving a resilience investment as unnecessary, is one of the top three reasons given for deciding against measures that would reduce the risk of damages from natural disasters. The other two reasons were perceiving the protective measures as too costly, and moral hazard, expecting insurance to cover damages caused by natural disasters (Chatterjee, Flugman, Jiang, Mozumder, & Chowdhury, 2018).

While the role of information is undoubtedly crucial, prior research has uncovered a number of decision-making biases related to both the decision to invest in disaster preparedness and the use of information in resilience investments. The gambler's fallacy, status quo bias, and optimism bias may each prompt underinvestment in economic resilience. Sunk cost bias may influence how information provided by consultants or experts may influence resilience investment decisions. Next, we briefly review some of the relevant research in the context of these biases.

First, the "gambler's fallacy" occurs when experience with an event leads a decision-maker to underestimate the probability of the event occurring (Tversky & Kahneman, 1971). In this case, an individual bases a perception of risk on a small, unrepresentative sample and believes, incorrectly, that the "rare" event is unlikely to occur in the immediate future. Subsequently, this mistaken belief may lead to increased risk when making a decision in the near-term after a catastrophic event.

Recent history has provided evidence supporting this theory about the law of small numbers bias. Immediately after Hurricane Katrina, evacuees were more willing to take risks closer to the time of the event (Eckel, El-Gamal, & Wilson, 2009). An Australian experiment found that victims directly impacted by floods took more risks in lottery gambles compared to neighbors who did not experience property damage from flooding (Page, Savage, & Torgler, 2014). When individuals underestimate probabilities or losses resulting from low-probability/high-consequence events they may allocate fewer resources toward

protective measures. This may explain a general lack of preparation for disaster events (Botzen, Kunreuther, & Michel-Kerjan, 2015) or underinvestment in economic resilience.

A second decision making heuristic that may also work to produce underinvestment in resilience is status quo bias. Associated with loss aversion, this bias occurs when perceived costs of moving away from a current position outweigh perceived gains and often results in no action by the decision maker (Kahneman & Tversky, 1979). A number of studies of financial investments reveal a remarkable tendency to avoid changing investment allocations following the initial decision (Bazerman & Moore, 2013; Samuelson & Zeckhauser, 1988). A severe event may be the only situation that can lead an organization to deviate from the status quo (Ballesteros & Kunreuther, 2018, Samuelson & Zeckhauser, 1988). According to Ballesteros & Kunreuther (2018), the decision-making processes associated with discontinuous or dynamic shocks is much more complex than other types of risk decisions faced by organizations and requires an organizational perspective. Dealing with rare or catastrophic events necessitates coordination among decision makers from different levels or divisions of an organization. In these situations, the intuitive thinking of individuals may be compounded while focusing on the short run may restrict the organization's capacity for implementing strategies to prepare for future catastrophic events (Ballestreros & Kunreuther, 2018).

Third, when individuals are susceptible to an illusion of invulnerability they tend to be biased towards optimism (Cherry, 2018). This bias contributes to an individual's underestimation of the likelihood of experiencing an adverse event by mistakenly believing the chances of the event are lower for the individual than those of others (Cherry, 2018). This type of optimism has been observed across a variety of contexts (Bazerman & Moore, 2013; Cherry, 2018). Education about risk factors may actually worsen the bias (Cherry, 2018). With respect to potential disaster events, people who do not prepare may not have full information about the threat or may not perceive that the threat applies to them (Shrikant, 2018).

Finally, sunk cost bias is a decision-making heuristic applicable to disaster planning and decision making. A fascinating finding across a number of disciplinary contexts is that when information is purchased, individuals are significantly more receptive to the recommendations, while free information is

consistently discounted or rejected (Gino, 2008; Hung & Yoong, 2010). Pre-paid expert advice is weighed significantly higher compared to advice that is paid for after it is given (Sniezek, Schrah, & Dalal, 2004). In Judge-Advisor System (JAS) studies a subject (a judge) is presented with advice from one or more reliable consultants before making a final decision (Gino, 2008). A number of JAS experiments have also observed a significant increase in receptivity to information that came at a cost as compared to information provided free of charge (Gino, 2008). This stands in opposition to a multitude of studies concluding that anchoring, differential information, and egocentric bias prompt individuals to regularly discount or disregard advice received from others (Gino, 2008). The exception is that individuals who invest money in procuring expertise are more likely to use the advice regardless of the quality of the information (Gino, 2008; Patt, Bowles, & Cash, 2006; Sniezek, Schrah, & Dalal, 2004). This phenomenon may be attributable to an increased perception of information credibility (Patt, Bowles, & Cash, 2006) or to the tendency to allow prior, irreversible investments to influence ensuing economic behavior, sunk cost bias. Perhaps in an effort to avoid regret about the information or consulting expenditure, an individual is more likely to use the purchased information (Gino, 2008).

In the context of resilient supply chains, risk or vulnerability to disruption is a function of both event likelihood and the severity of the disruption (Pettit, Fiksel, & Croxton, 2010). In the controlled experiment we present below, we provide the experimental subjects with information about the severity of a disruption but include information about the likelihood selectively by treatment. Aversion to ambiguity is another cognitive bias (Ellsberg, 1961; Montibeller and von Winterfeldt, 2015), and the decision to purchase information regarding the probability of the event helps reveal this aversion to ambiguity. We allow the subjects the opportunity to purchase information to reduce this portion of the uncertainty. Comparing between treatments in which information is free versus purchased informs optimism bias, sunk cost bias, and gambler's fallacy related to the decision to invest in resilience.

Experimental Design

In an effort to examine whether the decision-making biases described above influence resilience decision making in a repeated disaster environment, we draw on a controlled experiment to test these effects in the context of a firm facing potential repeated catastrophic events. Use of controlled experiments has grown rapidly in economics because of their strengths in testing social phenomena in a structured manner (Kagel & Roth, 1995; Plott & Smith, 2008) and in setting up scenarios in large samples that would not be possible with observational data. The literature on regional and community resilience is quite large, and the use of controlled decision-making experiments evaluating the effects of dynamic decision making in repeated games has been vast. However, we are aware of no similar studies evaluating individual-level resilience decision-making in the context of hazards management. Below we provide the operational details for our experiment and explain how it was designed.

Experiment Operation & Sample Selection

The experiment was designed as an online experimental survey administered by RTi Research, a professional business survey firm. Subjects were sampled from two pools. Professional subject experimental sessions made use of an existing subject pool of managers from a representative sample of mid-sized businesses and included mainly CEOs, COOs, owners, or executives tasked with making strategic corporate investment decisions. Because the National Center for the Middle Market funded this research and had existing collaborations with RTi Research, we have a high degree of assurance that the respondents took the experiment very seriously. More specifically, these subjects were drawn from the pool of managers who complete the Middle Market Indicator Report. (For more information on the sampling pool, see the FAQ at http://www.middlemarketcenter.org/performance-data-on-the-middle-market.) Undergraduate subjects were selected from The Ohio State University Experimental Economics Subject Pool, which consists of approximately 12,000 undergraduate and graduate students, one of the largest

university economics subject pools in the United States. Subjects in both pools were randomly assigned to the treatment conditions that are described below.

The experiment was conducted in two stages in late 2015 and early 2016 and includes 259 subjects in total, 143 student subjects and 116 managers, who were broken into separate treatment groups of 87 and 172 subjects. Table 3 provides the breakdown of student and manager counts by treatment group.

In addition to the random selection of subjects via the randomized invitations and sign-up process, subjects were randomly assigned into treatment groups through the survey software. The random assignment uses a conditional least-count uniform distribution algorithm to assign subjects to each treatment group. Although this algorithm assigns subjects randomly using a uniform distribution, it also weights the distribution more heavily toward those treatment and selection parameters that have the lowest count of completed surveys at that point in time. We also modified the uniform distribution to provide for approximately twice as many subjects in the second treatment group, where sample size is important because subjects could select into treatment conditions therein (i.e., purchasing information). We also oversample from female subjects in both subject pools to ensure an equal sex balance in all treatments.

