THE UNIVERSITY OF CHICAGO

STRATEGY AND COGNITION: REGULATING CATASTROPHIC RISK

A DISSERTATION SUBMITTED TO
THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES
IN CANDIDACY FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

DEPARTMENT OF POLITICAL SCIENCE

BY
JACOB E. GERSEN

CHICAGO, ILLINOIS
AUGUST 2001

UMI Number: 3019916

Bell & Howell Information and Learning Company
300 North Zeeb Road
P.O. Box 1346
Ann Arbor, MI 48106-1346

For my family, friends, and those who came before me.

ABSTRACT

This project explores the political economy of catastrophic risk from natural disasters in the United States. The core task for the project is to endogenize the institutional structure of natural disaster policy by exploring the interaction of citizen decision-making, legislative choice, and interest group activity. Unlike previous work on disaster behavior, this dissertation highlights the importance of behavioral heterogeneity on the part of the citizenry. The project begins by surveying the dominant economic and psychological theories of individual choice about risk. Hypotheses about risk perception and decision-making are developed and quantitative analysis proceeds using a panel dataset of disaster losses and hazard insurance. The findings indicate that individuals are responsive to risk exposure, use availability as a heuristic for evaluating risk, and tend to be ambiguity-seeking with respect to disaster risk. A formal model of individual decision-making about risk management strategies is developed and psychologically realistic actors are introduced into the game. Using an informational cascade model, the analysis shows that communities facing similar objective risk exposure may respond with remarkably divergent behavior. Allowing for biased actors in the game can either increase or decrease the probability that the group will adopt the optimal strategy, depending on the type and magnitude of the bias. Empirical testing of the cascade model relies on a parameterized variance model and a county-level dataset on risk exposure and risk management activity. Estimation proceeds using a mix of Maximum Likelihood (ML) and Markov Chain Monte Carlo (MCMC) methods, and the analysis offers preliminary support for the model. The project concludes by inquiring about the effect of citizen decision-making on the evolution of political institutions. Using a mix of historical legislative documents and basic quantitative evidence, the project offers a positive account of the legislative framework for catastrophic risk regulation. The project highlights the importance and potential productivity of jointly analyzing cognitive bias and strategic environment.

ACKNOWLEDGEMENTS

From start to finish, this project benefited from tremendous support from a variety of sources. Generous financial support was provided by a National Science Foundation Graduate Research Fellowship, a U.S. Environmental Protection Agency Science to Achieve Results (STAR) Graduate Fellowship, a Mellon Foundation Dissertation Fellowship, and the University of Chicago. Helpful comments or advice on various chapters was provided by Yasmin Abdullah, Tom Baker, Chris Berry, John Brehm, Matt Cleary, Ross Cheit, Daniel Diermeier, Dino Falaschetti, Sven Feldmann, Mark Hansen, Russell Hardin, Jonathan Katz, Randy Kroszner, Howard Margolis, Peter May, Paul Kleindorfer, Scott Page, Chris Rohrbacher, Gerry Rosenberg, Duncan Snidal, Cass Sunstein, and Alex Thompson. In addition the project benefited from questions and suggestions during panels at 2001 Midwest Political Science Association annual convention, 2001 Public Choice Society Meetings, and the 2001 American Law and Economics Association meetings. My appreciation to Arianne Chernock who helped inspire my initial interest in the topic of disasters. Thanks to Dave Wingerd at the United States Corps of Engineers and Joanne Dionne at the Hydrologic Information Center (NOAA/NWS) for providing historical data on flood losses, the Insurance Information Institute for providing data on flood insurance policies, Thomas Birkland for providing data on witnesses in Congressional hearings on earthquake and hurricane policy, the Federal Insurance Administration at the Federal Emergency Management Association for providing data on the NFIP, and Brian Hall and Geotrac for working with me to provide data on county flood zones. Some of the data used herein are drawn from data collected by the Center for American Politics and Public Policy at the University of Washington. A very special acknowledgment goes to Julia Gwynne who spent endless hours editing and commenting on the entire project. My undergraduate advisors at Brown University, Ross Cheit and Wendy Schiller both provided me with exceptional training that served me well throughout graduate school. Finally, I would like to acknowledge the members of my dissertation committee, John Brehm, Gerry Rosenberg, Mark Hansen, Duncan Snidal, and my chair, Cass Sunstein, all of whom provided exceptional guidance, pointed criticism, and detailed comments and suggestions throughout the project. I owe all of them a debt of gratitude not just for their help in seeing this project to fruition, but also for their dedication and genuine commitment to my graduate education.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

CITIZENS, DISASTERS, AND THE STATE

1.1 Citizens, Decisions, and Disasters

Natural disasters, be they floods, hurricanes, tornadoes, or earthquakes have long threatened the well-being of communities throughout the United States.[1] The "big ones" have been well-documented in the popular press, literature, the movies, and the academic study of disasters has spawned an abundant inter-disciplinary research agenda, not to mention an entire sub-field in sociology known as *disasterology.* In most of these media, citizens are portrayed as either helpless or foolish, unable to withstand the constant threats from Mother Nature, and unwilling to manage the risk effectively. The reality of disasters is somewhat different from the version we find in movies and literature, but the difficulties of risk perception and management clearly persist in one form or other. Problems of risk perception, risk management, and disaster response abound. Moreover, though natural disasters have proven thorny for citizens, they have been no easier for the State. Government disaster policy is a favorite whipping boy of the media and academics alike. Whereas one might think that technology and economic development would have eliminated, or at least diminished the threat from natural hazards, it seems quite possible that the reality is almost precisely the opposite (Davis 1999).

As National Public Radio commentator Daniel Schorr noted a few years ago,

> Yeah, if you can stand a little philosophy this early in the morning, here we have Southern California in the grip of earthquakes and the East in the grip of cold and last summer the Midwest in the grip of floods. And what do we learn from all of us? Here we are, this great civilization, planning information superhighways but we can't keep the roads going. And that all the centuries of progress, so called, we end up shivering in terror at the forces of nature like cavemen- oops, cavepersons. It may be another lesson that as we see our bureaucracies struggling but unable to cope with finding enough shelter for all the new homeless in Los Angeles. You know, since the Cold War, I mean, the other Cold War, we've been looking for some enemy, some new enemy. Well, maybe the new adversary is the oldest one of all. And we think of trillions that were spent on exquisite

1. For a discussion of the international disaster research agenda, see Alexander (1997).

> systems of alert and defense against some enemy, maybe it's time to think of turning resources to alert and defense against the forces of nature.[2]

The United States has an expansive system of disaster response and management. Yet, minimization and management of large environmental hazards continue to perplex policy-makers. If one looks at the advice academics give to politicians on the issue, it has scarcely changed in the past quarter century. Though our understanding of natural disaster risk itself and the way individuals respond to such risks has grown exponentially in recent years, the nature of the policy debate has changed only slightly.

Most scholarly studies of natural disasters start in largely the same way. An account of a particularly devastating disaster is offered. Tales are told of lives lost, belongings damaged, and the foundations of communities ravaged by one unfortunate event. Dollar figures of losses in the millions or even billions underline the tremendous human tragedy. The wrath of hurricane winds or the rapid collapse of buildings filled with honest citizens apparently make good reading. In recent years, the most popular of all are the three archetypes of modern disaster: Hurricane Andrew, the Great Midwest Floods of 1993, and the Northridge Earthquake. Together, these three disasters accounted for tremendous overall spending on disaster-related policies, prompting reform efforts by industry groups, citizens, and state and federal governments.

1.1.1 Hurricane Andrew

On August 24, 1992, Hurricane Andrew struck southern Dade County Florida after traveling from the west coast of Africa to the tropical north Atlantic. After devastating Dade County, Andrew traveled west and eventually crossed land again in south

2. Daniel Schorr, National Public Radio, January 22, 1994.

central Louisiana, causing an additional $500 million of insured losses despite striking a relatively sparsely populated region. Hurricane Andrew was the most costly disaster ever to affect the property-casualty insurance industry (IRC 1995). Total insured losses totaled $15.5 billion, but of course this is a drastic understatement of overall losses. The storm destroyed or damaged some 140,000 homes and six months after the storm nearly 20% of the local population reported being unemployed as a result of the storm (IRC 1995). Moreover, Andrew forever changed the face of the insurance industry in Florida. A total of nine insurance companies become insolvent as a result of Andrew and many others elected to severely curtail the writing of new policies (IRC 1995). The devastating winds killed 39 people, a number considered to be earily low, given the power and impact of the storm. The devastation that Andrew left in its wake remains even a decade later, not only in terms of physical impact, but also in the lore of local residents.

1.1.2 The Midwest Floods

In the Spring of 1993, record levels of precipitation caused flooding among many of the major river systems in the Upper Midwest.

> Rivers climbed above flood stage at approximately 500 forecast points in the nine-state region. Moreover, record flooding occurred at 95 forecast points in the upper Midwest during the summer of 1993. Flood records were broken at 44 forecast points on the upper Mississippi River system, at 49 forecast points on the Missouri river system, and at 2 forecast points on the Red River of the north System. ... At least 75 towns were completely inundated, some of which may never be rebuilt. In Hardin, Missouri, more than 700 coffins were washed out of grave sites, many of which have not be recovered (Brown, Baker, and Friday 1994).

Over 20 million acres of land across nine states were seriously affected and early estimates of the economic impact suggested losses in the range of $15-20 billion. The devastation during the summer months of 1993 destroyed most of the agricultural yield for that year, never mind the pollutants and raw sewage released by the flood (Brown, Baker, and Friday 1994). The entire state of Iowa was declared a Federal disaster area and the flood "destroyed family businesses, community schools, people's homes and property, and the treasures of their heritage"(Brown, Baker, and Friday 1994).

1.1.3 The Northridge Earthquake

At 4:31 A.M. Pacific Time on January 17, 1994, the ground began to shake in California, as it is known to do from time to time. The quake was centered in the Northridge district of Los Angeles, about 20 miles northwest of downtown (NYT 1994). The Northridge quake caused over $12 billion in federal disaster expenditures and $12.5 billion in insured losses, a figure three times larger than what insurers had received in premiums during the preceding twenty-five years (Moss 1999). The quake measured 6.7 on the Richter scale, killed 61 people and damaged over 30,000 houses, apartments and businesses (Noble 1996). In Northridge, an apartment building collapsed almost immediately killing 15 people; nearby in Sylmar, nearly 70 homes were destroyed by fires resulting from gas leaks; and, buildings and highways collapsed in San Fernando, Grenada Hills, Sherman Oaks, Resada, and other nearby communities (NYT 1994). Years later, the Federal government was still adding relief money to aid in the redevelopment of infrastructure and the economy.

1.1.4 The Punchline

What follows accounts like these, whether the author is describing earthquakes, floods, hurricanes, or even tornados is generally a condemnation of either individual behavior or government policy. How foolish for houses to be located so close to the river that they are destroyed by rising flood-waters. How careless that homes on a known fault-line are not constructed to withstand the force of even a modest earthquake. How absurd that local zoning regulations allow land-use in this manner, and how puzzling that the Federal government encourages risky behavior by subsidizing the cost of hazard insurance or doling out relief dollars after a disaster strikes.

As a general rule, there seem to be two points. First, natural disasters tend to be negative events. They destroy property, ruin lives, and often require enormous expenditures in order to recover. This is, of course, true, but it is not particularly pathbreaking. Second, the current situation is perverse. Towns hit by floods once are often hit by floods repeatedly; yet, these same communities often sit idly by, still unprepared for the next big one. Self-protective behavior is said to be minimal, and the costs are increasingly born by the Federal government and ultimately taxpayers. Why do those at risk consistently fail to protect themselves and why do the rest of us continue to pay the bill?

Much of what supposedly explains this situation is what Schelling (1978) referred to as a self-fulfilling prophecy. Citizens know that the Federal government will provide relief if a disaster strikes, so rather than spend their own money in the current period, they ignore the possibility of losses and do nothing. If a disaster does strike, the devastation is so widespread—because no one protected themselves ahead of time—that the Federal government faces enormous public pressure to help those in need. More often than not, the State does aid its citizens and the process repeats. Unfortunately, as discussed in the next chapter, the self-fulfilling prophecy story is filled with theoretical holes and is almost entirely inconsistent with the available empirical evidence, be it historical or contemporary. Yet, academics, politicians, and the popular press alike continue to subscribe to this theoretical orthodoxy. Indeed, it is an argument that seems quite intuitive. However, that should not stop us from engaging in empirical analysis, and when actual data are used to test the predictions of the self-fulfilling prophecy argument, it quickly falls. In the wake of its collapse, an old puzzle re-emerges in a slightly different form.

Historically, the question that drove most scholarly research on disasters was why do so few individuals protect themselves against serious and repetitive risk natural disaster risk. The self-fulfilling prophecy argument was a perfectly plausible response to that question. Unfortunately, in the real world, lots of people do manage catastrophic risk. In point of fact, there is tremendous heterogeneity in the way that people deal with disaster risk. While some populations choose to do nothing, many communities have developed extensive risk management and disaster response plans. Given this historical reality, the right question to ask is not why does no one manage catastrophic risk, but why do some people while others do not. How can we explain such divergent responses to similar threats and what does the answer tell us about our risk institutions in the United States? I return to this question repeatedly throughout the project since identifying an adequate answer is perhaps the most critical building block for the design of effective regulatory institutions.

1.1.5 Framing and Thesis

On the one hand, this project seeks to build a positive account of individual decision-making about disaster risk. By mixing insights from mainstream economics and cognitive psychology, a more comprehensive and accurate account of decision-making can be offered. On the other hand, as a political scientist, I am fundamentally concerned not just with individual decision-making, but also with the ultimate structure of government policy. Indeed, in this arena, as in many, the two issues are inextricably linked. To model individual decisions without an eye towards the structure of government policy is foolish, as is ignoring the social and economic context in which government risk institutions developed. A realistic account of our social response to catastrophic risk must craft a story that tacks back and forth between citizens and the State, and between theory and empirical evidence.

The thesis for this project is as follows. Individuals do not always make rational decisions about catastrophic or natural disaster risk. They use heuristics to evaluate risk and exhibit biases, some of which are consistent with insights from cognitive psychology and behavioral economics. Specifically, individuals rely on availability as a heuristic for evaluating risk, which often results in biased or mistaken beliefs. These individual level biases can sometimes spread through communities resulting in herd behavior. Individual biases can increase the probability that entire communities will engage a sub-optimal risk management strategy. Part of what we observe at the aggregate level is local homogeneity and global heterogeneity, controlling for the actual level of risk exposure. Local homogeneity and global heterogeneity implies that when disasters strike, some communities will be well-prepared and others will be completely unprotected. Given the nature of social sympathy and political pressure, politicians will often be driven to offer disaster relief, even when they realize there may be negative consequences of doing so.

Note that this is traditionally where a variant of the self-fulfilling prophecy argument would stop, simply asserting that citizens are aware of this fact, and will therefore, never start managing disaster risk. However, this is not the end of the story. Given this social reality, politicians should (and do) make strategic political choices about institutional arrangements. It is not just citizens who respond strategically to public policy, but also politicians who reply strategically to citizen behavior. Indeed, rather than focusing solely on the way that actions of the State create incentives for citizens, we should also be asking about how the behavior of citizens creates incentives for political actors. That is, rather than assuming institutions are exogenous and asking about their effect on citizen behavior, we can and should seek to endogenize the institutions of risk policy and ask about the conditions and contexts that gave rise to these institutions in the first place.

For example, historically, as disaster policy developed, politicians made choices that were partially a result of constraints imposed by patterns of citizen behavior. These patterns affected the internal political dynamics within Congress. Though the decisions that politicians made were reasonable, they also created unintended social consequences. One thing politicians did was to delegate primary responsibility for disaster policy to the bureaucracy. This may have been a reasonable response to the inter-temporal challenges of dealing with at-risk populations. However, centralizing disaster policy in the bureaucracy also created new incentives for organized interests to seek rents with greater fervor. As more interest groups became involved in the policy arena, the range of benefits expanded to the point of largesse that is generally criticized with such vehemence today. This is an excellent example of why studying disaster risk requires a foray into the way citizens perceive and evaluate risk, a model of how such evaluations translate into social behavior, and an understanding of how this social behavior constrains the strategies of political actors responsible for designing regulatory institutions. The project seeks to explain why we observe the particular social equilibrium that we do by clarifying the individual and institutional factors that gave rise to the current state of affairs. In this sense, the project is primarily positive in nature. However, part of what motivates this positive question is the normative challenge of creating effective and meaningful public policy.

1.2 Regulating Risk

Risk, either technological or natural, is virtually everywhere in modern society. Risk-bearing can be understood as an economic good like any other, which under many conditions, the market should distribute efficiently (Arrow 1996). However, historically the private market has had trouble distributing natural hazard risk. One reason is that individual disaster risks are thought to be highly correlated with each other. If a hurricane hits one member of a community, it is likely that it will hit other members of the same community. Thus, risk aggregation, if it is to succeed in reducing overall risk has to spread the risk across a larger pool of participants.[3] Another reason is that until recently, technology made it difficult to accurately distinguish between high and low risks in a region. Especially for flood risks, houses in close proximity to each other may have quite different levels of objective risk exposure. Though technological advances are helping somewhat, distinguishing high from low risks remains a challenge. Partially because of this fact, premiums for natural hazard insurance have historically been quite high, resulting in adverse selection. Low risk individuals opted out of the pool, leaving only high risk individuals, whose risks were often correlated. A final reason is the difficulty of creating accurate actuarial tables for natural hazards makes it harder for insurers to calculate an appropriate amount of reinsurance to purchase. In the months leading up to Hurricane Andrew, many

3. See generally the collection of essays in Froot (1999) or Freeman and Kunreuther (1997).

insurance companies did not carry adequate reinsurance, and when Andrew struck, scores of companies were sent into insolvency. For all these reasons and some not treated until later in the project, the private market for allocating catastrophic risk has historically functioned relatively poorly in the United States.[4]

The historical difficulties exhibited by the private insurance market have meant that local, state, and Federal governments have often become centrally involved in the management and regulation of catastrophic risk. The Federal government has offered its own form of hazard insurance, experimented with hybrid public-private ventures, and has developed an extensive array of legislative measures supposedly designed to minimize aggregate risk exposure. Few of these policies have proven particularly effective and the joint failure of both the private market and the public forum has led a number of scholars to recently reconsider the interaction between the market for catastrophic risk and government regulatory institutions (Arrow 1996; Epstein 1996; Kante 1996).

Though many scholars acknowledge that the policy problems arising from natural disasters are actually risk problems, far fewer conceive of the policy domain as a type of risk regulation. Risk regulation incorporates a fairly broad range of governmental policies which are designed to control the level of risk to which citizens and society are exposed. Most regulatory policy of this sort has targeted things like pollution or toxic substances that increase the odds of death or disease. The regulation of pesticides is a classic example, but the class of policies extends to things like automobile safety regulations (Cheit 1990) or even tobacco policy (Viscusi 1995). When cast in this light, it is clear that disaster policy, whether designed to give relief to those in need

4. Whether this is a bonafide case of market failure is up for debate. However, commentators have consistently suggested that the classical preconditions for effective and efficient functioning insurance markets do not exist for natural disaster risk.

after disasters, encourage people to plan for floods before the fact, specify standards or codes for building construction, or explicitly prohibit habitation in certain areas, is undoubtedly a form of risk regulation. All these policies create social incentives that decrease, or sometimes unintendedly increase, individual and aggregate social risk exposure. Moreover, like many forms of risk regulation, there are times when the interests of the State and the interests of private citizens diverge. These dynamics warrant specific attention as well. Just as the market is one potential mechanism for allocating risk throughout society, so too are the institutions of the State, and we should understand these regimes as alternative mechanisms for allocating risk. The challenge is to analyze the choices of individual citizens while giving adequate attention to the incentives created not just by the market, but also by the State. To understand the current legislative structure, we need to elucidate this nexus of private decisions, social risk, and public policy.

1.3 Methodology

Adequately explaining our risk institutions requires selecting the appropriate methodological tools. This project mixes quantitative, formal, and historical analysis. Though each of these methods comes with its respective pitfalls, I believe the collective sum provides far more convincing evidence than any one could provide alone. Each method allows for insights that the other two simply do not. Formal models allow for rigor and clarity that may be lacking in informal treatments. Quantitative methods allow us to test predictions that seem obviously true in the context of a formal model, but which may, in fact, be false in the real world. Empirical or historical analysis allows for attention to the details of underlying political dynamics that would otherwise be lost in summary statistics. The pitfall of mixing methodologies is that one antagonizes all readers, rather than satisfying a few. Nonetheless, for an interdisciplinary topic like this one, methodological diversity is essential.

1.4 Audience

The project speaks to at least three related audiences. First, the project addresses the ongoing debate between mainstream economists and cognitive psychologists about the way individuals make decisions about risk. Going back at least as far as the 1950's, an active scholarly debate has sought to clarify whether rationalist assumptions are reasonable proxies for actual decision-making. Originally, rational choice scholarship met with criticism from two flanks. On one side, work in the bounded rationality school sought to question the plausibility of economic models that emphasized full information and true utility maximization. An extensive body of work by March, Simon, and others tried to model individual behavior using less heroic assumptions about cognitive capacities. On the other flank, a group of scholars with psychological intuitions sought to question the rationality assumptions using largely experimental methods. These well known findings (e.g. Ellsberg (1961)) showed that individuals often do not exhibit risk preferences consistent with the rationalist paradigm. (Kahneman, Slovic, and Tversky (1982) and Kahneman and Tversky (2000) contain excellent summaries.) Moreover, individuals in these studies often made systematic mistakes when evaluating risk. They misperceived the probability of certain events, and had difficulty accurately comparing different levels of risk. By questioning the cognitive foundations of rational choice scholarship, cognitive psychologists and behavioral economists sought a revision if not an outright rejection of the mainstream paradigm. The debate now has its parallels in law (Jolls, Sunstein, and Thaler 1998;

Sunstein 2000), political science (Hogarth and Reder 1987; Green and Shapiro 1994), and continues to be an area of active scholarship.

There is little doubt that this debate has been healthy and productive. Yet as its duration passes five decades, it is also time to acknowledge that both schools of thought are likely partially correct. Though further clarification and more rigorous empirical testing is no doubt required, the time has also come for some modest integration. The strength of rational choice models is in their parsimony, rigor, and flexibility. But it is precisely these strengths that allow for strict rationalist assumptions to be relaxed and for more accurate cognitive regularities to be introduced into models. In certain real world decision-making arenas, we have a good sense of the biases that individuals tend to exhibit. In these cases, there is simply no compelling reason for maintaining contrary assumptions. At very least, we should endeavor to compare models using purely rationalist assumptions with those integrating insights from cognitive psychology. Given the nature of disaster risk, the readily available empirical evidence, and the enormous overall level of social risk exposure, the subject matter is clearly ripe for such an enterprise.

A related but more general issue is the design of efficient and effective government policy. The reality is that the logic of market incentives underlies a great deal of risk regulation in the United States (Wildavsky and Dake 1990; Spence 2001). Yet, in many cases, citizens respond to selective incentives in ways contrary to theoretical predictions. Especially when the stakes are life, death, and financial losses in the billions of dollars, as is the case with natural disaster policy, we should ensure that the models that guide our policies are the most rigorous and accurate ones available. Though a plethora of theories about risk management behavior abound, more rigorous empirical testing about the way individuals respond to social, market, and government incentives is an absolute must for the construction of effective legislative institutions. Though this project focuses on the catastrophic risk and natural disaster policy arena, the theoretical point applies more broadly. It applies at very least to other forms of risk regulation, and likely to a range of government policies that rely on the logic of selective incentives derived from a strict rationalist foundation.

Like the basic theoretical point, the central methodological approach also has more general applications. The methodological innovations of the project are two-fold. First, one piece of the project addresses the challenge of designing empirical tests for the existence and impact of heuristics and cognitive biases outside of laboratory contexts. Even today, the vast majority of evidence in behavioral economics comes from laboratory experiments. In order to move this research agenda forward, developing methods to test the predictions of behavioral economics outside the laboratory is an absolute must. By relying on a mixture of market, government, and industry data, this project devises original empirical tests of heuristics and biases in real world contexts. For members of the behavioralist research community, the development and application of these statistical methodologies may be of direct interest. Second, the introduction of non-rationalist actors into otherwise rational models is just now beginning to yield productive insights in other fields. The exposition of how one utilizes simple and straightforward game theoretic forms to understand the dynamic between biases and behavior is clearly methodologically relevant for those working well outside the substantive area of catastrophic risk. The basic intuition has potential relevance for mainstream political science, law, and economics.

1.5 Structure and Organization

Chapter 2 develops the background issues of natural disaster risk in the United States by discussing the dominant literatures from the social sciences. The chapter argues that neither rigid economic models nor purely psychological accounts are adequate characterizations of individual decision-making in this context. Theoretical treatments from both schools of thought are plentiful, but rigorous hypothesis testing is not. To compensate for this shortcoming, the chapter proceeds with an eye towards developing empirical hypotheses that can be tested using market data to verify or reject the respective theories. Chapter 3 contains the main empirical findings on this front, demonstrating that behavioral economics has something to say about real-world risk decisions, but that even after accounting for obvious causal factors, substantial heterogeneity with respect to risk behavior remains. Against this backdrop, chapter 4 develops a formal model of individual choice that integrates findings from cognitive psychology into otherwise rational models of choice. By working with an extremely simple game form, it is possible to clarify the potential effects of heuristics and biases on social equilibria. The chapter demonstrates that under fairly general conditions, communities facing similar actual risk exposure may respond with entirely different risk management strategies. In certain cases, individual level biases can spread through communities, making it harder for other individuals to make optimal choices about risk management. Herd behavior around sub-optimal decisions can easily result. In one sense then, chapter 4 develops the implications of individual behavior for social groups. After the theoretical development of the model, chapter 5 develops a new method to test the cascade model of chapter 4 empirically, using parameterized variance models from econometrics. The chapter provides an additional layer of empirical support for the model of risk management behavior by mixing Maximum

Likelihood Estimation (MLE) and Markov Chain Monte Carlo (MCMC) methods. With these empirical findings in hand, chapter 6 turns to the implications of these patterns of group behavior for the structure of government institutions. Using a mixture of historical data and basic quantitative analysis, the chapter offers an analysis of political choice about risk institutions. With an understanding of the pressures put on politicians by risk-taking citizen behavior, it becomes possible to recast political decisions about delegation and oversight, and better explain the social incentives created by the institutions of risk regulation. Chapter 7 concludes by reconsidering the challenges of policy development in light of the revised theory of citizen decision-making and political choice. In sum, the project begins with a foundation of methodological individualism, and from that starting point, adds layers of analysis that explore the interaction between individual and group decision-making, group behavior and political institutions, and political institutions and organized interests.

1.6 Definitions and Scope

Before moving forward, I want to clarify a few important terms. By catastrophic risk, I mean a low probability high consequence event whose occurrence is uncertain.[5] The project limits the class of events in question to those typically called natural disasters, including, but not limited to, hurricanes, floods, earthquakes, tornadoes, and other forms of severe environmental hazards whose probability of occurrence is small, but whose impact is extremely large. This limitation excludes a broad class of technological risks and catastrophes ranging from Three Mile Island to the Bhopal disaster.[6] This distinction is primarily one of convenience since the remaining class is

5. This definition is adapted from Camerer and Kunreuther (1989).

6. See Fischer (1996) for a discussion of the Bhopal disaster.

still far too large for comprehensive consideration. However, limiting the discussion to natural disasters has the beneficial byproduct of avoiding the controversy in the risk perception literature about "man-made" versus "natural" risks.[7] Moreover, since the project is concerned with political institutions, constraining the class of inquiry allows the policy discussion to be more specific since natural disasters have many of their own legislative measures.

Why does catastrophic risk warrant its own inquiry? According to conventional economic models, there is nothing particularly distinctive about catastrophic risk. To a rational actor, a low probability high consequence event is treated no differently than a high probability low consequence event. Both the probability and severity of the event are weighted, expected utility calculated, and an ultimate decision made. Yet, experimental work suggests this may oversimplify the reality of individual choice. Individuals often have trouble evaluating risks, and this propensity is especially intense for catastrophic risks. Individuals may systematically under- or over-estimate the likelihood that a negative event will occur; and, the severity of the negative event in question implies that mistakes may be particularly costly. They are catastrophic, by definition, for the individual, but in the United States at least, choices about catastrophic risk have implications for others since taxpayers often bear the costs of cleanup and recovery. Finally, because of the complex interaction between risk perception, management decisions, organized interests, and government incentives, the field is a particularly fertile one for scholars of risk and regulation.

In recent years, risk management has received tremendous attention both in the private market and in academia. For my purposes, I do not have a particularly complicated conceptual definition in mind. By risk management, I mean simply

7. For a discussion, see Slovic, Fischoff, and Lichtenstein (1985).

the engagement of a strategy to balance the risks one faces by using one or several of a series of management technologies including, but not limited to, structural mitigation, non-structural mitigation, insurance, self-insurance, avoidance, or other forms of risk-sharing, risk-spreading, or risk-transfer. Mitigation refers to efforts intended to minimize the consequences of an event should it occur. In the early part of this century, most efforts to deal with environmental hazards involved "structural mitigation," steps like the construction of dams or levees to avoid damages from floods. In the 1970's, experts began to emphasize "non-structural mitigation" involving individual-level actions like the installation of hurricane shutters to avoid wind damage or anchors on water heaters to minimize earthquake damage. Unlike mitigation, insurance mechanisms are designed to share or spread risk. Insuring for all or part of the loss from a natural disaster allows some of the risk to be transferred to a third party, though at a price. The actual consequences of the event are not minimized or avoided, but insurance mechanisms restructure the financial ramifications.

The range of both mitigation and insurance technologies has evolved substantially during the past century. The creation of *catastrophe bonds* and the development of a financial instrument indexed to overall losses in the property and casualty insurance industry traded on the Chicago Board of Trade (PCS Catastrophe Index) has yielded new and innovative ways to manage catastrophic risk.[8]

1.7 Summary

This chapter has tried to offer an introduction to the main questions with which the remainder of the project will grapple. Rather than a formal introduction to the issues

8. These instruments are not generally used by individuals. However, they provide some hope for the development of a larger and more efficient hazard insurance industry. For a discussion of some of these innovations, see Froot (1999).

of risk perception, natural disasters, and government policy, I have tried to give a flavor of the relevant issues and postpone formal definitions until required. In essence, the project asks about the relationship between how people behave empirically and the design and maintenance of regulatory institutions that target such behavior. The remainder of the project will move from the micro level of individual citizens to the macro level of government policy. Keeping this progression in mind may help as the project proceeds. While each piece of the project focuses on a specific level of analysis, the overarching goal remains the same: an understanding of the social treatment of catastrophic risk in the United States. This task is important not just for academic reasons, but also for the ultimate reduction of losses of life, capital, and resources that natural disasters claim each year.

CHAPTER 2

THEORIES AND EVIDENCE ON CATASTROPHIC RISK

2.1 Introduction

Fundamentally, this project is concerned with explaining how individuals respond to catastrophic risk and how citizen behavior affects political choices about regulatory institutions. Unlike much previous work on risk, which has asked why individuals view some risks as unacceptable while other risks as tolerable,[1] this project seeks to clarify how citizens make choices about one particular type of risk. Part of what drives this question is the economic reality that losses from natural disasters are large on a social scale, but also frequently devastating at the individual level. Intuitively, one might think that catastrophic risks would be particularly ripe for extensive management and avoidance. Yet, private citizens often elect not to engage in any meaningful risk management. This presents a puzzle. Given the potential for devastating losses and the relatively frequent media attention given to natural disasters, why do more individuals not engage in self-protective strategies to guard against catastrophic risk?

Two schools of literature tend to dominate this discussion. Both focus on the way individual actors perceive, evaluate, and make decisions about risk.[2] First, economic models of individual choice argue that individuals weight the probability and severity of a potential event to calculate the expected payoff of managing the risk. By relying on some basic form of cost-benefit analysis, individuals take steps to manage the risk if the expected benefits of doing so outweigh the costs. Theoretically, there is nothing particularly distinguishing about catastrophic risk, as opposed to more routine risk, and there is no reason not to rely on the same framework of expected utility theory

1. See, for example, Wildavsky and Dake (1990), Margolis (1996) or Rogers (1997).

2. To be fair, there are other dominant theoretical paradigms as well, though these tend not to be methodologically individualist. For example, the extensive work by Mary Douglas (1985) focuses on social norms and group relations as determinants of individual judgements about risk. Similarly, see Douglas and Wildavsky (1982). For the time being, I emphasize economic and psychological models because they operate at the same level of analysis.

or a modest variation.[3] On the other hand, cognitive psychologists and behavioral economists argue that individuals exhibit systematic biases when evaluating risk and that such biases can help explain individual behavior in this choice context. Experimental and market evidence indicate that individuals often exhibit choice behavior that does not conform to the maxims of expected utility theory, and may systematically under- or over-estimate objective risks. In one sense, this debate is no different than most debates between economists and psychologists. However, neither camp has been particularly adept at applying their respective theoretical models to the specific case of catastrophic risk. Moreover, neither has adequately evaluated their theoretical models with enough empirical evidence.

The underlying point of this project is not to reject either account of individual decision-making; both are clearly partially correct. Nonetheless, it is also clear that both approaches are incomplete accounts of choices in this arena. My point is not simply the stock claim that the two prevailing theories should be integrated or synthesized. On the contrary, the point is that cognitive biases and strategic interaction affect each other in systematic ways to yield social equilibria that may be sub-optimal, and that such processes have implications for the structure of institutional environments.

Though my theoretical approach necessitates mixing rationalist and cognitive models, much clarification is required before doing so. Many insights from experimental economics and psychology have been transplanted to the analysis of catastrophic

3. This statement not quite accurate. Because catastrophic risks are highly ambiguous, variance-based utility models or contingent valuation models would distinguish between catastrophic risk and other types of risk for which probabilities are better specified (i.e. specified with greater precision). A brief treatment of ambiguity is included later in this chapter.

risk though they clearly do not apply empirically. Decision-regularities like the gambler's fallacy or risk aversion are robust in other contexts, but they are inconsistent with the evidence here. Second, basic economic models of insurance or risk spreading match poorly with what we know about citizen behavior. For example, individuals simply do not purchase hazard insurance when a rational individual would do so. The underlying framework for analysis is still helpful, but it requires extension and reform to be properly applied. The extended economic model, popular in government and academic circles, argues that citizens who do not manage catastrophic risk are simply responding to perverse social incentives created primarily by government policy. Though I am sympathetic to analysis that suggests there are unintended consequences of government policy, these accounts do not go nearly as far as their proponents suggest. At best, they are inadequate; at worst, they are misleading and wholly inconsistent with the data.

The argument for this project is straightforward. The mixture of experimental and market evidence demonstrates that individuals exhibit certain cognitive biases in their decisions about disaster risk. Individual bias is important, but such biases can be magnified and spread through a process of strategic interaction within communities. As individuals interact, information about uncertain risk management technologies may not be efficiently aggregated. Private information can be quickly lost and herd behavior results, often around the wrong management technology. This social outcome implies that many communities will be almost completely unprotected when disaster strikes, leaving ex post relief as the only viable government response. Consistently biased citizen demand for legislative intervention (or inaction) puts a distinct type of pressure on politicians. Rational politicians may seek to create regulatory institutions that manage the predictable nature of public pressure, and strategic actors known as risk-entrepreneurs, who understand the social biases involved in natural disaster policy may be able to extract gains from the political process, further constraining the regulatory environment.

The central task for this chapter is to discuss the dominant approaches to individual decision-making about disaster risk. Though descriptive data are included, the tone is more positive in nature. How can individual behavior best be explained? The chapter is structured as follows. Section two provides an overview of the descriptive literature and introduces the competing theoretical frameworks. Section three discusses economic models of risk and section four treats psychological models. Section five summarizes my argument and discusses the path of the remainder of the project.

2.2 Empirical Evidence

How do citizens respond to the threat of natural disasters? The dominant account in the popular press is that citizens simply ignore such risks.[4] To the extent that citizens are even aware that such a risk exists, they are confident that the Federal government will bail them out with ex post relief should a disaster occur and as a result, they do not engage in any ex ante risk management. When disaster strikes, entire communities are left unprotected and without the resources to adequately recover. For some types of populations, in some regions, facing certain types of natural hazards, this is a fairly good short-hand; but in most cases, it oversimplifies and misrepresents the truth. There is actually substantial heterogeneity in the way that individuals and communities perceive and manage catastrophic risk. While some certainly elect to

4. For recent treatments of the economic aspects of catastrophes see Priest (1996), Zeckhauser (1996), Kunreuther and Roth (1998), Kunreuther (1996), or Dacy and Kunreuther (1969). For a discussion of political issues, see Platt (1999), Froot (1999), Noll (1996), or May (1985).

take no action, others invest in both mitigation and insurance with regularity, as evidenced in the following chapter.[5]

Although hard to believe when watching the aftermath of a hurricane on television, contexts do exist in which individuals are simply not aware that a catastrophic risk exists. For example, 100 year flood zone maps detail the probability of a serious flood occurring during the span of a given century. But, that implies that even high risk communities might not have experienced a serious flood within a reasonable period of historical memory.[6] Moreover, market incentives may inhibit the production and distribution of accurate information about natural hazard risk. For example, real estate agents are required to disclose the fact that a structure is located in a flood plain. However, such information is almost certain to decrease either the price of the property or the probability of a sale. Likewise, federally guaranteed mortgages on properties in flood plains are required to have hazard insurance; however, banks have virtually no incentive to enforce this requirement. Little incentive for honest information revelation exists since there is virtually no punishment mechanism and banks themselves do not have to bear the risk.

That said, most citizens exposed to natural disaster risk are aware of this fact. Public opinion data on citizen perception of natural risks indicate that nearly sixty percent of the population thinks that it is likely they will be struck by a major

5. For example, see the discussion of Olin and Rapids City Iowa in Chapter 4.

6. While many citizens exhaustively research the region, neighborhood, and property to which they are planning to move, others rely on real estate agents, developers, and financial institutions to guide their actions. Unfortunately, these institutional actors often have an incentive against providing accurate information about hazard risks since property value and/or the likelihood of a sale may decrease with accurate information. Although economic considerations may not dominate disclosure decisions, they do provide good reason to question whether information producing mechanisms might be warranted in this policy arena.

Table 2.1: Perception of Disaster Risk by Region, 1998

Region	Disaster Likely	(N)	Total Respondents
New England	67%	(86)	128
Mid-Atlantic	48%	(99)	207
East North Central	65%	(236)	363
West North Central	61%	(110)	181
South Atlantic	62%	(182)	294
East South Central	88%	(122)	139
West South Central	54%	(128)	238
Mountain	19%	(21)	111
Pacific	65%	(202)	311

Source: Insurance Research Council, 1999

natural disaster (IRC 1999; IRC 1995). According to experts, this is a drastic overestimation.[7] Table 2.1 presents the proportion of respondents who believe they are likely to be affected by a natural disaster in the next decade, broken down by region. At least at this basic level, natural hazard risk does not go unnoticed by most citizens. Though few residents of the Mountain region think a natural disaster is likely to affect them, most regions cluster at between fifty and sixty percent. Still, it is worth noting that even at this aggregate level, a good deal of heterogeneity exists. As few as 19% and as many as 88% of the regional respondents think they face, at least, moderate disaster risk. Moreover, public opinion surveys conducted by Kunreuther (1978) and Palm (1998) suggest that perception or awareness of disaster risk waxes and wanes substantially. In the immediate aftermath of a disaster, awareness is, not surprisingly, acute. However, in the years after a major catastrophic event, awareness fades.

7. The actual population at even modest risk is substantially lower (somewhere on the order of 10 percent), and the probability that any given individual will be struck during that time period is generally thought to be less than one percent, but certainly not greater than five percent.

Most available evidence on disaster risk comes from data on participation in hazard insurance markets, which have a fairly spotted history in the United States. Market participation has been sporadic and often controversial.[8] Even when property insurers were willing to offer hazard insurance, consumers generally viewed the premiums as too expensive.[9] Moreover, many companies that did enter the market exposed themselves to too much risk without enough reinsurance. For precisely that reason, a major catastrophe like Hurricane Andrew in 1992 forced many companies into insolvency and sent many others fleeing the market (IRC 1994). In response to the resulting dearth of affordable property insurance, regulators in Florida increased restrictions on market entry and exit, making the market an even more questionable venture for firms.[10]

The National Flood Insurance Program (NFIP), a Federal program that subsidizes the cost of flood insurance premiums, is one helpful source of data about citizen behavior. Historically, the program has been criticized for low participation rates even when participation was required by law. Participation has shifted between five and twenty percent of the households exposed to enough risk to qualify them for the program. As of 1997, the Federal Insurance Administration (FIA) estimated that 27 percent of the households located in high risk flood zones were insured (Palm 1998).