Decision-Making Scenario

Subjects were provided a resilience decision-making context, or vignette, in which they were asked to advise a firm's Chief Operations Officer (COO) on an important operational decision in the face of a critical supply chain vulnerability. In the possible event of an unnamed disaster/catastrophe, the firm's ability to acquire the needed production input would be substantially limited. Subjects were asked to advise the COO on an investment decision that could reduce the potential negative consequences of the production input curtailment that would occur if the catastrophic event were to ensue. The exact type of catastrophic event is not specified, as a contextualized decision could introduce exogeneity bias if subjects' individual heuristic biases (e.g., fear of hurricanes) influenced their resilience decisions.

In the face of catastrophic events, whether human-made or natural, firms have several micro-level operational strategies at their disposal. One of the most common strategies is building *redundancy* (e.g.,

use of inventories, back-up generators, mirrored servers). Dormady, Roa-Henriquez, and Rose (2019) provide a detailed description and the formal microeconomic theory for a more comprehensive list of firm-level resilience tactics, and Graveline and Gremont (2017) provide a survey-based assessment of a thorough list of resilience tactics. We focus on investment in *inventories*, a well-known and common enterprise-level resilience tactic (Bode et al., 2011; Kleindorfer & Saad, 2005; Lee, 2004; Sheffi & Rice, 2005; Tang, 2006). In this experiment, if a catastrophic event were to occur, the inventory invesment provides a stock of the critical input that would result in a minor reduction in the firm's production output. Subjects are thus faced with the decision of continuing to operate normally and face the risk of a catastrophic event that would nearly wipe out the firm's production capability or make an investment in inventories that would shield the firm from much of the adverse operational consequence of the input curtailment.

While inventories can reduce or eliminate business interruption given supply chain vulnerabilities in which the delivery or availability of critical production inputs is inhibited, they come with non-trivial costs to mid-sized firms. The payout/utility function was designed with the business environment faced by this population of firms in mind. Because the operational focus of our study is middle market businesses, resilience strategies of middle market firms tend to be limited compared to larger companies. This is critically important because middle market businesses that make investments in redundancy or inventories, for example, do so at a tradeoff to core production inputs in the present, notably investments in labor or capital. Larger firms can afford redundancy without the same degree of tradeoff. Moreover, in the globally competitive marketplace in which most middle market businesses compete, costly investments in inventories or other resilience investments can put them at a disadvantage to other firms that do not bear such costs or catastrophic risk. In more competitive industries that tend to be dominated by middle market firms or smaller firms, this can lead to a decision context akin to a prisoners' dilemma, in which less than societally optimal investments in resilience are made.

Decision Structure

Subjects received the decision-making payoff matrix in Table 1. The left column represents payoffs under the catastrophic shock scenarios. The cost of strategic inventories is set at $20 million per period. If a firm invests in resilience and a catastrophic shock occurs, the firm is only slightly negatively affected by the shock, and profits of $70 million per period are obtained, accounting for the inventory investment (top-left cell). If a shock were to occur and no inventories are in place, the firm generates only $10 million in profit (bottom left cell), reflecting the inability to produce without the requisite production input in the face of limited input substitution. The right column represents the payoffs under the scenarios in which no catastrophe occurs. Under these business-as-usual conditions, the firm would have profits of $100 million per period if inventories were not purchased (bottom-right cell). Finally, if the firm made the investment and no catastrophic shock occurs, profits would be $80 million per period, or $100 million minus the $20 million cost of inventories (top-right cell). This matrix also internalizes, within the framework of the experiment, the reality of positive spillovers from some resilience investments (i.e., some resilience strategies are cost-effective even in the absence of a shock).

Subject remuneration was aligned with standard experimental practices of incentivizing performance based on induced value theory. This is also consistent with corporate performance pay strategies that reward executives for management performance that is tied to market-based outcomes (Jensen & Murphy, 1990). Subjects in the experiment received payment at the ratio of one dollar for every $100 million the firm received in profits. The running calculation of remuneration earned was visible during the experiment; however, every other aspect of the vignette indicates the independence of decision-making periods. Specifically, to be consistent with the context of repeated natural disasters and the holding duration of inventories, inventories are not carried over from period to period. As such, at the introduction of a new period, subjects are provided the following instruction: “Some time has passed. The company is again faced with the option to invest in inventories that would limit the negative impacts of the catastrophic event.” This scenario signals a new, independent period without suggesting a type of inventory or type of disaster that could have activated individual heuristic biases, as discussed below.

Treatment Conditions

Subjects made resilience decisions across ten two-round periods. Regardless of treatment assignment, every subject made an initial investment decision in the first round of each period, before any information could be obtained. The second-round decision at the end of each period is the point at which a subject finalized the investment decision. Following the second and final resilience investment decision, subjects were then informed of the disaster outcome—either a disaster occurred or it did not.

Subjects were randomly assigned to two information treatment groups. In one group, information about the catastrophic event likelihood is provided at no cost at the end of the first round (free information). In this group, before making their final investment decision in the second round of every period, subjects were always (accurately) informed that the probability of a disaster was 25 percent.

The second treatment did not provide costless probability information. Subjects had the opportunity to hire a consultant who provided the information. Between the first and second rounds of every period, these subjects were given the opportunity to hire an external consultant who could provide them with this information for a fee of $10 million. Subjects who purchased external consulting were informed by the consultant of the same 25 percent event likelihood. In all treatments and in all periods, event likelihood was drawn from a uniform distribution, whereby the mean subject observed 2.5 catastrophic events across ten periods.

Figure 1 presents a depiction of the decisions made within each round across the 10 periods for the treatment that had the option to hire a consultant. In the majority of the cases (1,256 compared to 464), the first decision was to invest in inventories. Subsequent to the 1,256 decisions to invest, 310 hired information and 946 did not. Subsequent to the decision not to invest, 92 hired consulting information and 372 did not. The final column of the figure shows the distribution of the final investment decision in round two across all 10 periods.

In the free information treatment, immediately after making their initial investment decisions, subjects were informed that they “have the opportunity to finalize this investment decision to invest in

inventories based upon the following information: The likelihood that the catastrophic event will occur is 25 out of 100." The subjects were invited to consider this information and then make their final investment decision before learning if a catastrophic event occurred. All subjects in this treatment received the same information, and the information remained consistent across all ten periods varying only by the subject's selected exposure to that information.

In the treatment without free information, the consultant was described as having "significant expertise in the field of catastrophic events and can provide you with a highly reliable estimate of the likelihood that a catastrophic event will occur." The subjects were presented with separate payoff matrices showing the possible profit outcomes if the subject does not or does hire the consultant.

Catastrophic Event Likelihood

Subjects' decision calculus inherently depends on their risk tolerance and their willingness to take preventative action (Englander, 2015). However, this experimental design differs from classic risk experiments in three important ways. First, unlike many risk experiments, the subjects in this experiment are not all informed of the likelihood of the event (the catastrophic shock). Second, the actual decision environment is strategy neutral (it was designed for a mixed strategy equilibrium to explicitly observe changeover behavior responsive to the treatment conditions). That is, there is no dominant strategy in equilibrium. The expected value of profit, or expected monetary value (EMV) at the shock probability we utilized (Pr.=0.25) is equivalent for both resilience investment strategies ($77.5 million). The EMV for the Invest strategy is 0.25 ($70) + 0.75 ($80) = $77.5. The EMV for the Do Not Invest strategy is 0.25 ($10) + 0.75 ($100) = $77.5. For subjects who purchase consulting, the EMVs are still equivalent for both investment decisions, though the values are each $10M lower due to the hiring cost. Table 2 presents the EMVs for the probability of 0.25 as well as the probabilities of 0.5 and 0.1, two potentially likely guesses as to the event likelihood. If risk-neutral subjects know the probability, they would be forced to play a mixed strategy. As such, our experimental design attempts to mirror the pre-disaster planning decision environment that many firms face in an environment without a clearly dominant resilience strategy.