8. This is true for a number of reasons. Most importantly, natural hazards are remarkably hard to accurately predict, and even with modern technological advances it is difficult to create accurate actuarial tables to price insurance. Thus, functioning markets require a large population in a geographically dispersed region so that risks are not too highly correlated.

9. Some argue that this resulted in adverse selection. Generic adverse selection problems arise from an inability to separate high from low risks. Premiums that are too high will attract only high risk consumers.

10. For discussions of hazard insurance, see Froot (1999), Kunreuther and Roth (1998), or Freeman and Kunreuther (1997).

Some citizens are simply unaware of the availability or details of flood insurance. This was true some 20 years ago when Kunreuther (1978) produced his early work, and remains true today according to a 1995 survey (IRC 1995). When asked why they do not purchase insurance, individuals tend to cite either the cost, which can be substantial even at a government subsidized rate, or the fact that they do not think they are at much of a risk (IRC 1995).

Many commentators have suggested that the demand for flood insurance in the United States is virtually non-existent. Certainly, it is not high enough for a national insurance program to be self-sustaining (GAO 1990a). These claims are generally rooted in Government Accounting Office documents that evaluate the success of the NFIP as a self-sustaining insurance entity, rather than a government program concerned less with financial independence than regulating a certain type risk. GAO studies highlight the fact that nearly 80% of the communities that could participate in the NFIP elect not to do so, and that in some years, the program loses money (GAO 1990a; GAO 1990b). Moreover, even when carrying insurance is mandated by law,[11] the level of participation seems arbitrary. In Texas, after the 1989 floods, as few as 10 percent of the properties that were legally mandated to carry insurance had active policies. On the other hand, an audit in Maine during a similar time period (1987), found that coverage was as high as 70-80 percent (GAO 1990b).[12]

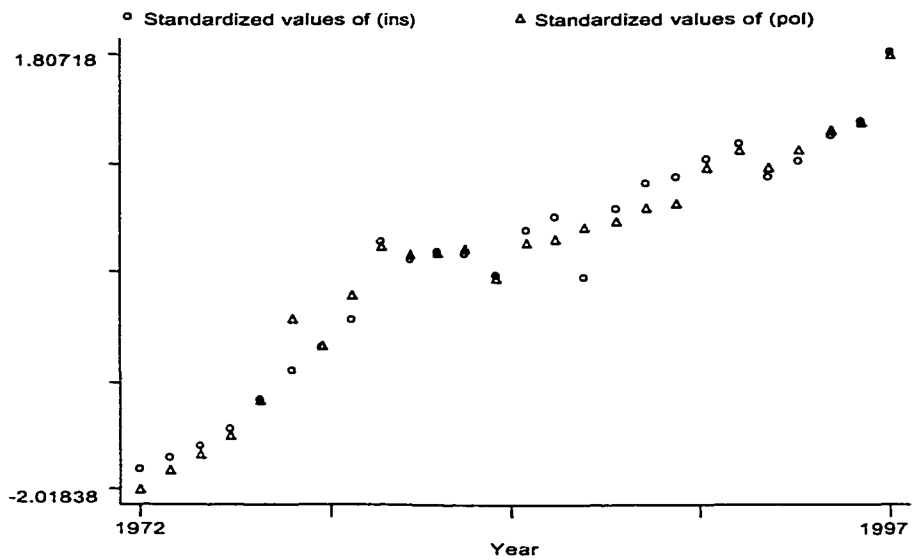
In reality, claims about the NFIP's failure are more hyperbole than anything else. Concerns about financial viability were raised in the late 1980's and early 1990's when the U.S. had been struck by a series of particularly costly floods. On average, the

11. Flood insurance is mandatory if a property is located in a government-designated flood plain and the dwelling has a government-backed mortgage.

12. Chapter 3 contains a discussion that sheds some light on regional differences like this one.

NFIP is self-sustaining, taking in premiums approximately equal to the payments it makes (across different years) (GAO 1990b). Since being implemented in 1968, overall participation in the program has grown steadily over time, as the plot of policies in force and the dollar value of policies in force in Figure 2.1 clearly shows.[13] The number of policies in force in 1972 was just 92,228 compared with 3,302,693 in 1997. The per capita figures are just as striking, moving from 0.44 policies per 1,000 people in 1972 to 12.37 policies per 1000 in 1997. Whether the shift is from a completely insignificant number to a moderately insignificant one is an open question. Nonetheless, there has clearly been a relative increase in the number of policies sold each year.

Figure 2.1: Flood Insurance Program Activity, 1972-1997



13. A plot of per capita policies or insurance in force looks almost identical. The values of policies and insurance are standardized so that the scale of the y-axis is the same. The transformation does not alter the time trend.

Even more important, there is tremendous regional variation in the insurance trends over time, a fact that is typically ignored by commentators seeking an overall characterization of the program. Table 2.2 contains the mean and median per capita flood losses and flood insurance policies by region. Irrespective of whether we rely on mean or median figures, there is obviously significant variation with respect both to per capita losses and to per capita flood insurance coverage. The two highest regional loss averages are the West North Central and West South Central regions. The West North Central region is made up of Iowa, North Dakota, South Dakota, Minnesota, Missouri, Nebraska, and Kansas. The West South Central region consists of Arkansas, Louisiana, Oklahoma, and Texas. Devastating floods often hit this area, and thus, the loss figures make general sense. What is somewhat more surprising is the low level of per capita losses in the South Atlantic region, which experiences frequent hurricanes that produce flood damages. Indeed, some of the highest per capita insurance coverage is found in regions with the lowest per capita flood losses. This is puzzling and a point I return to later in the chapter. In addition to the variation with respect to flood losses, there is also significant variation with respect to flood insurance coverage. The South Atlantic and West South Central regions have high mean levels of insurance coverage, while the East North Central region has the lowest mean level of coverage. What is particularly surprising is the high level of coverage in New England and the Mid-Atlantic states, relative to the level of losses they tend to experience. Why individuals are more likely to insure in the Northeast, despite relatively infrequent floods is a puzzle.

Figures 2.2 and 2.3 contain the per capita flood insurance policies for states in New England and the East North Central regions respectively. In New England, almost each state in the region seems to reach an equilibrium point (loosely speaking) at

Table 2.2: Per Capita Losses and Flood Insurance coverage, 1972-1997

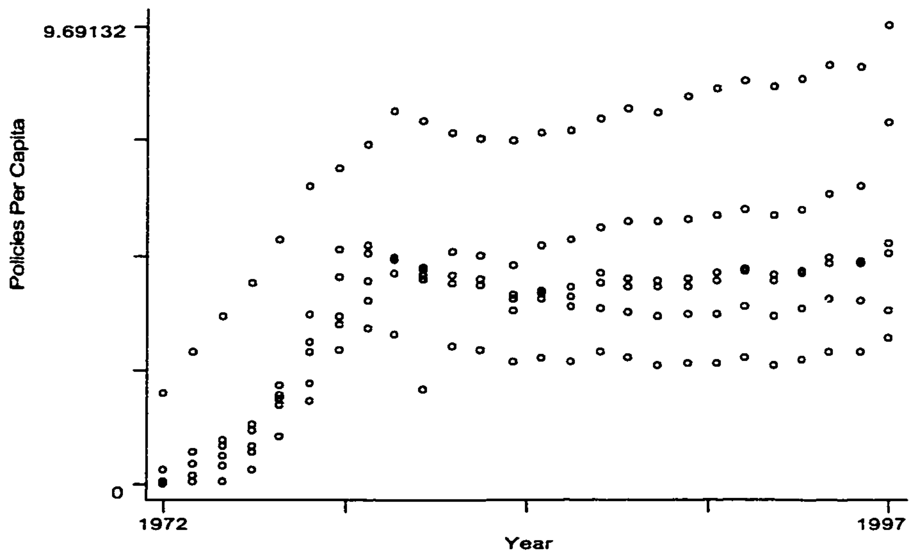
	Means		**Medians**	
Region	Policies	Losses	Policies	Losses
New England	4.03	4.98	4.18	.04
Mid-Atlantic	6.70	3.70	4.55	.39
East North Central	1.63	9.53	1.61	1.59
West North Central	3.17	103.03	2.54	2.84
South Atlantic	11.51	7.95	6.61	.301
East South Central	4.88	14.99	3.86	1.34
West South Central	16.37	39.36	3.99	2.88
Mountain	3.07	15.98	2.53	.39
Pacific	2.83	27.25	2.49	.53

about 1978-1979. Until that point every state in the region exhibits fairly constant policy growth, and from that point forward, the number of per capita policies levels off with only a slight drift upward over the next 15 years.

Though like New England, the East South Central region also sees a spike in the 1970's, after a brief pause, the number of policies increases at a similar rate afterward. The trend looks more like a continuous rate of growth during the past quarter-century. Perhaps even more to the point, Figures 2.4 and 2.5 show the level of policy coverage in the South Atlantic region (excluding Florida) and the data for Florida itself. The graphs are presented separately because growth in Florida significantly outpaces the growth in the rest of the region.[14] Nonetheless for the entire region, the number of policies in force each year increases steadily throughout the entire time period. In the aggregate, coverage looks like it has increased uniformly. However, at lower levels of aggregation, it becomes clear that patterns of insurance coverage differ substantially. Of course, this stands to reason, but it also means that heterogeneity is a key piece of

14. Including Florida suppresses the visibility of the trend in the rest of the states because of the uniform scale of the y axis in the plot.

Figure 2.2: Per Capita Flood Insurance Policies in New England

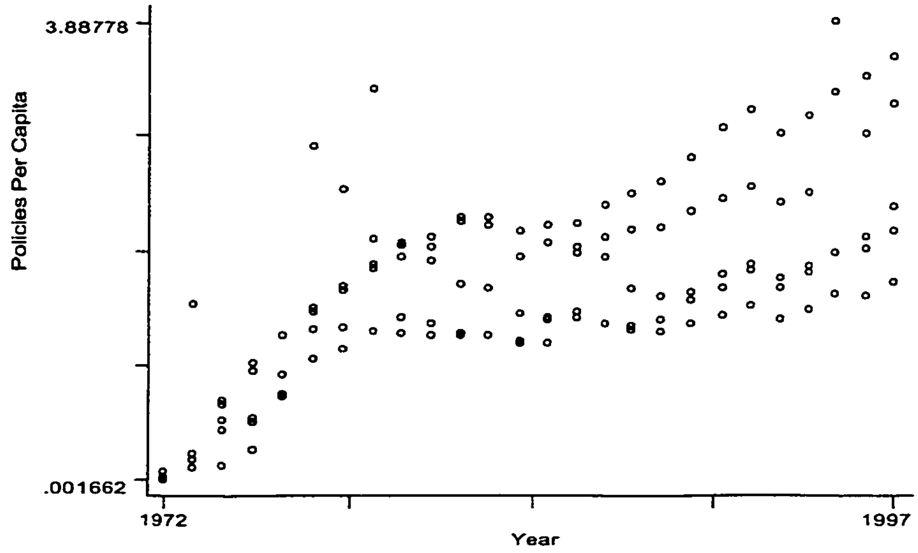


the overall puzzle. Patterns of hazard insurance coverage differ across regions, states, and time.

Evidence from the earthquake insurance market is largely similar, though much less comprehensive. Approximately, 35 percent of the U.S. population is exposed to earthquake risk; however, earthquake insurance is not required for high risk zones. Both the demand for and the supply of residential coverage is dominated by the California market, where earthquake insurance was privately offered as early as 1916, but with exceptionally low levels of participation (Kunreuther 1978).[15] After the 1926 Santa Barbara earthquake, market participation increased dramatically, but economic hard times during the depression again stemmed demand. During the next

15. Apparently demand was low because of a misconception that damage from earthquakes result primarily from fire, as they did in the 1906 San Francisco earthquake. Fire damage is generally covered by standard homeowner's insurance policies (Palm 1990).

Figure 2.3: Per Capita Flood Insurance Policies in East North Central Region

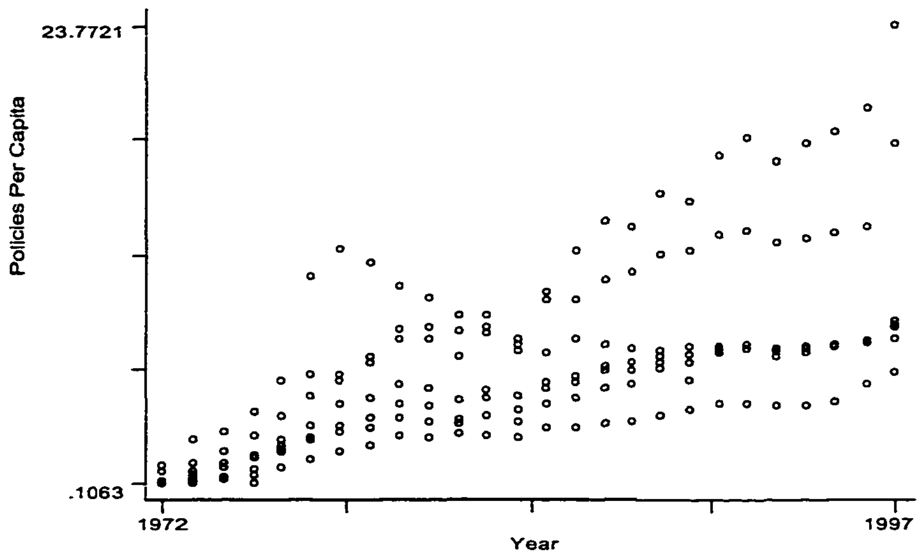


50-75 years, the level of coverage slowly increased again, but never to an overwhelming degree. As of 1976, Kunreuther (1978) found that fewer than five percent of homeowners in California carried insurance and a full quarter of those citizens were unaware that coverage was even available.[16] Kunreuther (1978) found that citizens who did carry insurance were more likely to assign a high or medium probability to a disaster event than those without insurance, and insured individuals expected a higher level of damage to their homes if a disaster struck.[17] Whether that finding is the result of a rational decision-making procedure or an ex post rationalization is

16. For related international work, see Asgary and Willis (1997).

17. That is, those who carried insurance had higher estimates of both the probability of disaster and the level of loss should a disaster strike.

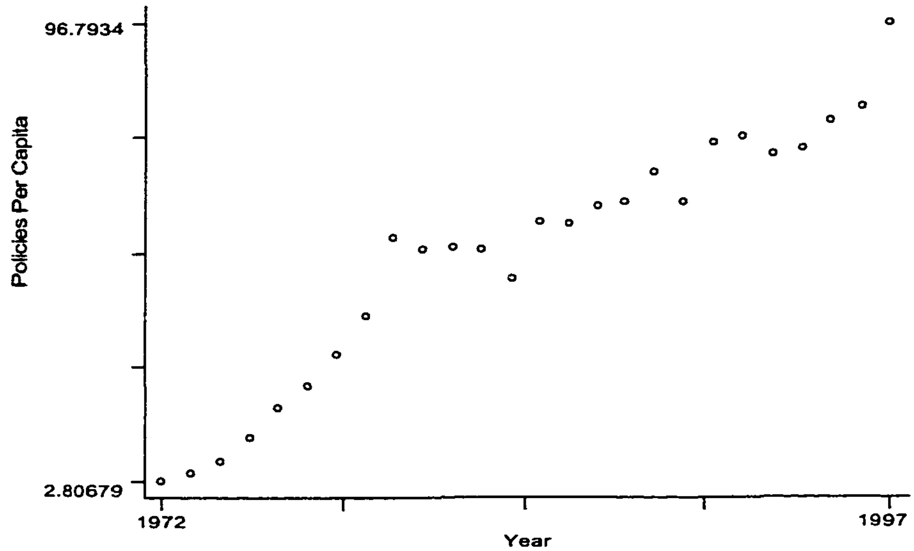
Figure 2.4: Per Capita Flood Insurance Policies in South Atlantic Region



hard to say. But, at least a loose association was found between perceived risk and the propensity to rely on risk management strategies.[18]

18. The survey data on catastrophic risk behavior developed at two levels. The first arose in the 1970's out of a scholarly debate about how to get local officials to invest in risk mitigating measures (Rossi, Wright, and Weber-Burdin 1982). The second strain of research, started by Kunreuther (1978) and continued by Palm (1998,1990) has focused on the views and actions of ordinary citizens. Strangely, the surveys of policy elites found virtually no link between perceived risk and the tendency to adopt a self-protective strategy (Rossi, Wright, and Weber-Burdin 1982). Though there was substantial heterogeneity in the opinions of officials about the actual level of catastrophic risk, increased risk perception did not translate into increased investment in risk management. At the governmental level, this makes sense since budget constraints and public opinion generally induce action on current period problems rather than potential future problems like disaster losses. Thus, it is difficult to claim that perceived risk is unrelated to action. It may simply be the case that other pressures are more severe, as the authors speculate. While we see no strong relationship between risk perception and risk management at the local governmental level, the implications are ambiguous and may result from the nature of inter-governmental relations, rather than issues of risk perception per se (May, Burby, Ericksen, Handmer, Dixon, Michaels, and Smith 1996).

Figure 2.5: Per Capita Flood Insurance Policies in Florida



Palm (1998,1990) continued Kunreuther's work by studying trends in earthquake insurance coverage and investment in mitigation during the 1980's and 1990's. She found first that the number of households covered and the total premiums paid have increased in the past twenty years. Somewhere between 20-25 percent of the surveyed households carried earthquake insurance. Second, insurance purchases increased dramatically in the immediate aftermath of an earthquake (Palm 1990, 65). When viewing purchase rates, spikes are clearly visible after a quake, suggesting that heightened awareness increases management behavior. Third, citizens justified purchasing insurance by referencing beliefs about the likelihood of an earthquake, the cost-benefit calculus of the value of insurance, and the perceived inadequacy of ex post government relief (Palm 1998). All these factors suggest some quasi-rational process of decision-making about catastrophic risk, in which people respond to beliefs and incentives about as we would expect. Still, it is surprising that fifty to seventy-five percent of

Californians think there is not a serious enough risk to warrant earthquake insurance. Why does such a large portion of the population elect not to manage catastrophic risk when the market is highly visible and the risk reasonably acute?[19]

One potentially helpful piece of evidence comes from experimental work by McClelland, Schulze, and Coursey (1993) who found a bi-modal distribution of decisions about insurance for low-probability events. In a controlled setting, roughly half of the subjects treated the probability of loss as if it were lower than it was objectively, and roughly half the subjects responded in precisely the opposite way. The portion that underestimated the risk tended not to purchase insurance and the portion that overestimated the risk was generally willing to pay more for insurance than it was rational to do. The bi-modal distribution of risk perception provides one potential explanation or, at least, illustration of the heterogeneity we observe in empirical hazard insurance markets. Perhaps both a downward and an upward bias exist in the way that individuals perceive disaster risk, but once the subjective probability estimate exists, decision-making proceeds in a more or less rational manner.

This account is plausible, but it is contradicted by at least some of the available evidence about risk perception. First, even among groups that believe they face substantial disaster risk, there is still much heterogeneity in the way they choose to respond. Though different preferences about risk might explain some portion of this puzzle, there is still much variability. Moreover, Kunreuther and Hogarth (1995) found that people rarely list probability as a justifying reason for purchasing

19. Government programs are one primary explanation. Such theories are treated in the following section.

warranties against low probability events.[20] Variation in the perception of probabilities does not always yield behavioral differences in markets. Similarly, other studies (Hsee 1996; Hsee, Loewenstein, Blount, and Bazerman 1999) suggest that isolated estimates of probabilities may not affect management behavior because such probabilities are not readily *evaluable*. Only when individuals are given information about relative probabilities does a probability estimate affect decisions about insurance or risk management (Kunreuther, Novemsky, and Kahneman 2000). Giving contextual information about relative risk or relative probabilities enhances the odds that individuals will use the information in their decisions. In the case of natural disasters, information about relative risk is rarely readily available and the variance of these estimates is large, complicating a straightforward application.

The empirical literature leaves us with a series of helpful clarifications on the one hand and several puzzles about the way individuals perceive and respond to catastrophic risk on the other. First, though the popular press account of individuals who ignore catastrophic risks is misleading, it is true that a substantial portion of the population at risk does not engage in self-protective behavior or risk management. Second, and related, heterogeneity in risk behavior seems an important piece of the overall picture. While some individuals take little to no protective action, others utilize extensive management strategies including non-structural mitigation, insurance, or other forms of risk spreading. Third, the link between perceived probability and individual behavior is somewhat confused. Some evidence suggests a bi-modal distribution of risk perception. Either people view the risk as substantial and manage it accordingly, or they view it as minimal and choose to do little. However, the causal direction of this relationship is questionable, and other studies question the

20. The study focuses on warranties for durable consumer goods like stereos, computers, or VCRs. The application is indirect, but the results are suggestive.

importance of isolated probability estimates in empirical decision-making. In sum, the evidence presents a fairly murky picture of the way that individuals perceive and respond to catastrophic risk. This project presents empirical evidence about the link between historical risk exposure and risk perception, risk perception and the propensity to manage risk, and the relationship between government policies and citizen decision-making.