Third, this experiment informs the relationship between risk and investment—specifically investment in *inherent resilience*. It is important to note that the economic resilience literature makes a critical distinction between *inherent* and *adaptive* resilience (Cutter et al, 2008; Rose, 2004; Rose, 2007; Martin & Sunley, 2014). The former consists of "built-in" resilience, including the availability of inventories or substitution among inputs. The latter consists of improvisation that occurs under duress, such as strict conservation measures or changes in production processes to continuing operating when faced with an event. While we are not aware of any research investigating the behavioral determinants of either strategy, this experiment provides the first behavioral analysis of the relationship between uncertainty and inherent resilience.

Given the 25% likelihood utilized in this experiment as the exogenous shock probability, the subjects' inherent priors about the likelihood of a catastrophic event and their risk preferences ultimately informs their resilience investment decisions. Subjects who believe that the likelihood of a catastrophic event is high are likely to choose the profit maximizing dominant strategy of investing in inventories if they are risk-averse profit-maximizing decision makers. Alternatively, if subjects believe that the likelihood of a catastrophic event is low, they will choose the profit-maximizing dominant strategy of not investing in inventories.

Experiment Data

Summary Statistics

We next provide summative experimental results/data for both treatment groups, focusing on the exposure of subjects to disasters and the hiring of external consulting. Given the exogenous event-likelihood probability utilized in all treatments, all subjects are exposed to the same mean count of shocks in total—an average of 2.5 out of ten periods. However, because the probability was drawn randomly from a uniform distribution, not all subjects receive the same number of shocks. We report the mean exposure to disasters in Table 3 (around 25 percent) along with the breakdown of subjects by subject type for both treatment

groups. No subject experiences more than seven disasters, though that was rare, occurring in fewer than five cases. We also report the mean total resilience investments by treatment. Upon first glance, we find no statistical difference between the mean resilience investment in either treatment, as subjects in both treatments invested in resilience around 70 percent of the time.

We also want to examine whether we observe differences in consultancy hiring by subject type, across time, or by exposure to disasters. We present these results for the consultancy hiring treatment in Tables 4 and 5. We generally observe declining rates of consultancy hiring across time, falling from 34 percent in the first period to 19 percent in the 10th. This is intuitive, as consultants provided the same event probability every time, and after at least two periods of hiring the consultants, subjects would—we assume—generally learn that this information was consistent each time, and select out of paying the extra $10 million for consultancy information. However, the across-time tapering off that we observe is less robust for managers, who settle to 25 percent in period 10 compared to only 15 percent of students who hire. This is consistent with the experimental economics literature that generally finds that professionals in experiments tend to operate more by rules of thumb than by strict EMV calculations (Kagel, 1995).

Another likely interpretation is that managers in middle market firms (i.e., our professional subjects) are familiar with liability-incentivized "CYA" decision-making to reduce their own personal liability. Though not incorporated into the design of the experiment, this can be a powerful incentive in business decision-making. It may be the case that some professional subjects more regularly hire consultants because in their own decision environments they pursue avenues to offset decision-making liability. We see some evidence of this in Table 4, namely that managers hire consultants at only a slightly lower rate by the end of the experiment. In total, 59 percent of managers never deviate from their preferred consultancy hiring decision (either hiring or not hiring) compared to only 36 percent of students. However, when broken down by disaster exposure, as provided in Table 5, we observe that there are generally no consistent differences in hiring across subject type or disaster exposure. Most subjects hire consultants at essentially the same rates by count of disaster exposure, with the notable exception being the small quantity of subjects who observed six disasters and who hire at a mean of half of the periods across the board.

Appropriately, we observe that resilience investment is positively associated with exposure to disasters in both treatments. We break these down by type of subject in Table 6. Because all subjects receive the disaster likelihood information in the control treatment and receive it if they hire a consultant in the consultancy treatment, we separate those out by disaster exposure. However, because consultant hiring is optional in the consultancy treatment, 42 percent of subjects in that treatment never hire a consultant. These subjects are an important group because they never actually observe an external information source informing them of the event likelihood. Their only source of disaster likelihood information was their own experience with disasters on a period-by-period basis. We include their mean resilience hiring information in the last column of the table as well. These three categories become important explanatory regression categories later in the paper.

However, reviewing the results in Table 6 does not provide any consistent patterns without further examination using regression analysis, which we provide in the next section. In general, subjects in the consultancy treatment who never hire a consultant invest in strategic inventories at a higher rate than subjects who hire a consultant at least once or who always observe the disaster likelihood information. This effect, however, is moderated by higher rates of disaster exposure.

Econometric Regression Variables

We provide three separate sets of econometric models to investigate consultancy hiring in the dynamic context of resilience investment. The explanatory variables provide controls beyond that provided in previous tables of summary statistics. These controls allow us to investigate these subject decisions dynamically across time. In this way, we can introduce dynamic models with lag terms, allowing us to observe whether subjects hire or invest in response to recent disasters. We also include cumulative running totals to observe whether subjects respond to build ups of recent disasters, and we introduce variables that account for periods in which subjects are, or are not yet, aware of the event-likelihood information.

All of the explanatory variables that we utilize in regression analyses are described in Table 7. They are a function of either exposure to disasters or information. The notable exception is the variable

anticipation. It provides a way to discriminate between the subjects' actual observed disaster exposure over time and their initial disaster likelihood prior. In other words, it provides a time-variant continuous measure of the degree to which a subject is anticipating, or expecting, "the big one" by accounting for what they initially thought the likelihood of a disaster was and their actual experience with disasters at the time. It is given by equation 1.

$$A_t = P_{(a,b)/2} - R_t \tag{1}$$

A_t provides this anticipation measure in period t. It is comprised of two separate measures. The first is the subject's disaster event likelihood prior, given by $P_{(a,b)/2}$. In our post-experiment survey, we asked subjects to think back to when they made their investment decision in the first period and tell us what they thought the probability of the disaster/shock was at that time (i.e., in period 1). Subjects provided a 1-5 Likert-type response, where probability bins were given in the following categories: 0-20%; 21-40; 41-60%; 61-80% and 81-100%. For purposes of estimating the prior, we utilize the midpoint value in the bin, denoted simply by the subscript (a,b)/2. For example, the prior midpoint for the second bin would be given by 0.3. This indicates that a given subject states that they believed at the start of the experiment that the likelihood of a disaster occurring was 30 out of 100.

R_t provides the subject's realized disaster odds based on the disasters they have experienced in periods leading up to the current period and under the assumption that no disaster would occur in the current period. It is given by equation 2.

$$R_t = \sum_{t=1}^{t-1} D_t \Big/ t \tag{2}$$

The numerator of equation 2 provides the lagged cumulative total of disasters experienced by the subject. The denominator simply provides the current period. For example, in the fifth decision-making period (t=5), subjects could have had a maximum of four possible disasters, one in each of the four prior

periods. A subject observing a disaster in the 2nd and 4th periods, would have an R_5 of 0.4. Put another way, 2 disasters by the end of the fifth period if no disaster were to occur in the current period.

The variable *anticipation* thus provides a proxy measure of the subject's anticipation of a disaster under even a more positive scenario. If subjects were to ask themselves, even if a disaster did not occur today, would I have already beaten the odds, or should I be expecting one to hit soon. Thus, *anticipation* has a range given by (-1, 1), whereby negative (positive) values indicate that the subject has experienced disasters at a frequency exceeding (exceeded by) their prior.

Econometric Results

We present results of econometric analyses of the experimental subjects' willingness to pay for disaster information (represented by the decision to hire a consultant) as well as the influence of the information received. The first series of models use Random Effects Logistic Regression to assess the differences between students and managers in how prior perception of disaster event likelihood, disaster anticipation, informs hiring decisions. Following that, we present the results from Multinomial Generalized Structural Equation models assessing the impact of purchased information in prompting switching (changing) the inventory investment decision based on the information received from the hired consultant.

Willingness to Pay for Disaster Information

We present the results of three Random Effects Logistic Regression models in Tables 8A (all subjects in total) and 8B (for professional subjects only) that predict the decision to hire event likelihood information from a consultant as a function the lagged decision to hire information and the lagged exposure to a disaster.