The following two sections discuss the major theoretical divisions within the literature on natural hazards and decisions about low-probability high consequence risks. The two dominant analytic frameworks are drawn from economics and cognitive psychology.[21] The challenge for scholars is to understand the process of risk perception and decision-making about risk management. The key empirical puzzle is that natural disasters represent a recurrent, well-publicized risk of high magnitude; yet, there is tremendous heterogeneity in the degree to which catastrophic risk is managed.

Both economic and psychological approaches tend to agree that individuals sometimes fail to manage catastrophic risk effectively. The conflict in the literature is primarily over why. Economists suggest that citizen inaction is a rational response to perverse incentives created by government policy. Cognitive psychologists and behavioral economists generally rely on the choice regularities that are the foundation of their work. Biases in the way citizens evaluate risk could imply that disaster risk is systematically under-estimated, making inaction a more attractive alternative.

In their simplest forms, both theories are perfectly plausible. Unfortunately, neither camp has been particularly good at adapting general insights to the specific case

21. From time to time, I refer to these as rationalist and cognitivist as a shorthand. The shorthand simply reflects the rational actor of economics on the one hand and the cognitive psychological actor on the other. I do not mean to imply that the economic model excludes cognitive processes or that the psychological model precludes any form of rational decision-making.

of catastrophic risk. Considerable empirical evidence has been accumulated during the past thirty years, and much of it is simply inconsistent with statements in the scholarly literature. Moreover, neither camp has done an adequate job of explaining social heterogeneity. Often the research is mis-stated as "why does no one engage in self-protective behavior?" rather than "why do some people engage in self-protective behavior while others do not?" The challenge is to offer a model that allows for heterogeneity across groups while still emphasizing the decision-making process of individual actors. In the remainder of the chapter my goal is to ferret out the plausible claims from those that are clearly erroneous. For claims that have at least an air of plausibility, more rigorous empirical tests are developed either here or in the following chapter.

Below, I detail precisely how and why the dominant theories are inadequate. A main reason is that neither gives credence to the reality that decisions about risk are made in a strategic environment. By strategic environment, I have nothing particularly sophisticated in mind. In its simplest form, I mean simply that the behavior of other actors matters for individual decisions. The choices of peers may yield important social cues about risk management choices. Even if payoffs are not explicitly inter-dependent, the strategic form still offers a more flexible way to model behavior. Indeed, for most of this project, I leave payoff interactions aside, focusing on the informational problems that citizens face, and the resulting impact on governmental action. Moreover, a strategic form allows us to integrate insights from cognitive psychology with traditional rational actor models to better model human behavior. I suggest that information environments and cognitive biases must be analyzed jointly for productive positive analysis. Cognitive biases can interact with the decision-making environment in systematic ways that can not only be modeled, but that can also yield better explanations of social behavior. However, before contemplating integration, a serious consideration of each approach on its own terms is warranted.

2.3 Rational Choice and Individual Action

In the last fifty years, formal economic models of individual choice under risk and uncertainty have come to dominate much of the social sciences. As a result, it should be no surprise that the most well developed models of individual decisions about risk come from economists, or at least scholars with rationalist intuitions. However, the theoretical literature contains a number of critical shortcomings.[22] First, much of the rationalist literature on catastrophic risk yields predictions that are inconsistent with the available empirical evidence. Clarification is needed to understand where traditional economic models succeed in this context and where they fail. Second, most formal models tend to incorrectly assume decisions about catastrophic risk are problems in decision science, rather than in game theory. Ignoring strategic interaction often yields convoluted findings, and this too, warrants clarification. My goal is not the wholesale rejection of rational choice models in the disaster context. Indeed, my own model presented chapter 4 is dominated by this approach. I want simply to note that as applied, rational choice models have not been up to the task of explaining citizen behavior and that interaction between citizens is an important, but often ignored part of this choice context.

22. For a related set of models of individual behavior during catastrophes or adversity, see Hirshleifer (1987).

2.3.1 The Parsimony of Rational Choice

Loosely rationalist explanations generally argue that citizens respond to economic or social incentives, maximizing expected utility (benefits), given their preferences. In the classic model of expected utility, citizen decisions about management are a function of the cost of mitigation or insurance on the one hand, and some mixture of the probability and severity of a potential catastrophe on the other.[23] Whether individuals choose to manage catastrophic risk depends on these factors, their preferences about risk, and any other relevant social incentives. Citizens might choose not to manage risk because it involves costs that they believe outweigh the lottery over benefits. This is a parsimonious model rooted in the notion that people balance potential costs of action against anticipated benefits (losses) and choose a course of action based on their calculations.

In truth, strict applications of the EU model are rarely put forward in the disaster context for two reasons. First, both market and laboratory evidence show that most exposed citizens are unwilling to purchase insurance at actuarially fair values, the price at which a rational actor should buy. Even heavily subsidized premiums (up to 50 percent) often do not induce individuals to purchase. For this group of actors, either their perception of the relative probabilities, costs, and benefits is incorrect, they are not behaving rationally, or they are responding to other social incentives. For the other class of actors, those who do purchase insurance, they seem to be willing to pay more than actuarially fair values, suggesting either significant risk aversion or misperceived probabilities. Fortunately, tests can be devised that examine how well subjective risk perception corresponds to actual risk exposure. In the process,

23. See Burby, Cigler, French, Kaiswer, Kartez, Roenigk, Weist, and Whittington (1991) for a related discussion and examples.

the role of misperception can be clarified. In general, the findings presented in the subsequent chapter show that subjective risk estimates are strongly correlated with both historical losses and the level of risk management.

Second, rational actor models applied in this context have been too simple, ignoring the potential for even extremely elemental forms of strategic interaction or any empirical analysis of the incentives created by government policy. The more common argument is that risk management is not cost-effective because of the perverse incentives created by government policy. The existence of government programs alters the choice environment for individuals deciding whether or not to manage disaster risk. Specifically, the existence of ex ante subsidies for insurance or mitigation and the possibility of receiving ex post relief for experienced losses fundamentally changes the nature of a rational actor's choice.[24]

As a result, to evaluate a rational model of individual decision-making, some discussion of the way citizens respond to government incentives is required. Moreover, once government policy is introduced as a variable, the analytic framework must be altered. Government policy does provide incentives for citizens; however, such policy and its accompanying institutions are endogenous to this system, not exogenously given. While an understanding of how government policies affect individual decisions is critical, we also need an understanding of how individual decisions affect the formation of government policy. This framing has been largely ignored in the literature and its analysis is a central piece of this project.

---

24. For a more extended discussion of the tension between descriptive and normative models of choice for low probability high consequence events, see Camerer and Kunreuther (1989).

2.3.2 Model Extensions: Government Incentives

The pessimist's view of government hazard policy is that citizens fail to self-protect precisely because they do not have to. People know that the Federal government will come to their aid should a catastrophe strike and thus are functionally able to ignore the possibility of a loss. This claim is so intuitive that it has hardly been questioned in recent years, at least in scholarly circles. On both theoretical and empirical grounds, I want to suggest that it is unlikely incentives created by government policy can be the sole culprit. Which is not to say that government policy plays no role at all. There is no doubt that for some citizens the possibility of ex post relief is an important determinant of risk-related behavior. However, these effects are either marginal ones or substantially more complex than generally thought. Alone, they cannot possibly constitute the core explanation of citizen decisions about catastrophic risk.

Both ex ante and ex post incentives from government policy potentially affect the calculation of citizen strategies. Ex ante incentives consist either of grants for risk-mitigating-measures (RMM's) or subsidies for the purchase of hazard insurance. For example, the National Flood Insurance Program's premiums are heavily subsidized to make flood insurance more attractive. Ex post incentives consist mainly of the provision of financial relief should a disaster strike. The possibility of receiving government aid that covers all or part of one's losses may make current period expenditures for RMM's or insurance less attractive. Critics claim that government risk regulation creates perverse incentives that encourage risk-taking behavior and discourage expenditures on mitigation and insurance that would otherwise be preferred. They are quick to argue that the real problem here is not citizen irrationality, but government foolishness. This is a seductive story and there is some anecdotal evidence to suggest it is correct on the margins.[25] However, as I suggest below, it cannot be the core positive explanation of citizen response to catastrophic risk.[26] Because ex ante and ex post policies create slightly different incentive structures, each is taken up separately, though the fundamental point is the same. Unintended incentive arguments are plausible and even intuitive, but the data simply do not support these hypotheses. Before turning to the detailed discussion, I want to emphasize again that I am not arguing against rational choice or perverse incentive arguments writ large, nor am I seeking their wholesale rejection in this context. However, I do believe the data

25. For example, Bill Legothetis purchased a relatively inexpensive home on the North Carolina shore only to have it destroyed by Hurricane Hugo in 1989. Said Legothetis, "What Hugo did was give me a great big October present, and that was the building of a new house out there." Legothetis was able to rebuild because he had insurance from the Federal Emergency Management Agency, which "sells flood insurance to just about anyone living along the coast. Even in areas that are known to be hurricane-prone, where no private insurance company would ever take the risk, FEMA offers up to $350,000 of insurance to anyone who will pay the premium, and advertises heavily" (Dateline NBC, Len Cannon reporting, August 26, 1998.)

26. Selective incentives may affect the location of new development, both residential and commercial, constrain whether new construction is built in line with existing hazard-proof building codes, and even whether existing enforcement mechanisms are effective. This process is a bit complex, but let me venture a stylized example to help clarify. Suppose one wants to build a house on the Florida coastline. The coastal plot of land is beautiful, but building there entails a series of risks and tradeoffs. First, hurricanes and the resulting storm damage are common in the area. Either one must shoulder the potential losses or some alternative means of funding repair and/or guarding against damage has to be found. The availability and price of hazard insurance will surely play some role here, as will the availability of disaster relief from the federal government should a hurricane hit. Is receiving relief easy, hard, or impossible? Will relief cover all losses or only a portion? How much will insurance cover? Will insurance be priced fairly, which will imply exorbitant costs, or will the government subsidize it? Does a local building code exist that calls for specific hurricane-proof construction methods that will increase the cost of building to begin with? When one goes to get a mortgage, will the financial institution that is required by law to see that the buyer has purchased hazard insurance, look the other way when they fail to do so or will they in fact deny funding? The answer to any and all of these questions will change the costs of constructing the house and they will help determine the type of self-protective behavior, if any, an individual adopts.

suggest their importance is overblown and that the role of rationalist decision-making is often misunderstood in the disaster arena.

2.3.2.1 Ex Ante Incentives

It is often argued that ex ante government programs distort citizens' true preferences and encourage risk taking behavior. Two types of policies are relevant. First, various programs try to get citizens and communities to plan for potential disasters. For example, FEMA regularly gives grants to local governments that either explore or implement hazard mitigation measures. Historically, these have been fairly unsuccessful.[27] While FEMA has not had much trouble giving away grant money, the payoff from the investment has been unclear. Moreover, such grants are targeted primarily at municipalities and state governments, rather than at individuals. The more direct effect on individual risk behavior is from the subsidization of hazard insurance premiums. The NFIP is the most extensive example. The program was begun in 1968 to ensure that an affordable form of flood insurance was readily available to all who desired it. The government's logic was straightforward. Unsubsidized hazard insurance is quite expensive;[28] subsidizing the price, all other things being equal, should increase citizen demand. When the NFIP was conceived, few citizens were purchasing insurance, many were having property damaged by floods, and because of the new institutionalized Federal role in providing disaster relief, the Federal government was getting stuck with a substantial and recurrent bill. At least some people in the

27. For a treatment of the impact of informational campaigns on risk behavior, see Smith, Desvousges, and Payne (1995).

28. See Freeman and Kunreuther (1997) for a discussion of why this is so.

government reasoned that if they subsidized flood insurance premiums, more citizens would purchase insurance, thereby decreasing the ex post government burden.[29]

Critics of such programs argue that subsidizing insurance creates more risk-taking behavior than would otherwise exist.[30] For example, citizens deciding whether to locate in a flood plain or in a coastal area with hurricane risk might be more likely to locate there if hazard insurance is subsidized. They might elect to build their house elsewhere so as not to pay $2000 per year for flood insurance, but if insurance is half that cost, the decreased expenditure might make them more likely to build in harm's way. Moral hazard could result and more risky behavior would occur than would be observed without subsidized insurance. By this reasoning, the program might actually encourage the development of hazard prone areas, thereby increasing the level of aggregate risk and ultimately the costs of bearing that risk for the Federal government. Thus, ex ante incentives intended to encourage risk management could yield counterproductive results by encouraging risk-taking behavior.

Regrettably, even a cursory glance at the empirical evidence renders this story imperfect. The basic logic of the moral hazard story hinges on two assumptions. First, for a program to figure prominently in the decision-process of individuals, people must first be aware that the program exists. Second, for an ex ante incentive to be driving risky behavior, individuals would have to actually *participate* in the program. It cannot be the case that individuals elect to expose themselves to risk simply because they can get heavily subsidized insurance, while simultaneously choosing not to purchase the said insurance. Without the cheap insurance that made the risk tolerable, the risk exposure remains just as unattractive as it was to begin with. It may be the

29. Importantly, the private flood insurance market has essentially ceased to exist as well.

30. The problem is a mild variant on the standard moral hazard problem from informational economics.

case that catastrophic risk is attractive to some people. The point here is simply that an ex ante insurance subsidy cannot be what makes the risk attractive to a citizen, if that person elects not to purchase the subsidized insurance. Both awareness and participation are prerequisites for ex ante incentives to meaningfully distort otherwise rational behavior. However, a remarkably small portion of the population facing serious flood risks knows that subsidized insurance is readily available. Many hazard insurance programs have folded completely because of a lack of participation.[31] Though participation in the NFIP has grown historically, the level of coverage is still far too modest to account for the majority of citizen behavior.

2.3.2.2 Ex Post Incentives

More scholarly attention is generally focused on citizen response to so-called ex post incentives, mainly those created by extensive Federal relief programs. For the past century, the availability, scope, and magnitude of Federal disaster relief programs have expanded substantially. Damages from catastrophes are often offset by low-interest loans, grants to individuals, or payments from the Federal government to municipalities. One positive explanation of citizen response to catastrophic risk argues that many citizens do not engage in self-protective behavior because ex post relief exists. If the probability of ex post relief is high enough, even modest current period outlays may not be justified. In the boundary case, if ex post relief is certain and complete, the only reason to invest in ex ante RMM's or hazard insurance would be if aid was given to both insured and uninsured losses, which it is not currently.[32] At

31. See various forays of the Federal Insurance Administration (FIA) into fire and earthquake insurance provision.

32. See Levmore (1996) for an interesting discussion of the potential effects of various disaster relief regimes.

lower levels of coverage and given uncertainty about the probability of government relief, individual decisions are more complicated.

Again, two points are critical. First, once uncertainty about the probability of ex post relief is introduced, this becomes a problem for strategic analysis, not decision-analysis (Tsebelis 1989). The probability and level of government relief are not exogenous factors. Both are endogenous to the system and thus joint analysis of government incentives and citizen decisions is required. This is not, traditionally, the approach employed which has utilized both rational and psychological models of individual actors, but rarely even loosely strategic ones. Second, even ignoring the methodological point, neither historical nor contemporary evidence is particularly supportive of this story. If the argument about ex post incentives is correct, then some corollaries are necessarily true as well. First, citizens must be aware of ex post relief programs and believe that relief will not only be forthcoming if a disaster strikes, but also be adequate. Second, increased provision of ex post relief should be associated with less ex ante spending on mitigation and insurance. Third, the occurrence of a disaster should have a minimal impact on decisions about mitigation and insurance. None of these claims is correct and their collective inaccuracy undermines the plausibility of the perverse incentives argument. Again, this is not to say that no citizens respond to government policy as scholars argue they do. It is to say that there is something more going on here, and government policy though perhaps condemnable on efficiency or equity grounds is not the primary culprit that causes citizens to avoid managing risk.

As noted above, many fewer citizens than one would expect are aware of government relief programs, and a majority of those who are aware do not believe government aid will be definite or adequate should a disaster strike (IRC 1995). As in the argument about ex ante incentives, awareness is a critical element of the perverse ex post incentives idea. If individuals are unaware or do not believe the government will provide adequate relief when a natural disaster strikes, the incentives potentially created by policy cannot possibly explain social behavior.[33]

Second, if the theory were correct then more ex post relief would be associated with less ex ante spending on mitigation and insurance. The logic here is that as the level and probability of ex post relief increases, there is less need for anyone to invest in costly measures before a disaster strikes. Disaster relief is often said to "drive out" citizen spending on insurance and mitigation. However, expenditures by individuals on mitigation and insurance are actually higher in communities that receive substantial disaster relief (Browne and Hoyt 2000). The logic of the distortion argument suggests that awareness of ex post relief should diminish if not eliminate ex ante spending on mitigation, but certainly not increase it. Ex post relief is associated with larger expenditures on self-protective behavior. This seems paradoxical from within the perverse incentives camp, but it is a finding that has yet to be explained away, and the analysis in chapter 3offers further support. It is possible to construct an argument that suggests investment in mitigation and insurance would be even *higher* without the possibility of ex post relief. This is plausible, but note that this is simply an ad hoc revision to rescue the theory in the face of actual evidence. Moreover, even

33. It is possible that the pricing mechanism in the real estate market could operate in a way that is consistent with the moral hazard model, even without individual awareness. For example, risks of all sort are built into the price of housing in different regions. It is possible that housing prices are responsive to changes in government programs as well. If so, housing prices in hurricane regions might be different before and after major shifts in disaster policy and we might observe regional variation that we could tie to either Federal policy or the level of disaster risk. Though it is difficult to parse out the relevant effects, a more detailed examination of this issue is planned for future work. At this point, I cannot rule out this possibility with my data. However, it is still surprising that awareness has been so relatively low historically.

if investment in risk management would be higher without federal relief, it seems clear that disaster relief is not doing anything like eliminating risk management behavior.

Third, if citizens are simply responding to the incentives created by government relief programs, the occurrence of a disaster should have no impact on decisions about mitigation and insurance. This corollary is a little less obvious than the first two, but may be even more important. If the ex ante decision about whether to invest in a self-protective strategy is fully determined by the government's provision of ex post relief, then decisions about insurance should not be affected by beliefs about the probability of disasters. Whether the probability of a disaster is five percent or fifty percent makes no difference since government aid will be forthcoming regardless, making ex ante expenditures unnecessary. But, if that were true, then perceived risk would have no impact on decisions about risk management, and insurance purchases would not increase following a disaster. In fact, the purchase rate should be entirely unrelated to the rate of natural disasters. If anything, citizens should be less likely to self-protect because they have experience demonstrating that ex post relief will be forthcoming. Once again, these predictions are not born out. First, surveys by Palm (1998) and Kunreuther (1978) show a positive correlation between perceived risk and the likelihood of purchasing insurance. The next chapter treats precisely this issue, adding further evidence of the association between risk perception and risk management. Moreover, a plot of the percentage change in insurance coverage over time shows clear increases in the immediate aftermath of a disaster. After a major catastrophe, insurance purchases tend to rise dramatically. The empirical reality is simply not particularly supportive of the assumptions required for the perverse incentives argument to function.

2.3.3 Summary

None of this is to say that the current governmental approach to managing catastrophic risk is a good one. That is a normative claim whose discussion I postpone until the end of the project. My primary concern here is offering a positive account of the way citizens respond to risk and how such tendencies affect the construction of government policy. A compelling positive explanation must tack back and forth between plausible theoretical insights and the available empirical evidence. When this approach is brought to bear on notions of rational response and perverse incentives, a handfull of shortcomings arise. Even at a superficial level, the data are not particularly supportive of the theoretical predictions. The reality of citizen choice tells a somewhat different story, a story in which the wholesale rejection of rational actor models is surely not warranted, but nor is a transparent application without specific revisions.