Models 2 and 3 also include the anticipation variable capturing subjects' expectations of an impending disaster. Models 1 and 2 include all 172 subjects in the treatment that provided an opportunity to hire information across the final nine periods (because variables are lagged, outcomes in the first period are lost). Model 3 excludes the 81 subjects who either invested in information every period (8 subjects) or

did not invest in information in any period (73 subjects) for a total of 91 subjects who changed their decision to invest in information at least once across periods.

Coefficients represent odds ratios. As can be seen in Table 8A, across all three models, there is high level of path dependence, as the decision to hire information in the previous period increases the odds of investing in information in the current period from three and a half times (Model 3) to five times (Model 2), all else constant. While experiencing a disaster in the previous period does not statistically significantly affect the decision to hire information about the likelihood of a disaster in the current period, the cumulative sum of previous disasters does reduce the odds of investing in information by 17 percent in Model 1, all else constant ($p < 0.05$). Notably, among the 91 subjects who did change their information investment decision at least once (Model 3), the coefficient of 2.465 on the anticipation variable indicates that a one unit increase in anticipation of a disaster increased their odds of hiring information by almost two and a half times, all else constant ($p<0.05$). The coefficient on the anticipation variable was of similar magnitude (2.683) but not statistically significant in Model 2. This positive coefficient on the anticipation measure is an indication that, controlling for previous decisions to hire information and experiencing a disaster in the previous period, anticipating a disaster (expecting the "big one") leads to a greater likelihood of purchasing information regarding the likelihood of a disaster in the current period.

Among the managers (Table 8B), many of the patterns are similar. Across all models, managers were more likely to invest in information if they did in the previous period, although the effect size, approximately twice as likely across the three models, was smaller than for all subjects. Among the managers, neither having experienced a disaster in the previous period nor the cumulative sum of previous disasters statistically significantly affected the decision to purchase information. The variable capturing anticipation of a disaster was very large (20.55 in Model 2 and 5.394 in Model 3) and statistically significant ($p<0.05$). To a large degree, controlling for other factors, managers anticipating a disaster were much more likely to hire consultants to provide information on disaster likelihood. This effect size is much larger than was seen for all subjects in Table 8A.

Resilience Investment Switching Behavior

Next, we turn to the results of Multinomial Generalized Structural Equation models that examined the role that purchasing information had on these same subjects' decisions to maintain or switch their initial inventory investment decision within a round. In the model presented in Table 9, the decision to maintain their initial inventory investment decision is the reference category. We model the effect previous disasters have on investment decisions as a function of an indicator of whether a disaster was experienced in the previous period. The first set of results represent the odds of investing for all 172 subjects and for just the 77 managers.

For both managers and all subjects, controlling for the effect of previous disasters, the decision to hire information had a significant ($p<0.01$), robust, and very large positive relationships with the subjects' switching from a decision to invest to not invest (with odds ratios ranging from 3.91 for managers to 6.20 for all subjects) and with the subjects switching from a decision not to invest to invest (with odds ratios ranging from 5.92 for all subjects to 9.0 for managers). This is an indication that the purchased information likely plays a role in influencing subjects' decisions to invest in resilience.

The effects of previous disasters have no significant relationships with influencing the decision to switch from investing to not investing in inventories, although previous disasters did reduce the odds of switching from not investing to investing in inventories for all subjects by almost 85 percent all else constant, with an odds ratio of 0.146 ($p<0.1$). As is discussed below, lagged disasters lead to a lower probability of investing in inventories, consistent with gambler's fallacy, and the results here indicate that subjects tended to stick with that decision within the round. However, the odds ratio of the interaction of the lagged disaster and hiring information (13.67, $p<0.05$) is a strong indication that hiring information can help overcome this gambler's fallacy and leads decision makers to update their mistaken beliefs that because a disaster occurred in the previous period it would be unlikely to occur in the current period.

Final Resilience Investment Decisions

Finally, in Table 10, we estimate random effects logistic regression models of the decision to invest in inventories as a function of information, lagged exposure to disasters, and the initial decision to invest in inventories in the first period for all subjects (columns 1 and 2) and just managers (columns 3 and 4). Model 2 also includes a lagged dependent variable to control for the decision to invest in inventories in the previous period. These regressions include both the 172 subjects in the treatment that examines the decision to hire information as well as 87 subjects in the "free information" treatment who are provided information about the event likelihood after making their initial investment decision.

For this model, we code "information" as being one if the subject is exposed to the event likelihood two or more times. Thus, for the information provided treatment, all of those subjects are coded as "information" in the second through tenth periods, or all of the periods, as the first period is excluded from the analysis due to the inclusion of lagged variables. For the "purchase information" treatment, subjects are coded as "information" only after the second time they purchase information.

As can be seen in the second row of Table 10, there is a great deal of status quo bias, as the initial decision to invest in inventories in the first period greatly increased the odds that a subject would subsequently invest in inventories, all else equal, with the odds ratio ranging from 19.64 to 29.59 ($p<0.01$) for all subjects. Status quo bias was even more pronounced for the managers, with the odds ratio ranging from 43.57 to 105.5 ($p<0.01$). The lagged decision to invest in inventories was also a strong predictor of the decision to invest for all subjects, as can be seen in model 2, with an odds ratio of 1.85 ($p<0.01$). However, this affect was not statistically significant for managers. The remaining odds ratios in the table report various combinations of interactions between lagged disasters and information for both treatment groups. To ease the interpretation of these coefficients, we calculate predicted probabilities of inventory investments from Model 1 and report those in Table 11 for all subjects, managers only, and students only.

For the subjects in the treatment that allowed them the opportunity to purchase information, the first row reports that those who did not have a lagged disaster and were not provided the information about the likelihood of a disaster more than once had the highest predicted probability of investing in inventories (77.08 percent). This held true for both managers (73.35 percent) and especially students (82.63 percent).

Thus, both receiving information and experiencing a disaster in the previous period lowered the probability of investing. Among all subjects, those who had some combination of either information or a lagged disaster had similar predicted probabilities, ranging from 64.86 to 68.93 percent. Those who had both lagged disasters and information had the lowest probabilities of investing, 58.13 percent for those who hired information and 49.38 percent for those for whom the information was provided for free. Notably, the change in probabilities of investing in inventories of 6.89 percent (a drop of 65.02 to 58.13 percent) for those who experienced a disaster and had to purchase information is much smaller compared to the drop of 19.55 percent (68.93 to 49.38 percent) among those who were provided the information for free. The finding that the probability of investing drops subsequent to experiencing a disaster is evidence of gambler's fallacy, the thought that because a disaster happened last period it will not happen this period. The finding that purchasing information helps to counteract the gambler's fallacy is consistent with sunk cost bias, that is because subjects paid for the information, they are more likely to act on it. The effect of purchasing information counteracting the gambler's fallacy is almost entirely driven by the student subjects, as the lagged disasters reduced their probability of investing by an average of almost 24 percent when information was provided for free, while lagged disasters only reduced the probability of investing by 5.08 percent among those who purchased information.

Discussion

When we analyzed hiring and investment decisions made within and between groups during the ten-period experiment, we made three important discoveries related to common decision-making biases. First, the decision to hire information is path dependent, reflective of status quo bias. The initial set of Random Effects Logistic Regression models predict the decision to purchase consulting information regarding the likelihood of a severe supply chain disruption. Specifically, businesses that purchased information in the previous period had odds three and a half to five times as likely to again purchase information in the subsequent period, with managers having around twice the odds. The results also indicate that businesses

with less information about the probability of a disaster were more likely to purchase information. Having more previous disruptions reduced the odds of purchasing information by four to 13 percent, and the anticipation of an impending disaster, partially a function of not experiencing a recent disaster, increased the odds of purchasing information by around two and a half times. Among the managers, however, the anticipation of an impending disaster increased those odds by five to 20.55 times.

Second, the provision of information clearly helped people to update their own priors and to make more informed decisions. That is, the information was influential in prompting individuals to change their position, or switch. Based upon Multinomial Generalized Structural Equation models, we found that the decision to hire information had a large impact in terms of increasing the odds that a business would switch from a decision to invest to not invest within a period after being presented with the event likelihood. The results range from an increase in the odds switching to not investing of almost three times for managers to over six times for all subjects. Likewise, the hiring information also helped increase the odds of switching from not investing to investing of six (all subjects) to nine times (managers).

Third, the results also demonstrated that purchasing information helped overcome the gambler's fallacy outcome, visible when subjects seemingly reduced their expectations of a disruption occurring in the period subsequent to experiencing a disaster. Interestingly, while business decision-makers are much less likely to switch from not investing to investing in inventories subsequent to a disaster, purchasing information helps to overcome this bias. Those who both had a previous disaster and who purchased information had odds of switching to investing over 13 times as high. We found a similar result in the model that estimated the probability of investing in inventories, as businesses that experienced a lagged disaster and had information provided to them for free had only a 49 percent probability of investing in inventories. However, those who purchased information had a 58 percent probability of investing, and the drop in probabilities due to experiencing a disaster was much lower (7 percent compared to almost 20 percent). The vast majority of that drop is attributable to student subjects. We argue that having purchased information, the businesses were able to counteract some of the gambler's fallacy with sunk cost bias, which is a decision maker's tendency to act on the information because they paid for it. We found evidence that

the students were more subject to gambler's fallacy, perhaps because of their lack of experience and tendency to treat the experiment more as a game, and the managers were more likely influenced by sunk cost bias.

These three findings have practical relevance to economic resilience. Every year, individuals and firms expend large sums of money for professional, expert advice (Gino, 2008). The complexity of social structures has meant that information has become increasingly disconnected from personal relationships and as Patt, Bowles, and Cash suggest, "The challenge of enhancing the credibility of expert advice becomes even more acute in situations in which legitimizing social institutions are weak and decision-makers lack access to the educational resource to judge the quality of the advice they are receiving" (2006, p 348). These credibility issues present impediments to the uptake or use of information. Policymakers and public organizations may continue to provide access to free information, but it remains an open question as to whether participants will find and act on the information (Hung & Yoong, 2010). In a disaster preparedness context, specifically, the findings in our study in conjunction with what is known about information biases suggests that government informational disaster resources may not be most impactful when distributed for free.

While there are challenges associated with vetting and adopting information, policies that successfully mitigate risk or enhance resilience capacity must include information regarding vulnerability and options (Chatterjee et al., 2018). Social complexity and ease of information sharing may be used to enhance the distribution and uptake of resilience information. Recent research on the access and use of climate information found that sustained interaction with effective boundary-spanning organizations improved uptake (Kirchhoff, Lemos, & Engle, 2013). Rather than producing and distributing information, the resources of public sector institutions may be more effective in building resilience capacity by helping connect individuals and organizations to facilitate more impactful information exchange and by helping to validate the accuracy of the information. There are many examples of how this can work. For example, at just the federal level, the Cyber Information Sharing and Collaboration Program (CISCP) in the U.S. Department of Homeland Security (DHS) shares and disseminates cyber threat information; the

Cybersecurity Risk Information Sharing Program (CRISP) plays a similar role in the U.S. Department of Energy (DOE); and the National Counterintelligence and Security Center (NCSC) in the Office of the Director of National Intelligence (DNI) serves to monitor foreign threats to industry supply chains and disseminates that risk information to firms.

Limitations and Future Work

Future research may build on the findings of this research by directly comparing policy alternatives and the potential for one known behavioral bias to serve as a correction for another. As described above, our findings suggest a potential hazard management policy pivot toward governments serving as an information facilitator and validator rather than supplier. Additional research should explore the effectiveness, potential tradeoffs, and suitable applications of public sector organizations serving an information exchange network creator and manager role, compared to a more traditional role of direct allocation of information as a free public service. Future studies should also examine whether the gambler's fallacy-correcting effects of sunk cost bias hold for other forms of information acquisition.

Conclusion

Economic development and population growth have created greater exposure to natural hazards, and vulnerability has increased because mitigation has not kept pace (Hallegatte, Vogt-Schilb, Bangalore, & Rozenberg, 2017; Whitehead & Rose, 2009). At the same time, a key element of local communities' and economies' preparation and response to natural disasters is the ability of the local business community to withstand and recover. Although resilience investment decisions, such as investments in inventories, stockpiles or system redundancy, are fundamentally different when the realities of repeated events are taken into consideration, this issue had been largely ignored. Most studies have examined firm behavior when facing a single disaster event or shock (Hosseini, Barker, & Ramirez-Marquez, 2016).

Thus, this study examined the economic resilience investment decisions of mid-sized firms in the context of repeated catastrophic events using a randomized controlled human-subjects experiment. Both professional manager and the more standard student subject pool subjects were utilized. Subjects faced severe supply chain disruptions and a decision to invest or not invest in business-reinforcing inventories. Depending on treatment group, subjects were either provided with free information about the probability of a destructive catastrophic event or had the option to purchase the information by hiring a consultant.

Several key findings about the role of heuristic biases in resilience investment decisions have important implications for hazard management research and practice. First, businesses that purchased information in the previous period were three and a half to five times as likely to purchase information again in the subsequent period. This path dependence reveals the influence of status quo bias in the decision to purchase information. Practitioners seeking to improve hazard management by expanding the acquisition of, and action based on, disaster information may enhance efficiency by targeting businesses that have not previously sought external advice.

Businesses with less information about the probability of a disaster were more likely to purchase information and the information was influential in prompting individuals to change their position, or switch. Subjects also seemingly reduced their expectations of a disruption occurring in the period subsequent to experiencing a disaster but, interestingly, purchasing information helped overcome this gambler's fallacy outcome and prompted a decision to switch. The value that private enterprise appears to place on purchased information suggests that the current practical strategy, among government agencies operating under the assumption that they play an important information sharing and disseminating role, should be revisited. The efficiency and effectiveness of public sector hazard management efforts may be enhanced by taking on a network management and information facilitation role, rather than producing and providing free information. Future research can play an important role in examining and focusing the potential forms that this policy pivot could meaningfully take, and under which hazard contexts it is most appropriate for information-poor private enterprises to have greater "skin" in the proverbial game. Several policy tools are likely candidates. These include public-private partnerships such as Washington State's Floodplains by

Design collaborative. These collaboratives not only serve an information provision and validation role but also engage private enterprise in community-level disaster risk management and support funding mechanisms. These also include policy tools that increase private-sector engagement with universities, national laboratories, and other agencies that generate disaster-risk information. One model of this is DHS's Centers of Excellence (COE) model which focuses heavily on meeting community and private-sector resilience needs including identifying multi-sector hazard-related interdependencies. COEs approach the information dissemination process differently than most university centers, in that they follow a technology commercialization model that requires basic research to identify customers for transition products (e.g., decision support software). In this way, actionable university-sourced resilience information is disseminated to customers. Ultimately, policy tools can take many shapes and forms. The findings of this research support the overall conclusion that there is an important role for government in not only improving the accuracy of disaster risk information but also supporting infrastructure that builds commitment to that information among private enterprise.

Data Availability

Data Availability Statement: All data, models, or code that support the findings of this study are available for purposes of replicating and/or validating its findings from the corresponding author upon reasonable request. However, while the results of this suite of experiments are being published in this, and other publication outlets, the data will not be posted to publicly-available repositories. Upon completion of the authors' use of the data, the finalized data will be posted online and publicly available, and requester's use of the data for subsequent publication and broader dissemination will be permitted.

Acknowledgements

The authors thank the National Center for the Middle Market and the Battelle Center for Science & Technology Policy for their generous financial support for this research. The authors also thank Sally Sadoff, Doug Farren, Matt Booth, John Houghton, John Conlon, and helpful discussants at the 2018 meetings of the Association for Public Policy Analysis and Management.

References

Arneson, E., Deniz, D., Javernick-Will, A., Liel, A., & Dashti, S. (2017). Information deficits and community disaster resilience. *Natural Hazards Review*, *18*(4), 04017010.