2.4 Cognitive Psychology and Behavioral Economics

Suspicious of the assumptions underlying rational choice models, a group of cognitive psychologists and behavioral economists has long sought to understand empirical decisions about risk and uncertainty.[34] This tradition of research constitutes the other dominant individualist school of thought on risk, arguing that individuals simply do not make rational decisions about risk.[35] Irrationality, in this context, refers to two often conflated issues. One strain of research has sought to demonstrate that

34. The tradition is rich and varied, but for a relatively recent summary, see Kahneman and Tversky (2000) or Kahneman (1994). On experimental evidence, see Kagel and Roth (1995). For a discussion in the legal literature, see Jolls, Sunstein, and Thaler (1998).

35. See Heimer (1988), Douglas (1985), or Douglas and Wildavsky (1982) for a discussion of more sociological approaches.

individual decisions often do not conform to the maxims of expected utility theory. That is, revealed preferences, identified by actual choices, are not always internally consistent. Preferences are often contingent on framing and decisions are easily manipulated by irrelevant information, yielding preference reversals and other similar phenomena. The other strain of research examines the correspondence between individual estimates of probabilities and "objective" states of the world. That is, the research asks how well individuals evaluate probabilities.[36] Though the two issues of internal coherence and external correspondence are often treated identically under the heading of irrationality, some care is warranted in discussing the research.[37]

Expected Utility Theory assumes or predicts that individuals rely on estimates of the probability and severity events to maximize expected payoffs. Expected Utility theory has a simple elegance and power to it; however, by this point experimental evidence and tests of General Expected Utility theories (GEU) suggest that Savage's original formulation does not fare all that well empirically. As a normative model of how people should make choices, the EU framework is quite plausible. However, as a descriptive theory of choice, EU is often questioned. Individuals appear to weight probabilities in a non-linear fashion (Bertrand and Machina 1994), treat losses differently than gains (Kahneman and Tversky 1979), exhibit perverse intertemporal choice behavior (Lowenstein and Elster 1992), produce systematically inaccurate probability estimates (Kahneman, Slovic, and Tversky 1982), and are often inept at managing ambiguity (Kunreuther and Hogarth 1995; Kunreuther, Hogarth, and Meszaros 1993). Many if not all of these complicating factors are present in the

36. A debate about the nature of probability and whether objective probabilities even exist continues to rage. I set the debate aside for the moment, but draw on its implications periodically throughout the project.

37. These precise issues are treated by Hammond (1996) with excerpts in Hammond (2000).

context of catastrophic risk. Moreover, individual inferences based on extreme events may exhibit systematic biases (Pratt and Zeckhauser 1982). Framing effects have been found to distort probability judgments and the resulting decisions about insurance (Johnson, Hershey, Meszaros, and Kunreuther 1993), and perceived probability appears to affect perceived costs or benefits, even though the two are not theoretically related (Siddiq and Slovic 1994).

As a result, it makes perfect sense to try to import findings from behavioral economics to explain behavior in this arena. Unfortunately, many insights from the study of risk decisions in general have been applied to the case of catastrophic risk without careful consideration. As a result, the literature typically rattles off six or seven of the key findings about risk perception, and assumes they are factors in choices about disaster risk without developing a theoretical story about how the effects cohere or an examination of how predictions fare empirically. A better understanding of how experimental findings fit together and how well they match up with data from the real world is still a much needed contribution.

2.4.1 Aversion to Risk and Ambiguity

One of the earliest findings on decision-making about risk was that individuals are often averse to risk or ambiguity. When expected utility theory was first developed, a debate between Savage and Allais emerged. Using a series experiments Allais consistently documented instances of individual choice that were inconsistent with the EU model. Most of these early studies were done using balls of different colors in an urn, and variants of the ball and urn model are still quite popular. Risk aversion has received sustained historical attention in the literature, while ambiguity aversion has begun to attract renewed interest in the last two decades. Both these factors are often invoked to undermine the validity of economic models of decisions about disasters, and supposedly explain why citizens sometimes fail to manage catastrophic risk.[38]

Risk aversion though, though one of the most well-documented divergences from expected utility theory, is not a particularly compelling explanation in this context. In a variety of choice settings, many individuals display an aversion to risk, preferring a known outcome of lesser value to a lottery of higher expectation. Risk aversion is not a universal phenomenon, but it is common enough that it warrants some exploration in this context. In general, risk aversion implies that individuals are willing to pay a premium to decrease or eliminate risky propositions.[39] A rational actor would purchase insurance when the probability that a disaster will strike in the time period multiplied by the expected damages if a disaster occurs is greater than the cost of hazard insurance for the time period in question. The risk averse actor would be willing to purchase insurance at a higher price since the value she is willing to pay incorporates a risk premium, a value over and above the level of expected loss.[40] Risk aversion implies that citizens would be willing to pay *more* than the actuarially fair cost of insurance. If this were true empirically, the market for hazard insurance would have prospered since insurers could charge more than fair rates and citizens would still be willing to purchase hazard insurance.[41]

38. See Mileti (1999) for an illustrative discussion.

39. The difference between the certainty-equivalent of the lottery and the minimum payment individuals would be willing to accept in lieu of the lottery is known as the risk premium (Kreps 1990).

40. One caveat is warranted here. A *prospect theoretic* account would argue that individuals are risk averse with respect to gains, but risk acceptant with respect to losses (Kahneman and Tversky 1979). Prospect Theory has some viability in the catastrophic risk context, but I put a full discussion on hold for the moment.

41. Strictly speaking, this is not quite true. However, we would have observed a higher consumer demand for insurance. Whether insurance would have been supplied at a higher rate is an open question.

Of course, that has not been the experience of hazard insurers. Although technological advances have allowed the insurance industry to develop more accurate estimates of disaster risk and losses, many citizens remain unwilling to pay anything even approaching an actuarially fair rate.[42] When citizens do purchase hazard insurance, it tends to be highly subsidized, as in the NFIP, or the result of mandatory purchase requirements. If anything, citizens appear to be risk acceptant with respect to high consequence and low probability losses.[43]

Estimates of the probability of catastrophes also generally have a high variance. Ambiguity aversion suggests that actors will pay a premium to avoid such ambiguity. As with risk aversion, ambiguity averse actors prefer risks with better specified probabilities and are willing to pay a premium to avoid ambiguous risks. A particularly helpful series of studies found ambiguity aversion on the part of producers of hazard insurance (Kunreuther and Hogarth 1995; Kunreuther, Hogarth, and Meszaros 1993). Individuals in charge of pricing hazard insurance required an increased premium (above the actuarially fair level) to bear the risk and provide insurance. This finding appears to be robust and could conceivably help explain part of the historical reluctance of insurance companies to enter the natural hazard insurance market. However, the finding has rarely been applied to the question of citizen decisions about risk management. Fortunately, the data employed in this project provide an easy way to test for the importance of variance or ambiguity in individual decisions. Because historical variability can be observed and summarized with a statistic, and because

42. For a discussion of technological changes in the pricing of hazard insurance, see Freeman and Kunreuther (1997) or Dong, Shah, and Wong (1996). For some of the difficulties of pricing various forms of insurance, see Viscusi (1993).

43. This fact can be understood to support the hypothesis of prospect theory, indicating individuals are risk averse with respect to gains and risk acceptant with respect to losses.

such variability is different across different states and regions, we can test empirically for a relationship. To foreshadow just a bit, the data support the importance of variance or ambiguity, but not in the direction ambiguity aversion suggests. The data demonstrate that greater historical variation of experience with disasters yields a decreased propensity to purchase hazard insurance, not an increased propensity as the ambiguity aversion hypothesis suggests. When there is more historical variation with respect to disaster losses, above and beyond the actual level of losses, individuals are actually less likely to purchase insurance.

2.4.2 Availability

In recent years, availability has received some of the most sustained scholarly attention in the literature on risk, and in my view, it is one finding from behavioral economics that appears entirely consistent with the data. Availability was originally termed a heuristic by which individuals form beliefs about probabilities.[44] If an event is readily "available," for example, if it has occurred recently, individuals tend to think it is more likely to occur again in the future. By the same token, risks that are not readily "available" tend to be under-estimated. What I refer to as an availability bias results if individuals consistently rely on the availability heuristic to evaluate risk. A bias will result, in the sense that they will consistently over-estimate available or recently-occurring risks and consistently under-estimate risks that are unavailable. Otherwise rational decisions made on a foundation of incorrect beliefs will likely produce undesirable outcomes for decision-makers. Examples in every day life are numerous. The demand for increased airline safety regulation is always high in the immediate aftermath of a crash, and then tails off shortly thereafter. Sunstein

44. For an early discussion of availability, see Tversky and Kahneman (1973).

and Kuran (1999) suggest a similar theoretical framework explains much demand for environmental regulation.[45] A bias exists in that events that are readily available to the individual are thought to be more likely than those that are not. The beliefs could be correct in a specific instance, but they will not be systematically accurate as a general proposition.

Simply put, the availability bias implies that estimates of the probability of a stochastic event will be biased upward if the event has occurred recently. Individuals will incorrectly update their beliefs by over-reacting to new information. Empirically, the behavior we observe is at least consistent with this theoretical framework. Following a natural disaster, the demand for hazard insurance rises dramatically, as do expenditures on risk mitigating measures. This is true, not just for flood insurance, but also earthquake insurance, and hurricane related self-protective measures.

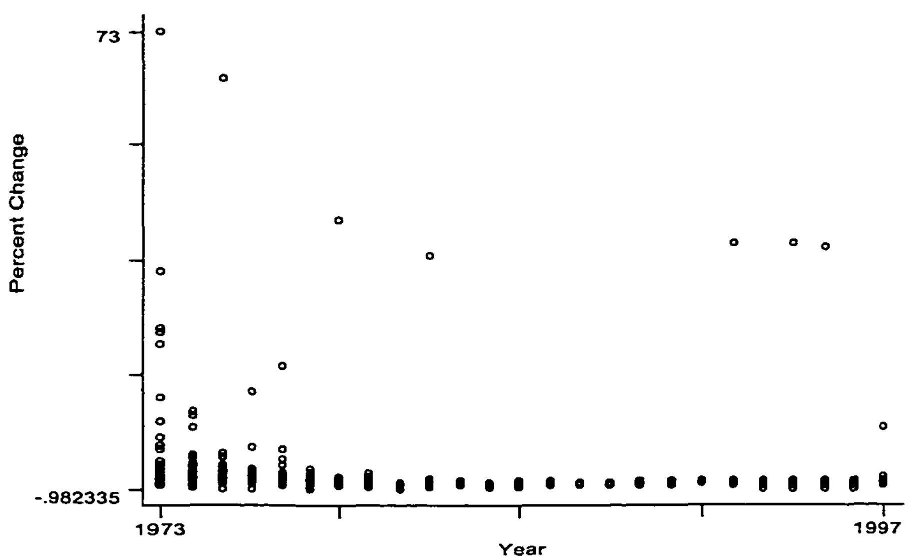
Consider the graph in Figure 2.6 which plots the annual percentage change in the number of flood insurance policies over time. Most years exhibit only modest adjustment. Only in years containing very serious flood events do patterns of insurance change much. For example, the Midwestern floods in the early 1990's show larger rates of change, Hurricane Andrew in 1992 yields a large blip,and there are periodic large shifts throughout the observed time period. Obviously, this is not overwhelming evidence, but it does support the plausibility of the basic proposition.[46]

---

45. As discussed in subsequent chapters, in the natural hazard context, a national debate about disaster policy almost always follows catastrophic events. However, this debate quickly wanes as time passes. Virtually all of the Congressional disaster policy reforms come on the tails of major catastrophic events. Indeed, initial passage of the 1950 Disaster Relief Act, the first piece of institutionalized Federal policy came after a series of unusually harsh catastrophes, as did subsequent reforms in 1970 and 1974.

46. Quick behavioral changes after a disaster are stronger evidence than a rapid decline in risk management activity. Because of the nature of capital investments in risk mitigation, once the investment has been made (e.g. in hurricane shutters) an annual expenditure is not required. Thus, we cannot simply interpret the ensuing decline in spending as evidence

Figure 2.6: Annual Percentage Change in Flood Insurance Policies



The key is to develop a way to test the implications of the availability hypothesis with a bit more rigor. One alternative is to use dynamic statistical models that capture how quickly or slowly behavior changes in response to changes in the environment. Though dynamic models are discussed briefly in the following section and more extensively in the following chapter, to the extent that most long-term adjustments happens instantaneously or within a short period of time, the data would support the availability phenomenon. On the other hand, if the behavioral adjustments are extremely slow, then it is unlikely availability is an important factor here. Because availability implies a quick over-response to new information, observing risk management behavior over time can help test the hypothesis empirically. For the time-being,

for availability. However, the same is not true of spending on insurance, which requires an annual renewal, and thus, is a far more informative piece of data.

I want simply to note that the availability bias is consistent with the empirical evidence already discussed, and more rigorous tests will be developed in the following chapter. Availability appears a potential piece of the risk puzzle.

2.4.3 Overconfidence and Selective Optimism

Overconfidence and selective optimism are the final issues from the heuristics and biases literature that I want to treat, though they have not been previously applied in the context of disaster risk. Most evidence for the overconfidence phenomenon comes from the calibration literature (Alpert and Raiffa 1982; Fischoff, Slovic, and Lichtenstein 1977). However, empirical applications have noted overconfidence in a range of professional fields, and among both lay decision-makers and experts.[47] The basic finding is that people tend to be overconfident in answering questions of moderate to extreme difficulty (Odean 1997; Yates 1990).[48] Moreover, people tend to be too optimistic about future events. They expect good things to happen to them more than to others, and expect to avoid negative events, even though they may have accurate beliefs about the probability of such events for the general population (Weinstein 1980). Overconfidence and over-optimism are slightly different effects, but both are potentially relevant here.

What overconfidence implies in the case of risk evaluation is that decision-makers do not update their beliefs adequately in response to new information. Decision-makers weight their own information too heavily and are too confident that initial decisions are correct. The empirical evidence on disaster management is mixed on this front. First, citizens are generally unresponsive to changes in the informational

47. For a discussion, see Odean (1997) or Lichtenstein, Fischoff, and Phillips (1982).

48. The exact opposite is often true when individuals are answering easy questions. Here, people tend to be underconfident in their judgments.

environment. Informational campaigns designed to increase mitigation or management behavior have had an uncertain impact (Smith, Desvousges, and Payne 1995). One interpretation is that people fail to update their beliefs based on this new information because they are too confident in their own judgments. Second, though individuals tend to over-estimate the probability that a disaster will strike their community in the next decade, they also under-estimate the probability that they will be personally harmed (IRC 1995). Individuals appear overly optimistic about their chances of avoiding negative events. Specific evidence on overconfidence is harder to come by in the disaster arena. However, one indirect way to get at this issue is to explore the short-term and long-term effects of disaster events on insurance purchase rates. To the extent that there is a good deal of drag in this process, that is, the level of coverage changes slowly rather than rapidly, one might interpret this as evidence in favor of the overconfidence hypothesis. Though excessive optimism has fascinating potential implications in this area, I have no data with which to get at the construct. The project continues to treat overconfidence mainly because there is no overwhelming evidence to contradict such a theory, and because the data the project employs can be used to test the overconfidence hypothesis empirically. Overconfidence implies that the instantaneous or short term adjustment to new information will be quite small, relative to the long-term effect. Using dynamic models pioneered in time-series analysis, both the long-term and short-term effects can be identified. To the extent that the instantaneous effect dominates the long-term effect, overconfidence is almost surely not playing a role.

2.4.4 Overview

The literature from cognitive psychology and behavioral economics argues that various heuristics and biases dominate the way individuals perceive and respond to risk. The above discussion has surveyed a handful of the most common decision regularities that supposedly explain much of the way citizens deal with catastrophic risk. Unfortunately, many theories fare poorly as predictors of empirical behavior in this specific case. However, the key is to develop ways to test for such effects in the context of actual decision-making. My goal is not to argue against the validity of the heuristics and biases literature. This collection of scholarship has produced tremendous insights and forms an important part of the theoretical foundation for my more general project. Nonetheless, general experimental findings from this school must be evaluated in specific empirical cases, just as findings from rational choice scholarship should be. In the natural disaster case, psychological biases get us part but certainly not all of the way home. While many individuals do seem to exhibit cognitive biases, substantial heterogeneity still exists. Psychological accounts of decision about risk are suggestive, but alone, they too offer an inadequate account of individual decisions about managing risk.

2.5 Strategy and Cognition

To this point, I have tried to highlight that neither conventional cognitive nor rationalist theories do an adequate job of explaining citizen disaster behavior, and I have tried to develop ways to test for effects empirically whenever possible. Along the way, we saw that some of the cognitive bias literature has been erroneously applied to decisions about disaster risk, and also that the rationalist account of individual response to risk, loss, and incentives did not go quite as far as its proponents suggest. What then would I like to propose in their stead?

In the following chapters, I sketch a model of behavior that uses both the rationalist and cognitive paradigms as critical theoretical building blocks. Beyond understanding the contexts in which each theory is and is not supported by the data, I also want to suggest that cognitive and rationalist factors may interact systematically to exacerbate certain social problems, while mitigating others. If I am correct, then scholarship rooted in a single tradition will miss these important effects.

For example, an entire class of problems in game theory rely on an equilibrium concept known as Perfect Bayesian Equilibria (PBE). This concept has proven tremendously helpful for information games, and it assumes that individuals update their beliefs about the world according to a Bayesian framework. Experimentally, some individuals update their beliefs in this way, but many fail to do so. One response would be to reject the equilibrium concept, but that step is unnecessarily harsh and entirely unproductive. Better to ask about the impact of a slightly different updating procedure on game equilibria than to reject the entire endeavor. As chapter 4 shows, sometimes individual biases have absolutely no impact on the behavior of other actors in a game; however, sometimes the impact is quite profound. We need to begin the process of understanding how psychologically realistic actors respond to strategic environments. The analysis of how psychological tendencies matter for game forms and vice versa is one way in which strategy and cognition intersect or interact.

In a similar vein, when individual citizens exhibit cognitive biases, their behavior sometimes creates a distinctive class of challenges for politicians and regulators. Noll and Krier (1990) raised this issue a decade ago in the context of risk regulation more generally, but rarely has the observation been developed. On the one hand, government programs designed to create selective incentives to affect citizen behavior may not have the desired effect. If programs explicitly or implicitly rely on a rational actor model when it is inappropriate, policies may be ineffective or even counter-productive. On the other hand, to the extent that politicians respond to demands for legislative intervention, biased behavior on the part of citizens may drive biased behavior on the part of politicians. Understanding when such biases rear their head can help us make sense of otherwise puzzling political actions. Finally, sometimes the strategic environment will minimize or eliminate the impact of individual level biases. An effectively functioning market might provide feedback when individuals make mistakes of perception or judgement, and allow them to better calibrate their beliefs. For example, when good actuarial tables exist for a risk, insurance prices provide feedback on individual beliefs. Though an individual might over-estimate or under-estimate the risk initially, premiums in an efficient market might substantially correct the initial bias.

The following chapters rely on a similar logic. In the context of disaster risk, sometimes either rationalist or cognitive factors might dominate; sometimes cognitive and strategic factors might interact to exacerbate the problems of disaster risk; and sometimes these factors might interact in a productive way that actually enhances the probability of achieving optimal social outcomes. Regardless, we should at least allow for these possibilities. As I endeavor to show, analyzing strategy and cognition together allows us to produce insights that are missed by more traditional approaches.

As an illustration, the following chapters note that decisions about mitigation and insurance are often made in low information environments. Non-experts may not have a good understanding of whether disaster insurance is actually warranted. After the fact, when the damage has been done, the correct decision may be clear. But before the fact, information may not be readily available or at least standard arguments about search or information costs apply. In such environments, one strategy for actors is to look to the behavior of others as a way of gathering relevant information. When cognitive biases exist in this information environment, bias can be quickly magnified and spread through communities. Unfortunately, as individuals interact, information about risk management technologies may not be efficiently aggregated. Private information can be quickly lost and herd behavior can result, in which virtually all members of a group choose the same sub-optimal risk management strategy. A model that allows for the integration of economic and psychological effects can help explain why communities facing similar objective disaster risk and similar financial constraints often exhibit strikingly different risk management behavior.

The model provides insights into the political environment as well. Subsequent chapters demonstrate that many communities will be almost completely unprotected when disaster strikes, leaving ex post relief as the only viable government option. In one sense, this pattern of behavior suggests the demand for legislative intervention will tend to be quite intense after a disaster and quite low prior to a disaster. The important point is that the behavioral pattern creates a distinctive constraint on political choice. In this area, as in most, politicians may respond strategically to constituents acting in this way. For example, rational politicians might seek to create regulatory institutions that manage the predictable nature of this public pressure. Depending on their political preferences, politicians might want to minimize or maximize their ability to respond to intense demands for legislative action. If that is correct, then choices legislators make about institutional structure or government policy likely reflect some of these concerns. We would be wise to at least take them into consideration. Moreover, social actors who understand the nature of this interaction might find ways to extract gains from the political process, further constraining the regulatory environment. Loosely, we might think of these actors as risk-entrepreneurs, rent-seekers who take explicit advantage of the challenges facing politicians when dealing with disaster risk.