Arnal, L., Ramos, M.H., Coughlan de Perez, E., Cloke, H.L., Stephens, E., Wetterhall, F., van Andel, S.J., & Pappenberger, F. (2016). Willingness-to-pay for a probabilistic flood forecast: A risk-based decision-making game. *Hydrology and Earth System Sciences, 2*, 3109-3128.

Ballesteros, L., & Kunreuther, H. (2018). Organizational decision making under uncertainty shocks. National Bureau of Economic Research Working Paper No. 24924. Accessed from https://www.nber.org/papers/w24924

Bazerman, M.H., & Moore, D.A. (2013). *Judgment in managerial decision making*. Hoboken, New Jersey: John Wiley & Sons.

Berkes, F., Folke, C., & Colding, J. (Eds.). (2000). *Linking social and ecological systems: Management practices and social mechanisms for building resilience*. Cambridge University Press.

Bode, C., Wagner, S., Petersen, K., & Ellram, L., (2011). Understanding responses to supply chain disruptions: insights from information processing and resource dependence perspectives. *The Academy of Management Journal, 54*(4), 833–856.

Botzen, W.W., Kunreuther, H., & Michel-Kerjan, E. (2015). Divergence between individual perceptions and objective indicators of tail risks: Evidence from floodplain residents in New York City. Judgment and Decision Making, 10(4), 365-385.

Britton, N.R., & Clark, G.J. (2000). From response to resilience: Emergency management reform in New Zealand. *Natural Hazards Review, 1*(3), 145-150.

Chatterjee, C., Flugman, E., Jiang, F., Mozumder, P., & Chowdhury, A.G. (2018). Insights from a stated preference experiment of Florida residents: Role of information and incentives in Hurricane Risk Mitigation. *Natural Hazards Review.*

Cherry, K. (2018). Understanding the optimism bias. Accessed from https://www.verywellmind.com/what-is-the-optimism-bias-2795031

Cutter, S., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change, 18*(4), 598-606.

Cutter, S.L. (2016). Resilience to what? Resilience for whom? *The Geographical Journal*, *182*(2), 110-113.

Dormady, N., & Ellis, R. (2018). Energy-transport sector interdependence in extreme events: The case of a hurricane event in Boston. *Current Sustainable/Renewable Energy Reports*, *5*(1), 1-13.

Dormady, N., Greenbaum, R.T., & Young, K.A. (2017). Resilience decisions of the firm: An experimental analysis of dynamic decision making in repeated disasters. Presented at the

Association for Public Policy Analysis & Management Fall Research Conference, Chicago, Illinois.

Dormady, N., Roa-Henriquez, A., & Rose, A. (2019). Economic resilience of the firm: A production theory approach. *International Journal of Production Economics,*

Eckel, C.C., El-Gamal, M.A., & Wilson, R.K. (2009). Risk loving after the storm: A Bayesian-Network study of Hurricane Katrina evacuees. *Journal of Economic Behavior and Organization, 69(2),* 110-124.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics, 75(4),* 643-669.

Englander, A. (2015). Multidimensional ambiguity and individual willingness to take preventative action. Senior Thesis. Department of Economics, The Ohio State University.

Flynn, S. (2007). *The Edge of Disaster: Rebuilding a Resilient Nation*. New York, New York: Random House.

Ganguly, A. R., Bhatia, U., & Flynn, S. E. (2018). *Critical infrastructures resilience: Policy and engineering principles*. New York, New York: Routledge.

Gino, F. (2008). Do we listen to advice just because we paid for it? The impact of advice cost on its use. *Organizational Behavior and Human Decision Processes, 107,* 234-245.

Graveline, N., & Gremont, M. (2017). Measuring and understanding the microeconomic resilience of businesses to lifeline service interruptions due to natural disasters. *International Journal of Disaster Risk Reduction, 24,* 526-538.

Graves, S.C., & Tomlin, B.T. (2003). Process flexibility in supply chains. *Management Science, 49*(7), 907–919.

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., & Rozenberg, J. (2017). *Unbreakable: Building the resilience of the poor in the face of natural disasters.* Washington, DC: World Bank Group.

Holling, C.S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics, 4*(1), 1–23.

Hosseini, S., Barker, K., & Ramirez-Marquez, J. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety, 145,* 47–61.

Hung, A.A., & Yoong, J.K. (2010). Asking for Help: Survey and Experimental Evidence on Financial Advice and Behavior Change. RAND Working Paper. Accessed from https://www.rand.org/pubs/working_papers/WR714-1.html

Jensen, M. C., & Murphy, K. J. (1990). Performance pay and top management incentives. *Journal of Political Economy, 98*(2), 225-264.

Kagel, J., & Roth, A. (1995). *The Handbook of Experimental Economics.* Princeton, New Jersey: Princeton University Press.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263-292.

Kirchhoff, C.J., Lemos, M.C., & Engle, N.L. (2013). What influences climate information use in water management? The role of boundary organizations and governance regimes in Brazil and the U.S. *Environmental Science & Policy, 26*, 6-18.

Kleindorfer, P.R., & Saad, G.H. (2005). Managing disruption risks in supply chains. *Production and Operations Management, 14*(1), 53-68.

Lee, H. 2004. The triple-A supply chain. *Harv. Bus. Rev.*, 102-112.

Lee, K.H., & Hatcher, C.B. (2001). Willingness to pay for information: An analyst's guide. *The Journal of Consumer Affairs, 35*(1), 120-140.

Lee, A. V., Vargo, J., & Seville, E. (2013). Developing a tool to measure and compare organizations' resilience. *Natural Hazards Review, 14*(1), 29-41.

Leviakangas, P. (2009). Valuing meteorological information. *Meteorological Applications, 16*, 315-323.

Martin, R., & Sunley, P. (2014). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography, 15*, 1-42.

Montibeller, G., & Von Winterfeldt, D. (2015). Cognitive and motivational biases in decision and risk analysis. *Risk analysis, 35*(7), 1230-1251.

National Research Council. (2012). Disaster resilience: a national imperative. The National Academies Press.

Orr, L. M., & Orr, D. J. (2012). *When to Hire—or Not Hire—a Consultant: Getting Your Money's Worth from Consulting Relationships*. New York, New York: Apress.

Page, L., Savage, D. A., & Torgler, B. (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review, 71*, 121-131.

Patt, A.G., Bowles, H.R., & Cash, D.W. (2006). Mechanisms for enhancing the credibility of an adviser: Prepayment and aligned incentives. *Journal of Behavioral Decision Making, 19*, 347-359.

Pettit, T.J., Croxton, K.L., & Fiksel, J. (2013). Ensuring supply chain resilience: development and implementation of an assessment tool. *Journal of Business Logistics, 34*(1), 46–76.

Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: development of a conceptual framework. *Journal of Business Logistics, 31*(1), 1-21.

Pindyck, R.S., & Rubinfeld, D.L. (2013). *Microeconomics* (8th ed.). Upper Saddle River, New Jersey: Pearson Education.

Plott, C., & Smith, V. E. (2008). *Handbook of experimental economics results Volume 1.* Amsterdam: North-Holland Press.

Repo, A. (1989). The value of information: Approaches in economics, accounting, and management science. *Journal of the American Society for Information Science, 402*(2), 68-85.

Rose, A. Z. (2004). Defining and measuring economic resilience to disasters. *Prevention and Management: An International Journal, 13*(4), 307-314.

Rose, A. Z. (2007). Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions. *Environmental Hazards, 7*(4), 383-398.

Rose, A., & Dormady, N. (2018). Advances in analyzing and measuring dynamic economic resilience. In, Trump, B. D., Florin, M.V., & Linkov, I. (Eds.), *IRGC resource Guide on resilience: Domains of resilience for complex interconnected systems Volume 2.* Lausanne, Switzerland: EPFL International Risk Governance Center.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision-making. *Journal of Risk and Uncertainty, 1,* 7-59.

Shafieezadeh, A., & Burden, L.I. (2014). Scenario-based resilience assessment framework for critical infrastructure systems: Case study for seismic resilience of seaports. *Reliability Engineering & System Safety, 132,* 207-219.

Sheffi, Y., & Rice, J.B. (2005). A supply chain view of the resilient enterprise. *MIT Sloan Management Review, 47*(1), 41-48.

Shrikant, A. (2018). The psychology behind the pre-hurricane run to the grocery store. Accessed from https://www.msn.com/en-ie/news/world/the-psychology-behind-the-pre-hurricane-run-to-the-grocery-store/ar-BBOe5mR

Sniezek, J.A., Schrah, G.E., & Dalal, R.S. (2004). Improving judgement with prepaid expert advice. *Journal of Behavioral Decision Making, 17,* 173-190.

Tang, C.S. (2006). Robust strategies for mitigating supply chain disruptions. *International Journal of Logistics: Research and Applications, 9*(1), 33–45.

Tang, C., & Tomlin, B. (2008). The power of flexibility for mitigating supply chain risks. *International Journal of Production Economics, 116*(1), 12–27.

Tierney, K. (2006). Businesses and disasters: vulnerability, impacts, and recovery. In: Rodriguez, H., Quarantelli, E.L., Dynes, R.R. (Eds.), *Handbook of Disaster Research.* New York, New York: Springer.

Tierney, K. (2014). *The social root of risk.* Palo Alto, California: Stanford University Press.

Tierney, K. (2019). *Disasters: A sociological approach*. Hoboken, New Jersey: John Wiley and Sons.

Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science, 52*(5), 639–657.

Tversky, A., & Kahneman, D. (1971). Belief in the law of small numbers. *Psychological Bulletin, 76*(2), 105-110.

Whitehead, J., & Rose, A. (2009). Estimating environmental benefits of natural hazard mitigation: Results from a benefit-cost analysis of FEMA mitigation grants. *Mitigation and Adaptation Strategies for Global Change*, *14*(7), 655-76.

Williamson, R.W. (1982). Presenting information economics to students. *The Accounting Review*, *57*(2), 414-419.

Wong, P.P., Losada, I.J., Gattuso, J., Hinkel, J., Khattabi, A., McInnes, K.L., Saito, Y., & Sallenger, A. (2014). Coastal systems and low-lying areas p. 361-409. In C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, & L.L. White (Eds.) *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects*. *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Cambridge, United Kingdom: Cambridge University Press.

Wu, H. C., Greer, A., & Murphy, H. (2020). Perceived Stakeholder Information Credibility and Hazard Adjustments: A Case of Induced Seismic Activities in Oklahoma. *Natural Hazards Review*, *21*(3), 04020017.

Zhai, G., Sato, T., Fukuzono, T., Ikeda, S., & Yoshida, K. (2006). Willingness to pay for flood risk reduction and its determinants in Japan. *Journal of the American Water Resources Association*, *42*(4), 927-940.

Figure and Tables

Figure 1. Outcome Tree of Decisions to Invest in Inventories and Hire a Consultant

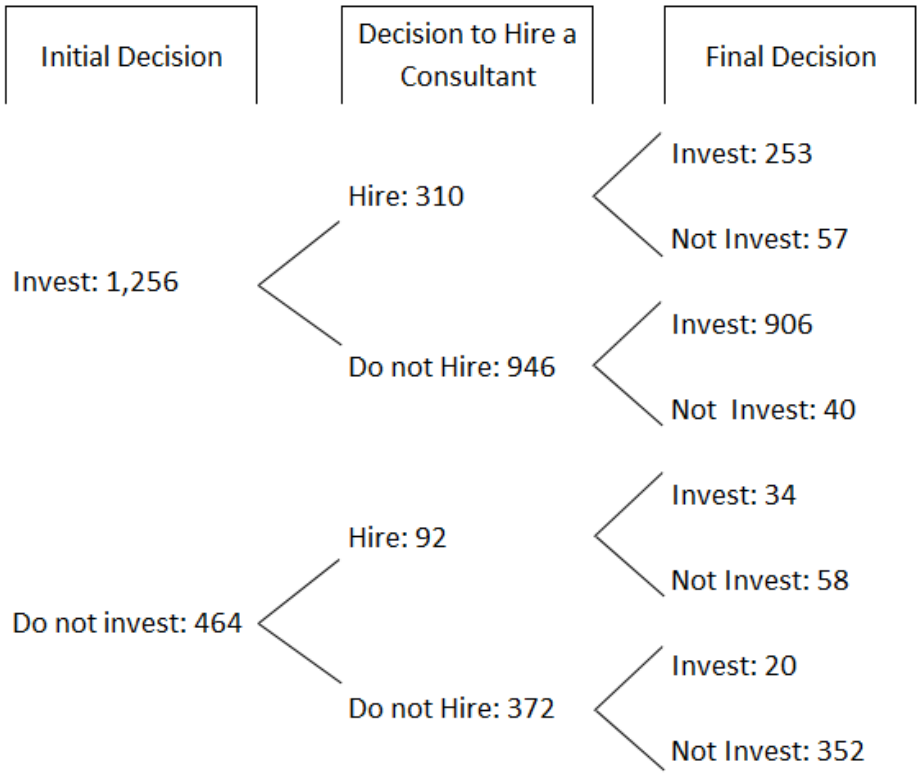

Table 1. Resilience Decision Payoff Matrix

Resilience Decision	Event Determination (Exogenous)	
	Catastrophic Event Occurs	*Catastrophic Event Does Not Occur*
Invest in Resilience	$70 Million	$80 Million
Do Not Invest in Resilience	$10 Million	$100 Million

Table 2. Expected Monetary Value Conditional on Common Likelihood Priors

Resilience Decision	Expected Monetary Value		
	Pr.=0.5	Pr.=0.25†	Pr.=0.10
Invest in Resilience	$75 Million*	$77.5 Million	$79 Million
Do Not Invest in Resilience	$55 Million	$77.5 Million	$91 Million*

Notes: Table provides EMVs for possible likelihood priors subjects may have considered. The actual event likelihood utilized in the experiment was 0.25. *Indicates dominant strategy. † Indicates mixed-strategy catastrophic event probability utilized in this experiment.

Table 3. Treatment Summary Statistics

Treatment	N (subjects)	Mean Exposure to Disasters	Mean Investment in Resilience
Control *(Disaster Likelihood Info Given Freely)*	87 (48 students; 39 managers)	2.59 (26%) (out of 10 periods)	6.95 (70%) (out of 10 periods)
Treatment *(Disaster Likelihood Info Sold)*	172 (95 students; 77 managers)	2.50 (25%) (out of 10 periods)	7.05 (70%) (out of 10 periods)

Table 4. Consultancy Hiring Frequency Statistics

Period	All Subjects Mean [St. Dev.]	Students Mean [St. Dev.]	Managers Mean [St. Dev.]
1	.34 [.47]	.39 [.49]	.29 [.45]
2	.31 [.46]	.33 [.47]	.29 [.45]
3	.29 [.46]	.32 [.47]	.26 [.44]
4	.22 [.42]	.20 [.40]	.25 [.43]
5	.22 [.42]	.20 [.40]	.26 [.44]
6	.21 [.41]	.15 [.36]	.29 [.45]
7	.17 [.38]	.16 [.37]	.19 [.40]
8	.19 [.39]	.16 [.37]	.22 [.42]
9	.19 [.39]	.15 [.36]	.23 [.43]
10	.19 [.39]	.15 [.36]	.25 [.43]

Note: Table reports the period-by-period mean and standard deviation of consultancy hiring in the *Consultancy* treatment for all subjects, then separately by manager and student sample.

Table 5. Consultancy Hiring by Disaster Exposure

Disaster Exposure (total 10 period count)	**All Subjects** Mean [St. Dev.]	**Students** Mean [St. Dev.]	**Managers** Mean [St. Dev.]
0	.11 [.32]	.16 [.38]	0 [0]
1	.26 [.44]	.22 [.41]	.33 [.47]
2	.26 [.44]	.24 [.43]	.29 [.45]
3	.23 [.42]	.22 [.41]	.23 [.42]
4	.17 [.39]	.18 [.39]	.17 [.37]
5	.23 [.42]	.23 [.43]	.23 [.42]
6	.50 [.51]	.50 [.53]	.50 [.51]

Note: Table reports the mean and standard deviation of consultancy hiring in the *Consultancy* treatment by total ten period exposure to disasters (max=7).