At one level then, analyzing strategy and cognition together can provide us with explanations of social behavior when strict economic or psychological models alone have proven inadequate. At another, a model of strategy and cognition can offer insights into the reality of political decisions, legislative behavior, and institutional environment. However, before developing the implications of citizen behavior for government institutions, a better picture of empirical decision-making about disaster risk is required. The following chapters take up this task using a mix of quantitative and formal methods. Theoretical explanations cannot convincingly proceed without rigorous use of empirical evidence. By relying on original data about historical experience with disaster risk in the United States, the next chapter tests the theoretical predictions raised in the preceding discussion.

CHAPTER 3

DECISIONS ABOUT DISASTERS

3.1 Introduction

The previous chapter surveyed some common theoretical claims regarding the way people make decisions about natural disaster risk. Both rationalist and cognitive claims run up against stubborn empirical evidence that is inconsistent with the theoretical predictions. That said, a number of important empirical predictions do result from each respective tradition. Specifically, loosely rational frameworks predict relatively accurate perceptions of probability estimates, and an increased propensity to insure risks as the level of risk exposure rises. Cognitive theories about ambiguity predict an important effect of risk variance, while the EU model predicts that risk variance should have no effect on decisions to insure. Moreover, two theories from within the cognitive camp yield different predictions about the way information is incorporated into decision-making procedures. Availability suggests that individuals will be overly responsive to new information, whereas overconfidence predicts that social behavior should be slow to adjust to changes in the level of risk exposure. To evaluate these hypotheses, we require evidence about the way citizens form subjective estimates of disaster risk, how such subjective beliefs translate into strategies for risk management, and how the empirical findings about decision-making bear on the theoretical debate in the literature. This chapter seeks to fill some of the existing gaps in the literature by analyzing original data drawn from government sources, the insurance industry, and historical publications. The data represent one of the few opportunities to analyze the link between risk exposure, risk perception, and risk management activity across regions, states, and time. Even more importantly, tests for the relevance of cognitivist factors like ambiguity, overconfidence, and availability can be developed, moving behavioral economics out of the laboratory and into the real world.

Whereas in the preceding chapter, my goal was to filter out those explanations that were simply implausible or clearly inconsistent with the empirical evidence, the standard for this chapter is necessarily higher. Precise predictions from the remaining theories are derived and the appropriate statistical methodology is brought to bear. By relying on diverse quantitative methods, hypotheses commonly thought to be difficult to test can be readily evaluated.

3.1.1 Structure and Organization

The remainder of the chapter is organized as follows. Section two offers a regional analysis of beliefs about risk. Section three goes on to analyze decisions about risk management activities. Each section provides empirical tests of rationalist and cognitive propositions about the management of natural disaster risk. Both sections rely on original data, and because the structure of the data in each analytical section is distinctive, a number of methodological sections are included. In general, the methodology subsections can be skipped without a loss of coherence. Section four offers some caveats and concludes.

3.2 Beliefs about Risk

A longstanding question in the study of risk is whether subjective perceptions of risk correspond to "objective" reality. Are individuals able to form accurate or at least meaningful estimates of the risks they face? For strict subjectivists, there is no such thing as objective probability, and, therefore, the question of correspondence is moot. There can be only subjective probability.[1] The debate between frequentists and

1. See for example, de Finetti (1972).

subjectivists notwithstanding, for policy makers and scholars of risk regulation, the question of correspondence cannot be so easily avoided. In recent years, academics have increasingly relied on the inability of citizens to accurately evaluate risk as a justification for extensive regulatory programs. Such programs may be entirely warranted, but the evidence on empirical decision-making about risk is ambiguous at best. There remains substantial uncertainty about how good ordinary citizens are at evaluating risk, and the extent to which such beliefs factor into market and lifestyle choices.

This section evaluates two hypotheses about the way citizens form beliefs about risk. The first hypothesis, generally assumed by rationalists, is that individuals are able to accurately characterize the risk they face. That is to say, individuals facing higher levels of actual risk should believe that they face higher levels of risk. Many cognitive psychologists are fond of highlighting the fact that individuals are notoriously poor at forming accurate probability estimates. Both camps have a plausible case, but ultimately the issue is an empirical one. To the extent that individuals living in regions characterized by a higher level of environmental risk consistently think they are more likely to be affected by natural disasters than individuals living in regions with lower environmental risk, we have identified some basic evidence in favor of the straightforward correspondence proposition. Second, previous work suggests that ambiguity or risk variance plays a role in the construction of beliefs (Hogarth and Einhorn 1990; Hogarth and Kunreuther 1985; Viscusi and Chesson 1999). In the domain of losses, individuals tend to over-estimate more ambiguous risks for low probability events and under-estimate the probability of more ambiguous risks for high probability events, holding the level of actual risk constant. The basic idea is that ambiguity or risk variance should matter systematically in the formation of risk beliefs from a cognitive perspective, whereas it should technically have no effect from a rationalist perspective. These hypotheses can be tested to offer evidence about the plausibility of each theoretical camp.

To meaningfully analyze the relationship between actual risk and risk perception, ideally one would want individual level data on the subjective beliefs that citizens hold and the actual level of catastrophic risk that they face. To my knowledge, such ideal data do not exist. The survey data that do exist suffer from one primary weakness. The data tend to exhibit a regional or hazard bias. The regional specificity makes it hard to ensure variation with respect to the risk that citizens actually face. Thus, it is difficult, if not impossible, to make claims about the relationship between actual and perceived risk. For this reason, previous surveys have rarely included meaningful indicators of both actual and perceived risk. This is not a fault of the existing data, per se. It is simply an inevitable problem with adapting such data to answer the questions of this chapter. Some variation is certainly contained in the previous data, but maximizing the amount of variation can only produce more efficient estimates. Because rigorous testing of the hypotheses requires variation with respect to both the dependent and independent variables, limiting the scope of analysis to either a specific hazard or a particular geographic region undermines our ability to make reasonable and unbiased claims. To compensate for this potential shortcoming, this section combines an original dataset, containing indicators of historical disaster risk in different geographic regions with aggregate survey data published by the Insurance Research Council (IRC 1995; IRC 1999). By relying on tools for aggregate data analysis, tests for a relationship between actual and perceived disaster risk can be developed.

3.2.1 Data and Measurement

Indicators of perceived risk, actual risk, and risk ambiguity are required. To measure perceived risk, it would be ideal to have individual responses to questions about risk perception. However, lacking such data, we can rely on aggregate summaries of such data. The Insurance Research Council publishes periodic independent surveys on natural disaster risks and citizen views on insurance and disaster related policies (IRC 1995; IRC 1999). Citizens are asked to evaluate the likelihood that they will be struck by a natural disaster during the next decade. Though the IRC will not release the original data, their publications contain tables that allow a good deal of the original data to be reconstructed. Thus, the proportion of people in a given region who believe it is likely that they will be affected by a natural disaster is used as an indicator of perceived risk.

The primary option for an adequate indicator of actual risk is a summary of the amount of governmental disaster relief funds received in a given year, which is a relatively generalizable indicator of disaster risk. Because disaster relief funds are available for a wide range of natural hazards, no one region-specific hazard will dominate. And, disaster relief expenditures, especially in recent years, correlate highly with actual losses. That is to say, though per capita relief will almost always be less than actual per capita losses, on average, per capita relief should be a good indicator since it will under-estimate consistently across the range of losses. Obviously, the indicator is imperfect as different states and different regions may exhibit a greater ability to extract disaster relief payments from the Federal government. However, such effects are likely to be minimized at the regional level; and, a number of studies have explored the link between disaster relief and the political characteristics of recipient states or regions without finding any meaningful associations (May 1985; Platt 1999).

Thus, though the measure is flawed, it serves as a fairly good indicator of actual catastrophic risk.

Though a direct effect between actual risk and subjective risk perception should be observed, previous work has demonstrated the importance of risk ambiguity or risk variance for the formation of probability estimates and subjective beliefs (Kunreuther and Hogarth 1995; Kunreuther, Hogarth, and Meszaros 1993). When considering losses, individuals tend to over-estimate low probability ambiguous risks, while under-estimating high probability ambiguous risks (Viscusi and Chesson 1999). At first glance, natural disasters appear to be low probability high consequence events, and so we would expect ambiguity aversion as Viscusi and Chesson (1999) find in a controlled experiment. Alternatively, it could also be that individuals have more difficulty accumulating useful information when the variance of observed events is high. Irrespective, when there is greater historical variation with respect to catastrophic events, subjective risk estimates should change systematically according to a cognitivist framework. If ambiguity or variance affects the formation of beliefs at all, such evidence argues against the viability of a simple rationalist model in this decision-making context. Including some operationalization of variance in the model also allows us to test hypotheses about the performance of strict expected utility models, relative to more general variance-dependent formulations of individual choice. In an EU or Bayesian decision framework, variance should have no effect on belief formation. To the extent that an effect is observed, we have some support for questioning strict applications of the rationalist framework. The model includes an indicator of risk variance, operationalized as the observed standard deviation of regional disaster relief over the time period for which data are available.

With the three discussed measures in hand, the data consist of nine observations, each representing a region, and each of which contains the number of individuals who believe a disaster is likely,[2] an indicator of actual disaster risk, and a measure of the variability of the historical risk.[3] To summarize, the analysis asks whether the perceived level of risk is responsive to either the level or variance of historical risk experience.

3.2.2 Statistical Estimation

Given the structure of the data, a block probit (equivalently, a dose-response probit) model can be reasonably applied for estimation. The block probit model is used here because the individual-level observations are unavailable. However, we know the total number of individuals in a region who think a disaster is likely, as well as the total number of respondents in the region. The presented data, originally published by the IRC (1999) represent proportions of individuals in each region who believe a natural disaster is likely in the next ten years. In the block probit model, conceptually individual-level data are grouped and then stacked by group for analysis. The distribution will be binomial, where the likelihood function for multiple observations in the aggregate is given by:

$$\mathcal{L}(\pi|y_i) = \binom{N_i}{y_i} \pi^{y_i}(1-\pi)^{N_i - y_i} \tag{3.1}$$

Since π must be bounded by the interval $[0, 1]$, we can use a probit link function:

2. Out of the total number surveyed in the region.

3. The disaster relief expenditures data were assembled from government publications including "Federal Aid to States" published by the U.S. Treasury Department prior to 1982, "Federal Expenditures by State" published by the Bureau of the Census from 1982-1995, and "Federal Aid By State" also published by the Bureau of the Census starting in 1995.

$$\log \mathcal{L}(\beta|y) = \sum y_i \log \Phi(x_i\beta)(N_i - y_i)\log(1 - \Phi(x_i\beta)) + \log \binom{N_i}{y_i} \qquad (3.2)$$

The last term drops out since it is not a function of β, and we can estimate the equation using maximum likelihood methods. The model allows for individual level inferences, even though the data is only available in aggregate form.

3.2.3 Analysis

In the 1998 survey of just under 2000 participants, respondents were asked how likely it is that a major natural disaster might occur in the area where they live in the next ten years. Twenty-five percent of the respondents thought it was "very likely," 35 percent "somewhat likely," 19 percent "somewhat unlikely," and 16 percent "not likely at all" (IRC 1999). These figures are remarkably high. By any conventional measure, the actual probability that a given individual will be affected by a major natural disaster is somewhere on the order of 10%, at most. It is surprising that so large a proportion of individuals think that a disaster is likely to occur given the actual average probability of being affected. To the extent that there is a bias in risk perception here, it looks to be an upward bias, not a downward bias, as many scholars suggest.

The results from the dose response probit model are presented in Table 3.1.[4] First, note that the primary indicator of actual disaster risk has a positive and statistically significant association with risk perception. Individuals in regions that have had

4. First Differences summarize the change in predicted probability of a shift from the mean to maximum value of the variable of interest, holding all other values constant at their mean.

Table 3.1: Block Probit Estimates of Actual Disaster Risk on Subjective Perceptions

Variable	Coefficient	Standard Error	First Difference
Disaster Relief	.200***	.052	.22
Variance (DR)	−.024*	.012	−.20
Constant	.080	.077	

N=1972
Likelihood Ratio $\chi^2_2 = 16.80$
Log Likelihood = -1317.64
***p< .001,*p< .05

larger historical losses from natural disasters are more likely to think that a natural disaster is likely to affect them in the future. Second, the coefficient on the indicator of historical risk variance is negative and statistically significantly associated with risk perception. As there is more variation in the historical record of natural disasters in a given region, individuals are less likely to believe that a disaster will strike in the future. As variance increases, subjective risk estimates are deflated. A wider spread of historical exposure tends to depress the level of perceived seriousness of natural hazard risks. The finding highlights the importance of ambiguity and variance in the formation of citizen beliefs, but it is contrary to previous work that found ambiguity tends to inflate estimates of small probabilities, rather than diminish them as the analysis shows. One potential explanation is that individuals seem to think disaster risk is more serious than it actually is. Thus, individuals might think that they are operating in a high probability domain, rather than a low probability domain. If that were the case, then the findings would be consistent with previous work. This is mere speculation, but the clear contradiction of prior work is certainly intriguing.

Table 3.2 contains the observed and predicted proportions of each region who believe a disaster is likely to affect them. The correspondence is fairly strong; however, the model predicts higher than observed values in the Mid-Atlantic, West South

Table 3.2: Observed and Predicted Proportions of Individuals who Think a Natural Disaster is Likely to Affect Them in the Next Decade

Region	Actual Proportion	Predicted Proportion
New England	67%	62%
Mid-Atlantic	48%	62%
East North Central	65%	63%
West North Central	61%	64%
South Atlantic	62%	55%
East South Central	88%	54%
West South Central	54%	61%
Mountain	19%	58%
Pacific	65%	65%

Central, and Mountain regions, while substantially under-predicting in the East South Central, and, to a lesser extent South Atlantic region. It is not clear what underlies the over-prediction in the Mountain region, but it is possible that the smaller population in that region is inflating the per capita disaster relief figures. On the other hand, the East South Central region has a much higher proportion of individuals who think a disaster is likely than the model predicts. It is not clear what underlies this finding, but future exploration is planned.

In all, the analysis suggests that increased risk in the real world does yield increased subjective beliefs about the likelihood of natural disasters. Moreover, the model clarifies the importance of risk variance or ambiguity in the estimation of perceived hazard risk. The data analyzed indicate that ambiguity depresses probability estimates of disaster risk. Regardless of the theoretical explanation one adopts to explain this phenomenon, it is clear that in regions characterized by greater historical risk variability, citizens are less likely to believe that they will be affected by serious natural disasters.

3.3 Deciding about Disasters

The previous section demonstrated that subjective beliefs about disaster risk are responsive to the level and variance of historical risk exposure. What remains is to ask what drives actual risk management behavior. As Viscusi (1999) has recently suggested, stated beliefs do not always translate into market behavior. The analysis below uses one of the few national data-sets on hazard damage and hazard insurance to test for a relationship between risk exposure, risk perception, cognitive tendencies, and risk management. The challenge is to find a way to evaluate decision-making about risk management across a unit of analysis that allows for variation with respect to actual catastrophic risk.

Virtually all the hazard surveys explicitly select survey respondents from geographic zones that are considered high-risk.[5] Palm focuses exclusively on California because her interest is in earthquake insurance and California represents the only market of any significance in the United States. Kunreuther (1978) looked at citizens in a number of different states, but the respondents were selected specifically because they lived in high risk zones. The implicit assumption is that risk perception will be low outside of high-risk regions. From a statistical point of view, this will only bias the analysis if there is a correlation between the independent variable on which the data were selected and some other variable that is also associated with hazard behavior. At a minimum though, such analysis will decrease the efficiency of the estimates.[6] More importantly, citizen perception of catastrophic risk appears to

5. The one exception that I know of is the Public Attitude Monitor published by the Insurance Research Council (1999,1995) used above, in which citizens across all domestic regions are surveyed about their views on natural disaster risk, government policy, and hazard insurance.

6. Probably a problem less for Kunreuther than for Palm.

be relatively high across regions of high and low risk. Sixty percent of respondents across all regions think it is "very likely" or "somewhat likely" they will be struck by a significant natural disaster in the next ten years (IRC 1999). This raises a greater possibility of bias in studies that focus only on high-risk zones. The point is not that these surveys are unhelpful; indeed, they constitute the core of our knowledge about how people respond to catastrophic risks. Nonetheless, they represent a component piece of a more general research agenda, which needs to pay greater attention to trends in risk perception and management behavior across levels of actual exposure.

3.3.1 Hypotheses

The primary task of this chapter is to offer empirical tests of rationalist and cognitive hypotheses introduced in the previous chapter. The nature of the data offers a relatively rare opportunity to devise empirical tests for the impact of cognitivist explanations on risk management behavior. Specifically, the chapter develops a way to evaluate the impact of availability, overconfidence, and ambiguity on risk management behavior.

An ambiguity effect predicts that risk variance should impact decisions about insurance and risk management. If the decision-making process proceeds according to an EU framework, then no effect of variance or ambiguity should be observed. As discussed above, ambiguity tends to be closely aligned in the literature with notions of risk variance.[7] As the variance of a probability estimate increases (alternatively as the variance of an agent's subjective beliefs about the probability of an event occurring increases), the choice context is inherently more ambiguous, relative to a probability

7. Unfortunately, there is an ambiguity in the literature with respect to the definition of ambiguity. See Mukerji (1998) for an alternative conception.

estimate that is more precise. In a variety of experiments, participants display an aversion to ambiguous risks in some contexts, but an affinity for ambiguous risks in others. If actors are averse to ambiguous probabilities, then they will be more willing to insure risk that is characterized by higher variance, holding the level of risk constant (Kunreuther and Hogarth 1995). Thus, as historical variation in observed disaster risk increases, individuals should be more willing to purchase hazard insurance if they are ambiguity averse. Previous theoretical and experimental work predicts ambiguity aversion in this area because natural disasters are thought to be low probability loss events, a domain in which ambiguity aversion is regularly observed. There is an alternative however. Individuals might display ambiguity-seeking behavior, which would imply they are less likely to purchase insurance for more ambiguous risks. Such behavior is frequently observed for events that have a relatively high probability of occurring (Viscusi and Chesson 1999). Both these hypotheses can be tested by simply including an indicator of historical risk variance in the regression model. If the coefficient is not statistically significant, then there is no evidence for the importance of ambiguity, providing support for the EU framework.

Devising tests for availability and overconfidence requires slightly more conceptual work, but is only modestly more challenging from a methodological perspective. Both availability and overconfidence have to do with the way that new and prior information is weighted in current period decisions. Over-confident decision-makers do not update their beliefs adequately in response to new information.[8] Because overconfident actors are more likely to believe their initial management decisions were correct, such individuals will react (more) slowly to new information. As a result, there will be a good deal of "drag" in the social process.

8. Recall that overconfidence is not equivalent to over-optimism, though we can tell a story about how they might be related.

On the other hand, individuals using availability as a heuristic for judging risk will be overly-responsive to new information (Tversky and Kahneman 1973). To review, availability is a heuristic with which individuals often evaluate risks. Risks of events that have occurred recently (i.e. events that are "available") are generally over-estimated and risks of events that have not occurred recently are generally under-estimated. In the previous chapter, I suggested that beliefs formed using the availability heuristic will exhibit systematic biases, and thus, it is reasonable to speak of an availability bias in addition to an availability heuristic.[9] Information that is available will tend to dominate prior historical information in the decision-making process of individuals using availability as a heuristic. If the availability hypothesis is correct, then people should be overly-responsive to new information. In this sense, availability and overconfidence can be thought of as opposite sides of the same coin, at least in terms of the predictions they yield about social behavior. Overconfidence predicts slower adjustments over a longer period of time, whereas availability predicts virtually instantaneous changes in behavior.

As a result, tests for availability and overconfidence can be devised by examining the process of adjustment or adaptation to new information. Some version of a dynamic econometric model offers an ideal solution. Dynamic models explore the level of adjustment in the dependent variable over time with respect to changes in the independent variables. If all the change in the dependent variable takes place instantaneously, in the current period, then there is no "lagged" effect and the model is essentially static. However, if the impact of changes in X are spread out over several time periods, then the model can reasonably thought to be dynamic, and the duration and rate of adjustment can be meaningfully explored. In the hazard

9. A bias will result, in the sense that they will consistently over-estimate available or recently-occurring risks and consistently under-estimate risks that are unavailable.

insurance context, the question is how quickly does the level of insurance coverage change when new information about the level of disaster risk is revealed (e.g. in response to disaster events). Is the adjustment instantaneous or does it take longer to occur? Is the rate of adjustment rapid or is relatively slow? Dynamic models do not provide particularly cumbersome implementation challenges in this context, and thus offer a feasible way to test the plausibility of availability and overconfidence as empirical phenomena.

In sum, three groups of predictions can be tested. First, almost any form of a rational model requires that risk management decisions are positively responsive to increases in the level of risk. As risk exposure increases, all else equal, the level of insurance coverage should increase as well. The one compelling exception comes from the perverse incentives camp, which suggests individuals might elect not to insure because of the availability of Federal disaster relief. That proposition predicts a negative relationship between the availability of disaster relief and the level of insurance coverage, a prediction that is clearly incorrect given the data, as discussed below. Second, most rationalists would predict that risk variance should have no effect on insurance decisions whereas most behavioral economists predict a positive impact because of ambiguity aversion. Third, availability and overconfidence predict different dynamic responses to changes in the risk environment. Each of these propositions can be tested using relatively straightforward quantitative methodology.

3.3.2 Methodological Issues

A dataset was assembled of time-series cross-section observations for each of the 50 states from 1972-1997. Each observation contains information on the number of flood insurance policies purchased during the year in the given state, the dollar amount of insurance in force in the state,[10] population,[11] a dollar estimate of the amount of flood losses experienced in the state during a given year (1983-1997),[12] the amount of disaster relief received from the Federal government, and median income.[13]

Unlike most of the survey work on natural hazard behavior, the data contain a good deal of geographic variation. The variation allows us to increase the efficiency of our estimation and also prevent some forms of possible bias, as noted in the literature discussion. This section develops some relevant methodological issues and the statistical approach used for estimation.[14]

3.3.2.1 Approaches to Panel Data

The data used are Time-Series Cross-Section (TSCS) data, otherwise known as panel data. Each of the fifty states is observed annually for a period of time. The general model can be written as

$$y_{i,t} = x_{i,t}\beta + \epsilon_{i,t}, \qquad i = 1, 2, ..., N; \quad t = 1, 2...T \tag{3.3}$$

where $x_{i,t}$ is a vector of k exogenous variables, and the observations are indexed by the state or unit (i) and time period (t). Ordinary Least Squares (OLS) produces

10. The flood insurance data were assembled by the author from annual publications of the Insurance Information Institute.

11. Taken from the "City and County Factbook" published by the U.S. Census

12. Provided by the U.S. Army Corps of Engineers and the Hydrologic Information Center at the NOAA/NWS, Department of Commerce. Both the HIC and the Corps of Engineers provide disclaimers about the use of their data for research purposes. The figures are almost surely under-estimates of the true losses experienced. However, I have no reason to believe that they are not consistently under-estimated from year to year.

13. Also taken from the City and County Factbook.

14. The following two subsections can be skipped without a loss of coherence.

unbiased and efficient estimates of β if the errors are independent and identically distributed (iid), which is to say, the errors are uncorrelated with a constant variance. But, the structure of the data makes both these assumptions rather heroic. In this case, because states are of different size and experience different actual hazard risks, the assumption of constant variance or homoscedasticity is unlikely to be correct; and, because the same states in different time periods constitute different observations, it is also unlikely that the errors are independent across observations. Moreover, the errors across states in close proximity or within the same geographic or risk region are likely to be correlated as well. If the assumptions are not met, OLS coefficient estimates will still be unbiased, but estimates of the coefficient standard errors will be incorrect. As a result, tests for statistical significance will wrong, and researchers may make incorrect judgments about associations in their models.

Fortunately, there have been ample methodological innovations to resolve these issues. There are two major techniques that warrant consideration: Panel Corrected Standard Errors (PCSE) advocated by Beck and Katz (1996) and the "cross-sectionally heteroskedastic and timewise autocorrelated" (CHTA) model suggested by Kmenta (1986).[15] Both CHTA and PCSE have desirable theoretical properties; however, using OLS coefficient estimates with PCSE's for inference has been shown to be a superior method in small samples for most error structures (Beck and Katz 1996).

Using either CHTA adjustments or uncorrected OLS estimates of the coefficient variance will result in overconfidence in the coefficient estimates by somewhere on

15. In political science, scholars often use a FGLS approach proposed by Parks (1967). The Parks method cannot be computed if the number of groups is greater than the number of time periods. In this case, the number of states is 50 > 15, the number of time periods, so the Parks FGLS approach is not plausible, irrespective of its undesirable properties (Beck and Katz 1995).

the order of 50-100%, depending on the actual structure of error correlation and the degree of panel heterogeneity. As a result, researchers not using PCSE's would be more likely to conclude there are statistically significant relationships in the data, when in fact, a correct estimate of the error variance matrix would not allow for the rejection of the null hypothesis at any conventional standard.[16] PCSE's are used in all calculations of statistical significance herein.

3.3.2.2 Measurement

Ultimately, this project seeks to understand how individuals perceive and respond to catastrophic risks in their environment. Issues of measurement are central challenges to this agenda. Because of the explicit emphasis on maximizing variation in the level of actual risk and the desire to focus on empirical decision-making, one of the few available alternatives is to use the number of flood insurance policies as the major indicator of risk management behavior. However, within this class of indicator there are still methodological choices to be made. First, one could simply use the annual number of policies purchased in a state, either raw or per capita figures, as the indicator. Second, one could use the annual total dollar value of insurance in force, again either raw or per capita adjustments. Fortunately, the number of policies and the dollar value of the amount of insurance in force are extremely well correlated ($r = .98$) and the historical distribution is virtually identical. Thus, statistically, either measure would fare equally well. However, the number of policies purchased each year has somewhat more intuitive interpretation, and thus, from this point forward, I rely on policy figures, rather than dollar value estimates.

16. See the appendix for a discussion of the error variance matrix and computation of PCSE's.

The major weakness of the indicator is that it fails to capture the wide range of available risk management technologies available to citizens. Though insurance partially covers ex post repair costs, citizens might rationally (or otherwise) prefer to invest in management technologies that would reduce the level of damage were a flood to occur, instead of purchasing insurance. Unfortunately, I have no way to measure such alternative responses. That said, in surveys of hazard prone areas, investment in mitigation technologies is highly correlated with investment in insurance. Moreover, to the extent that individuals respond to risk events by investing in mitigation rather than insurance technologies, my estimates of the relationship between experienced losses and insurance coverage will be biased downward. If the analysis shows no relationship between experienced risk and insurance purchases, I cannot rule out the possibility that individuals change their behavior by mitigating losses, rather than insuring them. However, to the extent that the analysis does find a relationship between experienced losses and insurance, the finding is likely to be robust. In other words, given the measurement challenges, I can make only weak claims for the lack of an impact of experience on risk management behavior, but can make particularly strong claims for an effect if the analysis shows a statistical relationship.

Measuring perceived risk outside of a laboratory or survey environment is no less challenging, but measuring experienced risk is a close second best. Indeed, given the results from the block-probit analysis, we have an empirical finding in hand that links historical risk with perceived risk. The data used herein are much more generalizable than most, but obviously they do not contain subjective risk estimates. Thus, we have to fall back on the analysis in the previous section that demonstrates a positive link between risk exposure and risk perception. The experienced risk figures can be thought of as an indicator of subjective beliefs.

Two potential measures of experienced risk are at least somewhat relevant. First, the most intuitive measure of experienced risk is the level of damages from natural hazards. A financial damages estimate is appealing, but figures on flood losses have been collected only since 1983, and the figures are almost certainly biased downward, in addition to containing a fair bit of noise. A second potential indicator comes from figures on Federal disaster relief, as used in the preceding analysis. The volume of disaster relief, measured either in raw dollars or more likely per capita, is a reasonable indicator of the level of experienced hazard risk. However, relying on disaster relief figures is not without its pitfalls either. The primary indicator of risk management behavior is some indicator of the propensity to purchase flood insurance. General disaster relief figures will encompass a host of non-flood hazards like earthquakes, tornadoes, particularly serious blizzards, etc. Thus, on the one hand, disaster relief figures are an overly inclusive (and perhaps even poor) indicator of flood risk. On the other hand, to the extent that individuals consider flood risks a specific instance of a more general class of natural disaster risks, it might well be that increased awareness of all disaster risks would increase the propensity to manage other members of the risk class. Disaster relief figures have the additional benefit of being collected for a longer period of time, which will help increase the efficiency of the estimates. Both flood loss figures and disaster relief figures are included in the model as indicators of historical risk.

3.3.2.3 Dynamic Models

Testing hypotheses about availability and overconfidence requires utilizing information about the short-term versus long-term effects of changes in the risk environment. To reiterate, effects can either be instantaneous in which case the entire effect of a change in X on the dependent variable occurs in a single time period, or more spread out, in which case there is an instantaneous effect followed by decreasing effects in future periods. In the econometrics literature, these models are known as distributed lag models because "lagged" values of the independent variables have an effect on future values of the dependent variables. A comprehensive treatment of dynamic models is beyond the scope of this chapter. Nonetheless, the way one proceeds methodologically is to include a lagged version of the dependent variable (LDV) on the Right-Hand-Side (RHS) of the regression equation.[17] Using the coefficient (λ) from the LDV and a theoretical foundation of the Koyck model, the instantaneous, long run, Median lag, and mean lags can all be used to summarize the period of adjustment.[18] The statistics measure the rate at which the dependent variable changes in response to changes in the independent variables. Thus, with relatively straightforward interpretations of the coefficient on the LDV in the regression model, we can examine whether availability or overconfidence is a part of this more general process. Fortuitously, the LDV form of the dynamic model both eliminates serial error correlation, and given the conceptual assumptions on the table, allows for dynamic effects to be analyzed.

3.3.2.4 Imputation and Missing Data

The indicator of flood losses is only available after 1982, while the rest of the data continue back for another decade. While including data on flood losses in the model

17. Whether a Koyck model, partial adjustment, or adaptive expectation model, coefficient estimation proceeds identically. For a clear introduction to these models, see (Gujarati 1995), Chapter 17.

18. The median lag is given by $(-\frac{\log 2}{\log \lambda})$. The mean lag is simply $(\frac{\lambda}{1-\lambda})$. The Koyck model assumes that the β's are all of the same sign and that they decline geometrically such that $\beta_k = \beta_0 \lambda^k \qquad k = 0, 1, \ldots.$

is theoretically quite important, it also results in a significant loss of information. Especially given that the project is interested in time-related phenomena, sacrificing the decade of additional data is a highly undesirable alternative. One way to proceed would be to run the analysis twice, first deriving estimates with the flood loss indicator over the shorter time period, and then excluding the flood loss variable over the entire time-frame. Of course, that results in two sets of coefficient estimates and it is difficult to think of a theoretical reason to adopt one or the other. Rather than make an atheoretical choice, I rely on simulation methods to impute flood loss estimates for previous time periods. Because the parameter distribution is known, and because the covariation of the flood loss indicator with other observed variables is known in the later time period, various algorithms can be used to impute probable values of the flood loss variable for earlier time periods. This process can be repeated an arbitrary number of times to yield several datasets that are identical except that missing flood loss figures differ as they are draws from a probability distribution. Separate coefficient estimates can be computed from each sample, and then a summary measure of the coefficient and coefficient variance matrix derived. As a general rule, as well as in this specific case, the imputed data do not drive the other coefficient estimates, but the approach allows all the available information to be used in the estimation.[19]

3.3.3 Analysis

The dependent variable of interest is the propensity to manage catastrophic risk, operationalized as the number of per capita flood insurance policies purchased in a given state during a given year. Log transformations are used for both the dependent

19. The imputation was performed using *Amelia* (Honaker, Joseph, King, Scheve, and Singh 1999). For a discussion of the methods, see either King, Honaker, Joseph, and Scheve (1998) or the *Amelia* documentation.

and most of the independent variables.[20] Including a lagged dependent variable in the equation results in a loss of the first year of data (n=1250).[21] Presented coefficients are averaged across the 20 simulated samples, and the coefficient standard errors encompass the within data-set variance, plus the across data-set variance, using Panel Corrected Standard Errors as within-sample coefficient variance estimates.[22]

---

20. The transformations do not alter the substantive relationships between the variables in the model, but they do allow the realized data to better conform to the assumptions of classical regression estimation.

21. Fixed-effect dummies are included the model, but not the presentation of findings. One additional dummy is excluded from the model (N-2 dummies included) so that model can be estimated with the disaster variance term included, which does not vary over time within units.

22. Precisely, the coefficient vector is the mean coefficient vector, where each element is $\bar{b} = \frac{1}{m}\sum_{j=1}^{m} q_j$, m is the number of simulated datasets (m=20). The standard error of a given coefficient is given by

$$\mathrm{Var}(b) = \frac{1}{m}\sum_{j=1}^{m}\mathrm{Var}(b_j) + S_b^2(1 + 1/m) \tag{3.4}$$

where $S_b^2 = \sum_{j=1}^{m}(b_j - \bar{b}/(m-1))$.

The estimation results are presented in Table 3.3.[23] "Lagged Y" is simply the value of $y_{i,t-1}$. Again, the term is included to eliminate serial error correlation and to account for the dynamic component of the model, discussed in the previous section (Beck and Katz 1996).[24] Table 3.3 illustrates a number of important findings. First, the coefficient on disaster relief is positive and statistically significant at conventional levels ($p < .05$). When experienced losses from natural disasters rise, so too does the demand for flood insurance. A percentage point increase in per capita disaster losses (relief) results in approximately a .04 percent increase in the number of per capita flood insurance policies purchased.

---

23. Browne and Hoyt (2000) estimate a model of flood insurance demand using similar data for years 1984-1993 that bears a superficial resemblance to some of the analysis herein. They find that the demand for flood insurance is negatively related to price, positively related to recent flood losses, and positively associated with both income and spending on disaster relief. Unfortunately, their work contains a methodological flaw that renders their findings incorrect. The dependent variable in the model they estimate is the demand for insurance, operationalized as the amount of per capita insurance in force in a given state during the given year. One of their main explanatory variables is the price of insurance, operationalized as the total premiums paid in the state during the year, divided by the total amount of insurance in force in the state during the same year. The "total volume of insurance" enters the equation as the numerator in the dependent variable (insurance demand) and the denominator in the independent variable "price." A similar equation looks something like

$$\frac{a}{b} = \alpha + \frac{c}{a}\beta + \epsilon \tag{3.5}$$

Browne and Hoyt (2000) hypothesize and find a negative relationship between price and the demand for insurance. But, this is true by construction. All else equal, as a decreases, the fraction on the Right-Hand-Side (RHS) increases (i.e. price rises) and the fraction on the Left-Hand-Side (LHS) (i.e. insurance demand) decreases. Including the same variable on both sides of the equation results in virtually perfect prediction, as the $R^2 = .99$ they report suggests. The t-statistic on the price coefficient is also exceptionally large, exceeding 49, another indication that a problem exists.

24. Including a lagged dependent variable does not necessarily eliminate serial correlation as a general theoretical proposition. However, empirically it often does and one can test for the existence of serial correlation before and after including the LDV. In this model, including the LDV does purge the autocorrelation.

Table 3.3: Model of Risk Management Adoption

Variable	b	PCSE	T
Disaster Relief	.039	.014	2.75
Flood Losses	−.004	.006	−.58
Income	.013	.008	1.61
Variance	−.330	.035	−5.31
Lagged Y	.698	.11	19.97
Constant	.642		
N=1250			
R^2=.957			

Second, the variance coefficient is negative and statistically significant. As there is greater historical variation of disaster events/losses, less per capita insurance is purchased. Just as increased variance diminished subjective beliefs about the probability of a disaster occurring, so too, does increased variance diminish the propensity of citizens to invest in risk management, holding the level of historical risk constant. In combination with the variance findings from the prior section, the data demonstrate the importance of variance not only for subjective belief formation, but also for ultimate market choices about risk management. This contradicts previous work on low probability ambiguous risks that have found ambiguity aversion in this domain. My analysis suggests that individuals may actually be ambiguity seeking when it comes to natural disaster risk. Moreover, unlike some studies that have found market forces or real-world choice contexts eliminate the importance of cognitive tendencies, this study suggests variance is as important in the market as it is in experimental settings. Again, note that the significance of variance in the model in either direction is inconsistent with the EU model. At very least, it suggests extensions or revisions are required for accuracy.

To evaluate the relative merit of the availability and overconfidence hypotheses, analysis of the lag-structure is required. In essence, we are inquiring about the magnitude of short-term or instantaneous effects relative to the long-term effects. As a starting point for analyzing the lag structure, note that the coefficient on the lagged dependent variable is $b = .69$, which implies a relatively brief period of adjustment. The median lag is 1.87 and the mean lag is 2.2, indicating that half the ultimate adjustment takes place within two periods. Two years is a relatively short time period for adjustment, given that overconfidence posits individuals will be very slow in reacting to new information. Given the large instantaneous or short-term impact of changes in the explanatory variables, availability is a far more likely hypothesis than overconfidence. The model presents preliminary support for the availability hypothesis, and undermines the plausibility of overconfidence as a dominant explanation of citizen choice about risk management. Though the substantive findings are important, also note that cognitive or behavioral explanations are not nearly as untestable as critics often suggest. The key is utilizing the appropriate statistical methodology, and identifying reasonable predictions that the data can verify or reject.

The model explained roughly 95 percent of the variance, but that figure includes the lagged dependent variable on the RHS of the equation.[25] Thus, a bit more nuance is required. Regressing y_t on only a constant and y_{t-1} explains between 88-89% of the variance alone. The additional variance that the remaining regressors pick up is thus relatively modest. Finally, though many surveys have found a positive relationship between median income or per capita income and the propensity to purchase insurance, this state-level analysis finds nothing of the sort. Though the coefficient is

25. The presented R^2 is the averaged explained variance across the samples. The individual sample estimates vary very little from dataset to dataset.

positive, it does not approach statistical significance. The analysis shows no meaningful effect (in the aggregate) of income on the propensity to manage disaster risk.

3.3.4 Discussion

What does the analysis actually tell us about risk management decisions? On the one hand, the findings provide support for a number of basic hypotheses. First, when losses are higher, so too is investment in risk management. People are responsive to higher levels of risk exposure in their environment. More people manage risk when the level of risk increases, which supports the basic capacity of citizens for information gathering and the importance of subjective beliefs in the process of individual decision-making. Second, the findings undermine the claims of critics who suggest ex post disaster relief diminishes the demand for ex ante insurance. This analysis suggests that it does precisely the opposite. When losses are high, resulting in more Federal disaster relief, investment in hazard insurance clearly increases. Thus, the available evidence undermines the plausibility of at least one aspect of the perverse incentives argument.

It is also clear that cognitivists have something meaningful to add in this context. Individuals are responsive to factors like variance and exhibit behavior that is consistent with the predictions of availability. The analysis also highlights the tremendous heterogeneity that exists with respect to risk management trends. States facing similar loss patterns do not necessarily exhibit similar management trends. Heterogeneity remains a key piece of this overall puzzle, and it is one that is generally overlooked. Yet, for policy-makers, such heterogeneity is perhaps the most important component of individual behavior. Understanding why individuals facing similar objective risks respond differently should remain a key theoretical concern. The following chapter offers one potential explanation of heterogeneity in this arena. Because decision-making about catastrophic risk takes place in a low-information environment, weak informational signals can often yield herding around arbitrary strategies.

3.4 Conclusion

As we saw in the previous chapter, both rationalist and cognitivist schools have sought to explain decision-making about risk and natural disasters. The empirical analysis presents partially supportive evidence for each school of thought. For rationalists, it is clear that citizen decision-making about disasters is not nearly as arbitrary as some behavioral commentators have suggested. Yet the empirical evidence also elucidates some departures from standard expected utility theory. Part of the goal for this project is to take cognitive psychology out of the laboratory and into the real-world. Were this transition easy, it would have been attempted with greater regularity and rigor than recent scholarly history has exhibited. Yet, the pitfalls and difficulties of this task not withstanding, the transition from laboratory to locale is pivotal to the long-term success and continued relevance of behavioral economics.