Table 6. Mean Resilience Investment by Risk Information Exposure (Tenth Period)

Disaster Exposure (total 10 period count)	**Subjects who Always Received Info** Mean [St. Dev.]	**Subjects who Hired Consultant At Least Once** Mean [St. Dev.]	**Subjects who Never Received Info** Mean [St. Dev.]
0	.50 [.58]	.50 [.58]	~
1	.53 [.52]	.32 [.48]	.69 [.48]
2	.62 [.49]	.69 [.47]	.76 [.44]
3	.83 [.38]	.58 [.50]	.64 [.49]
4	.91 [.30]	.90 [.32]	.67 [.49]
5	.71 [.48]	.60 [.55]	~
6	~	.60 [.55]	~
7	~	~	~

Notes: "~" Indicates fewer than 5 subjects, not enough to report meaningful values. This is a cross-sectional table.

Table 7. Main Regression Variables Utilized

Variable Name	**Description**	**Mean**	**Min**	**Max**
Investment	The subject made a final decision to invest in strategic inventories in the second/final round of a given period.	.70	0	1
Hiring	In the consultancy treatment, the subject hired external consultants to provide disaster information.	.23	0	1
Information	The subject observed the disaster information in at least two periods either by hiring a consultant or by receiving it freely.	.57	0	1
$Disaster_{t-1}$	A disaster occurred in the prior period.	.23	0	1
$Cumulative\ Disasters_{t-1}$	The cumulative running total of disasters a subject has observed prior to the current decision-making period.	1.26	0	7
Anticipation	A continuous estimate of the expectation a given subject may be observing given their exposure to disasters prior to the current period, and their probability prior.	.16	-.56	.9

Note: Summary statistics provide mean values across all subjects, treatments and periods (N=2,590).

Table 8A. Decision to Hire Information Regarding Event Likelihood (All Subjects)

Model	**1**	**2**	**3**
Variables	**All[1]**	**All[1]**	**Changers[2]**
Hired information in previous period	4.923***	5.030***	3.479***
(=1 if hired)	(1.107)	(1.134)	(0.627)
Experienced disaster in previous period	1.136	1.273	1.301
(=1 if previous disaster)	(0.226)	(0.269)	(0.265)
Cumulative sum of previous disasters	0.829**	0.896	0.960
	(0.0767)	(0.0923)	(0.0818)
Anticipation of disaster		2.683	2.465**
		(1.660)	(1.098)
Constant	0.117***	0.0896***	0.247***
	(0.0228)	(0.0231)	(0.0480)
Log likelihood	-608.78	-607.54	-480.23
Observations	1,548	1,548	819
Number of subjects	172	172	91

Notes: Models estimated with Random Effects Logistic Regression. Odds ratios presented with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] Models 1 and 2 estimated on all 172 subjects in the "opportunity to hire" treatment across the final nine periods (period one dropped due to the lagged variables)

[2] Model 3 estimated for the 91 subjects in the "opportunity to hire" treatment who did not make the same hiring decision across all 10 periods.

Table 8B. Decision to Hire Information Regarding Event Likelihood (Managers)

Model	**1**	**2**	**3**
Variables	**All[1]**	**All[1]**	**Changers[2]**
Hired information in previous period	2.221**	2.289**	1.999**
(=1 if hired)	(0.783)	(0.823)	(0.621)
Experienced disaster in previous period	0.697	0.981	0.898
(=1 if previous disaster)	(0.225)	(0.346)	(0.291)
Cumulative sum of previous disasters	0.998	1.217	1.149
	(0.140)	(0.199)	(0.141)
Anticipation of disaster		20.55**	5.394**
		(26.940)	(3.945)
Constant	0.0752***	0.0427***	0.301***
	(0.0353)	(0.0226)	(0.0945)
Log likelihood	-249.10	-246.74	-179.72
Observations	693	693	279
Number of subjects	77	77	31

Notes: Models estimated with Random Effects Logistic Regression. Odds ratios presented with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] Models 1 and 2 estimated on all 77 managers in the "opportunity to hire" treatment across the final nine periods (period one dropped due to the lagged variables)

[2] Model 3 estimated for the 31 managers in the "opportunity to hire" treatment who did not make the same hiring decision across all 10 periods.

Table 9. Decision to Switch Investment Decision within Period (All Subjects & Managers)

Model	1		2	
	All Subjects[1]		Managers Only[2]	
Variables	Invest to not invest	Not invest to invest	Invest to not invest	Not invest to invest
Hired information	6.197***	5.919***	3.911***	9.001***
(=1 if hired)	(1.840)	(2.281)	(1.920)	(5.867)
Experienced disaster in previous period	1.229	0.146*	1.285	0.000
(=1 if previous disaster)	(0.467)	(0.153)	(0.754)	(0.000)
*Hired info*Lagged disaster*	1.102	13.670**	1.911	0.000
	(0.606)	(15.730)	(1.650)	(0.000)
Constant	0.015***	0.006***	0.011***	0.006***
	(0.004)	(0.003)	(0.006)	(0.003)
Log Likelihood	-518.84		-217.38	
Observations	1,720		770	
Number of subjects	172		77	

Notes: Models estimated with Multinomial Generalized Structural Equation Models. Odds ratios presented with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] Models estimated on all 172 subjects in the "opportunity to hire" treatment across the ten periods.

[2] Models estimated on all 77 managers in the "opportunity to hire" treatment across the ten periods.

Table 10. Decision to Invest in Inventories (All Subjects & Managers)

Model	1	2	1	2
Variables	All Subjects[1]		Managers Only[2]	
Invested in inventories in previous period		1.849***		0.894
(=1 if invested)		(0.301)		(0.225)
Invested in inventories in first period	29.590***	19.640***	43.570***	105.500***
(=1 if invested)	(9.825)	(7.683)	(20.360)	(69.780)
Opportunity to hire information treatments				
(= 1 if no lagged disaster &_no information)	0.527**	0.414**	0.343**	0.215***
	(0.167)	(0.143)	(0.146)	(0.108)
(=1 if no lagged disaster & information)	0.291***	0.257***	0.360**	0.255**
	(0.098)	(0.093)	(0.171)	(0.141)
(= 1 if lagged disaster & no information)	0.324***	0.264***	0.316**	0.189***
	(0.120)	(0.102)	(0.156)	(0.105)
(= 1 if lagged disaster_& information)	0.248***	0.219***	0.269**	0.172***
	(0.094)	(0.088)	(0.148)	(0.107)
Information provided treatments				
(=1 if no lagged disaster & information)	0.339***	0.270***	0.201***	0.059***
	(0.107)	(0.108)	(0.091)	(0.038)
(= 1 if lagged disaster & information)	0.165***	0.135***	0.170***	0.051***
	(0.060)	(0.060)	(0.094)	(0.036)
Log Likelihood	-1090.80	-992.12	-468.66	-423.65
Observations	2,590	2,331	1,160	1,044
Number of subjects	259	259	116	116

Notes: Models estimated with Random Effects Logistic Regression. Odds ratios presented with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] Models estimated for the 259 subjects in the "opportunity to hire" and "information provided" treatments.

[2] Models estimated for the 116 managers in the "opportunity to hire" and "information provided" treatments.

Table 11. Predicted Probabilities from Final Investment Models

	All Subjects		Managers Only		Students Only	
Treatment	**Pr(I)**	**Δ**	**Pr(I)**	**Δ**	**Pr(I)**	**Δ**
Opportunity to hire information treatment						
No lagged disaster & no information	77.08	12.22	73.35	7.12	82.63	13.17
Lagged disaster & no information	64.86		66.23		69.46	
No lagged disaster & information	65.02	6.89	70.64	8.66	66.36	5.08
Lagged disaster & information	58.13		61.98		61.28	
Information provided treatments						
No lagged disaster & information	68.93	19.55	61.64	9.43	77.82	23.97
Lagged disaster & information	49.38		52.21		53.85	