The key findings from a cognitivist perspective are the importance of risk variance in the models and the support for availability as an empirical phenomenon. First, increased risk variance seems to depress probability estimates of future events. This finding speaks to the way individuals process information. Most strict rationalists rely, quite reasonably, on an assumption that individuals update their beliefs using the tenets of Bayesian analysis (Viscusi and Magat 1992). Yet, the empirical evidence presented here is inconsistent with that hypothesis. Importantly, the inconsistency arises not because individuals fail to update their beliefs in response to historical exposure. Recall that there was a strong and clear direct effect of risk exposure on beliefs about future disasters. As individuals observe more disasters in the past, they believe that disasters are more likely to occur in the future. The empirical inconsistency arises because the process of belief updating should be insensitive to risk variance. Importantly, utility models capable of incorporating a variance component do exist. Yet, these are rarely models used by mainstream rational choice scholars, and certainly not in this context.

Second, risk variance also affects people's propensity to insure natural hazard risks. In laboratory experiments, it is a common finding that for low probability risk, individuals are ambiguity averse. The data analyzed here suggest that controlling for the actual level of risk, individuals are actually less likely to insure disaster risk of higher variance. One potential explanation is that it is more difficult to form beliefs when observed signals vary a lot. People may actually have more subjective uncertainty about their beliefs, and thus, may be less willing to invest scarce resources in hazard insurance or other management technologies. Another alternative explanation is that individuals mis-understand the risk domain they are in. Recall that a substantial portion of the surveyed population seemed to over-estimate the probability of being struck by a natural disaster. A seemingly robust experimental finding is that individuals are ambiguity seeking with respect to high probability losses (Viscusi and Chesson 1999; Hogarth and Einhorn 1990). Though disaster risk should accurately be thought of as low probability risk, it is possible that ordinary citizens conceive of disaster risk as relatively high probability, in which case ambiguity seeking behavior would be consistent with previous work. Third, the dynamic analysis suggests that overconfidence is unlikely to be driving citizen behavior in this arena. The adjustment to environmental changes is too quick for overconfidence to be a compelling explanation. At the same time, the large instantaneous effects provide some early empirical support for the availability hypothesis outside of experimental settings. On the whole, there is something for both rationalists and cognitivists to take from the empirical analysis. Cognitivists can note the departure from expected utility theory, and rationalists can highlight the positive responsiveness of individual action to levels of risk exposure. Moreover, the data demonstrate the potential productivity of exploring rationalist and cognitive factors together for understanding decisions about risk.

There are a few points to keep in mind as we move forward. First, a puzzle about heterogeneity remains. Though the models in this chapter explain a good deal of citizen behavior, some variance remains unexplained. One ongoing task is to analyze this variation. Second, though this chapter has shown the feasibility of testing for both rationalist and cognitivist factors simultaneous in quantitative analysis, I want also to establish a similar point for other methodologies. In particular, I hope to demonstrate that taking more cognitively realistic approach to formal modeling can produce insights that would otherwise be missed. If we acknowledge that there is something to the insights of behavioral economics, we have three choices as modelers. We can simply reject any approach to modeling that uses rational choice, a strategy that I have tried to argue strenuously against. We can keep the basic strategic form and adjust our equilibrium concepts, as some behavioral game theory purports to do. Or alternatively, we can keep the basic structure of the formal model and simply introduce more psychologically realistic actors into the analysis to clarify their impact on existing game equilibria. It is this latter approach that I believe has the greatest potential both for producing productive insights in specific contexts and for contributing to the broader research agenda. By using the quantitative analysis presented above as a theoretical foundation, the next chapter focuses on the interaction of cognitive bias and strategic environment in order to help explain patterns of social decisions about disaster risk.

CHAPTER 4

INFORMATIONAL CASCADES AND COGNITIVE BIAS

4.1 Introduction

As should be clear by this point, some portion of the U.S. citizenry faces the possibility of catastrophic losses from natural hazards each year, whether from floods, hurricanes, or earthquakes. A broad class of legislative activity is aimed at getting citizens to protect themselves from these potential risks. In academic circles, these policies fall under the heading of *risk regulation.*[1] Indeed, on many classical accounts protecting the citizenry is one of the primary tasks for the State. Of course, some measures are more effective than others and in a substantial number of cases, citizens regularly fail to protect themselves from potential hazards despite extensive government efforts. To reiterate an earlier observation, much of the scholarly literature tends to ask why no one engages in risk management behavior. However, recall also that Chapter 3 suggested framing the question in this light was a bit too vulgar to be helpful. Asking why no one engages in self-protective behavior obviates the fact that many communities do effectively manage catastrophic risk. Against this backdrop, a better question to ask is what underlies the fact that some communities respond to the threat of catastrophic risk while others do not.

The logical answer to this question is that different communities face different levels of objective risk. Indeed, we saw in the previous chapter that communities facing greater risk do utilize risk management more than communities facing lesser risks. However, risk level is a far from perfect predictor of behavior. There is a good deal of remaining variation, even after accounting for differences across levels of actual risk exposure. Similar levels of risk yield diverse levels of responsiveness. Even after accounting for risk perception, risk exposure, demographic, and economic variables,

1. For discussions of risk regulation generally, see Breyer (1993), Margolis (1996), Noll and Krier (1990), Pollack (1996), Slovic, Fischoff, and Lichtenstein (1985), or Lohmann and Hopenhayn (1998).

much variability was left unexplained in the preceding empirical analysis. Earlier, I argued that variation in the historical experience of different regions contributes to the ability of citizens to incorporate information from their environment into their belief structure. This chapter also focuses on the role of information and beliefs in the selection of risk management strategies. However, it is concerned mainly with offering a positive account of the heterogeneity that exists in the way that citizens deal with disaster risk.

4.2 An Illustrative Example

In May of 1999, Iowa was hit with torrential rains that swelled the Cedar River well above flood level. Ten Iowa counties were declared federal disaster areas. A CBS evening news story spotlighted the two towns of Cedar Rapids and Olin, a smaller town of about 650 people. What was unusual about this story was that it highlighted not the devastating losses that disasters tend to yield, but the remarkable organization and mitigation activity undertaken by Cedar Rapids.

> The rapids of the Cedar River are now contained with new floodgates and levees. These odd-looking contraptions keep the sewers capped. The city is so organized this time it even provided pumps to homeowners on the river, keeping them high and dry.[2]

Cedar Rapids responded like a model FEMA community. As the news report said, apparently Cedar Rapids had learned the lessons of the past and when the flood came this time, they were prepared. As a result, although the community received some modest damage from the high waters, the vast majority of the municipality emerged

2. CBS evening News (6:30 P.M), May 21 1999.

unscathed. As a local flood planner put it when asked how the town had fared on this test: "Well, I think I'd score ourselves at 99.9."[3]

During the same flooding however, not all towns fared as well as Cedar Rapids. Olin, a small nearby town was devastated by the floodwaters. One resident noted: "I just don't know what we're gonna do. I mean, it was our first home. We don't have flood insurance."[4] The main street in town was under several feet of water and the Olin Mayor called the flood a nightmare. Said the Mayor, "The water got higher than we expected. I mean, we had a lot of warning. We—we just—it's hard to believe it got that high."[5]

But, why was it hard to believe the water got that high? In 1993, floods devastated the entire Midwest. Was 1993 such a distant memory? Moreover, why did Cedar Rapids have no problem believing the water could get that high? What propelled Cedar Rapids to adopt a self-protective strategy that mixed mitigation and flood insurance? How is it that two communities facing a virtually identical risk of flood responded so differently to the threat? When geography and risk are so remarkably similar, what cognitive process could underlie such radically divergent decisions about what sorts of self-protective measures are warranted when faced with a potentially catastrophic hazard?

The optimist may be tempted to ask whether such a story is the exception rather than the rule. After all, even experts make errors and certainly citizens far less familiar with the reality of flood risk could err in their judgment as well. Perhaps Olin, the town devastated by the floodwaters, simply got it wrong this time, will

3. CBS evening News (6:30 P.M), May 21 1999.

4. CBS evening News (6:30 P.M), May 21 1999.

5. CBS evening News (6:30 P.M), May 21 1999.

learn from their mistake, and respond earnestly to the continuing threat of flood damage in the future. Unfortunately, this example is hardly unique. Throughout the country, communities facing identical levels of objective risk respond to that risk with tremendous heterogeneity. The central task for this chapter is to offer positive account of that variation.

4.3 Information, Strategy, and Catastrophic Risk

The basic proposition is straightforward. Decisions about managing catastrophic risk almost always contain a high degree of uncertainty or ambiguity (Kunreuther and Hogarth 1995). Not only are individuals unsure about whether or not a disaster will strike, but they are also unsure about what sort activity constitutes a reasonable response. Should hazard insurance be purchased? If so, at what level? Are hurricane shutters worth the added expense? Is any action at all warranted or is one's dwelling constructed in accordance with existing building codes and likely to withstand the force of a small to moderate disaster? In most cases, individuals living in hazard prone areas will have a mixture of public and private information about these questions. In some cases, their information will be quite good. In others, it might be noisy or even inaccurate. The challenge for individuals is to evaluate the information they do have and collect as much new information as possible, given the costs of search.

One way for individuals to gather information is to rely on the actions of others in their community as conduits of information. Not just in the context of natural hazards, but also in a wide range of other consumer behavior can the actions of others yield significant information about the desirability of available alternatives. Consider a decision about which new automobile to purchase. Even with research readily available, the choices of like-minded individuals are reasonable proxies for such information. Indeed, we often see so-called clustering effects where members of similar social groups purchase similar products.[6]

A series of surveys starting in the mid-1970's sought to understand what drives decisions about disaster insurance and mitigation. The findings are largely consistent with this informal model of information gathering. Kunreuther (1978) found that knowing someone who had purchased hazard insurance was a strong factor in one's own decision about whether or not to invest. In recent work on earthquake insurance, Palm (1999,1998) suggests that other explanatory factors have gained prominence over the past twenty years; however, knowing someone who has purchased hazard insurance remains a factor in individual decisions about risk management.

This finding is often noted, but the implications for community level behavior are rarely developed. Viewed in this light, decisions about self-protective behavior are, at least in part, informational problems that have strategic content. That is, decisions about mitigation will depend on the observed actions of other individuals, suggesting that hazard-related decisions should be analyzed in a strategic context, not just as individual maximization problems.[7] More specifically, decisions about risk management strategies are ripe for analysis in the framework of technological adoption from economics.[8]

---

6. I am not actually concerned with the precise dynamics of this situation. I intend it only as a loose illustration of the information gathering mechanism.

7. By strategic context, I mean not a game in which the payoffs are inter-dependent, but rather, an information environment in which actions by other players affect the choices a given individual makes. In this sense, the model occupies a ground on the border of decision sciences and game theory, though there are those that would disagree with this characterization. The term strategic is included because the form can easily be extended to involve inter-dependent payoff functions, a move which is currently being explored.

8. Various forms of the basic model exist. See for example, Anderson and Holt (1997,1996), Bikhchandani, Hirshleifer, and Welch (1992), Chamley and Gale (1994), Lee (1993), or Zhang (1997).

Technological adoption models rely on a sequential choice structure in which individual actors—be they firms, citizens, or government organizations—must decide whether or not to adopt a new technology. In the context of technology markets, the quality of new innovations is often uncertain and it can be difficult for firms to know whether adopting will be advantageous. Moreover, there may be network externalities, implying that payoffs depend not just on picking the superior technology, but also on picking a technology that many other firms have selected. In informational environments like this one, where both private and public information is available, a rational firm will often look to the actions of other firms as a way of gathering information about the superiority of one technology over another.

The problem of evaluating and managing catastrophic risks takes place in an essentially identical choice context. Given an unknown probability that a disaster will occur and uncertainty about the proper strategy to select should a disaster occur, an ordinary citizen may have tremendous difficulty selecting the proper course of action. Moreover, this is a choice with serious ramifications; the losses, by definition, may be catastrophic. A choice about whether to adopt self-protective measures against a flood, hurricane, or earthquake centers on, what are for the average citizen, uncertain technologies. Hurricane mitigation measures may protect against some storms, but not a particularly violent one. Extensive expenditures on mitigation may simply not be warranted if no hazard is particularly likely to strike in the current or near future time period. Meteorological predictions may be relevant here, but as anyone caught without an umbrella when the forecast said sun knows, signals from weather prediction are often imperfect. The point here is a simple one: decisions about managing catastrophic risk contain a high degree of uncertainty. In such contexts, it is theoretically rational for individuals to cull information from the actions of others.

In point of fact, it is not only theoretically rational, but this theoretical insight has also been verified empirically. The mixture of empirical and theoretical data suggests the potential productivity of exploring the dynamics of technological adoption models in this context.

The remainder of the chapter proceeds as follows. Section four introduces the basic structure of model. Section five provides analysis and applications in the context of disaster risk. Sections six and seven extend the model, and section eight concludes. At the most general level, I argue that what underlies the heterogeneity of community level mitigation behavior is the decision environment in which private information about risk is aggregated.

4.4 The Model

The basic game is a sequential choice structure in which actors choose to adopt or reject a new technology based on their beliefs about the state of the world. Actors observe the history of the game, receive a private signal, and then select a strategy. Payoffs are based on the ability of actors to make the correct choice, given the underlying state of the world. The model is adapted from the literature on informational cascades and technological adoption (Bikhchandani, Hirshleifer, and Welch 1992; Banerjee 1992; Chamley and Gale 1994; Lee 1993).

4.4.1 Actors

Actors are indexed ($i = 1, 2, ..., n$). Actors choose in an exogenously given sequence denoted by their index number i. Each actor in the game can be thought of as a citizen in a community facing a decision about whether to respond to the threat of a natural disaster. Faced with a potential hazard, a citizen will try to evaluate the probability and severity of the potential damage, and then choose an appropriate action.

4.4.2 Strategy Sets

The basic strategy set can be understood in two parts: the empirical risk management strategies available to citizens and the theoretical manifestations of those choices in the model.

4.4.2.1 Empirical Choice Set

When citizens are faced with a potential loss from a natural hazard, they have two basic types of strategies: mitigation and insurance. Loosely construed, mitigation entails taking ex ante measures that decrease either the probability or severity of losses should a disaster strike. For example, purchasing hurricane shutters is a fairly common mitigation strategy in parts of Florida, and purchasing a cover for a water heater is an oft-prescribed if not adopted approach to limiting home damage if an earthquake strikes. These types of action are known as non-structural mitigation since they try to decrease the resulting damage, if a hazard occurs. In essence, mitigation seeks to avoid or decrease losses should a catastrophe strike.

Insurance on the other hand reallocates the ex post cost of recovering from a hazard. Most homeowner policies do not cover flood damage, but separate flood insurance policies can be purchased from private insurance companies with the support and subsidization of the Federal government (IRC 1995). Although most hazard planners recommend coverage of a home's entire value, lower levels of coverage are also available. While neither limiting the probability nor the level of losses, insurance helps pay for reconstruction, relocation, property replacement, etc. For a relatively modest ex ante expenditure, a citizen can eliminate the potential for unrecoverable catastrophic losses.

Ideally, mitigation and insurance play a complementary role (Kunreuther and Roth 1998). Mitigation helps decrease losses and insurance helps pay for the remaining costs. In reality, the relation is somewhat more complex and the subject of considerable debate. For the time being, I want simply to note that the empirical choice set contains not only these two major strategy types, but also numerous alternatives within each main category. The type and level of mitigation vary substantially, as do the types and level of insurance. That said, both insurance and mitigation and can subsumed under the general heading of self-protective behavior. When faced with catastrophic risk, an individual must decide whether or not to engage in self-protective behavior or risk management. In the remainder of the chapter, mitigation and insurance are treated equivalently, and referred to as self-protective behavior or risk management interchangeably unless explicitly otherwise stated.

4.4.2.2 Theoretical Choice Set

Actors select a strategy from a finite set $\sigma_i = \{A, R\}$ where A represents a decision to Adopt the given technology and R is a decision to Reject it. Extensions of the model demonstrate that similar conclusions hold for mutichotomous choices; however, the computation is substantially more involved. Moreover the dichotomous form is actually more appropriate in the context of catastrophic risk. At the most elemental level, individuals faced with the prospect of a catastrophic event must make a decision about whether to manage the risk or simple ignore it. While it is true that the subsequent decision about what type of mitigation strategy to utilize is critical, the initial decision to self-protect is both analytically and normatively prior. Each individual in the game chooses to Adopt a self-protective strategy like purchasing hazard insurance or Reject it. Playing Adopt involves a constant cost c, where c is nontrivial (Bikhchandani, Hirshleifer, and Welch 1992).[9]

4.4.3 Information Structure

4.4.3.1 States of the World

There are two possible states of the world, $\theta_t = \{\mathrm{G(ood)}, \mathrm{B(ad)}\}$, randomly determined by Nature. If $\theta_t = B$, the payoff from adopting the technology is greater than the payoff from rejecting. If $\theta_t = G$, the opposite is true, and the payoff of rejecting is greater than the payoff of adopting. There are two ways of interpreting the structure in this context. First, uncertainty about θ_t can be thought of as uncertainty about whether a natural disaster will strike in the current time period. If the players are in a disaster state, then Adopting a self-protective strategy is warranted. If no disaster will strike, players should Reject because the costs of adopting are non-trivial and there will be no gains. An alternative interpretation is to understand uncertainty about θ_t as uncertainty about the type of action that is warranted, given a positive probability of avoiding damage entirely even if a natural disaster does strike, and some probability of receiving adequate government relief if damage is extensive. While these issues warrant independent investigation, for our purposes they can be collapsed into uncertainty about θ, and the analysis can focus on how this uncertainty translates into patterns of community behavior. The key challenge for the actors in the game is to form accurate beliefs about the state of the world, a process that mixes public and private information as detailed in the next section.

9. The non-triviality assumption requires that the losses from adopting, given a state of the world in which rejection is the correct action are substantial.

4.4.3.2 Private Signals

Each individual receives a private signal about the state of the world. The signal has a quality q such that $0.5 < q < 1$.[10] Like real-world private information about the likelihood of and proper response to natural disasters, the signal is noisy. Many individuals living in hazard prone areas have personal experience with prior disasters but that information is often vague. The severity of the last flood in an area is not a particularly good indication of how severe the next one will be, or whether there will be one at all. A community may go several decades in between major natural disasters (Davis 1999). The farmer's almanac may contain some indication of how wet or dry a season will be, but like the other real world potential sources of information, it is imprecise.

Each individual receives a private signal drawn from a conditionally independent and identical distribution, $s_i = \{H(igh), L(ow)\}$, where

$$Pr(s = H|\theta_t = B) = q_i > Pr(s = L|\theta_t = B) = (1 - q_i) \tag{4.1}$$

and

$$Pr(s = L|\theta_t = G) = q_i > Pr(s = H|\theta_t = G) = (1 - q_i) \tag{4.2}$$

Note that the probabilities are symmetric and that the symmetry assumption is a rather restrictive one. Though the results generalize, strong symmetry assumptions are used here simply to ease exposition. Given that the true state of the world is $\theta_t = B$, a signal of H is more likely and given that the true state of the world

10. This is often referred to as "precision" in the literature. However, in Bayesian analysis precision is related to variance, denoted $\tau = 1/\sigma^2$. What I am calling quality, and what is referred to as precision in the cascade literature is simply a statement of expected conditional probability. Because variance and its inverse are critical conceptual pieces of the disaster puzzle in their own right, the conceptual distinction is actually quite important.

is $\theta_t = G$, an L signal is more likely. How much more likely helps determine the equilibrium of the game.

4.4.4 Choice Sequence

The choice sequence is exogenously given and individual i chooses i^{th} in the game. The i^{th} actor observes his private signal $s_i = \{H, L\}$ and takes a publicly observable action $a_i = \{\text{A(dopt)}, \text{R(eject)}\}$.

4.4.5 Game History

The history of the game is common knowledge. The history observable to the n^{th} actor is summarized by the actions taken by the first $(n-1)$ actors. Let a_i denote the action chosen by the i^{th} individual and let the history of the game be summarized

$$(H_i = a_1, a_2, ..., a_{i-1}) \tag{4.3}$$

An example of a history observable to the fourth actor would be $H_4 = ARR$, representing a decision to adopt by the first actor, and two subsequent decisions to reject by individuals two and three. Each actor can observe the entire history of the game, but does not know the true state of the world. Because the choices of earlier actors are observable, individuals will sometimes be able to infer the private signals of prior actors and incorporate that information into their own process of belief formation and decision-making.

4.4.6 Payoffs

The most transparent way to understand the payoffs is simply to note that when the true state of the world is $\theta_t = B$ individuals always want to Adopt and when the state of the world is $\theta_t = G$, individuals always want to reject. For simplicity, let the payoffs of adopting be 1 if $\theta_t = B$ and 0 if $\theta_t = G$. And let the payoffs of rejecting be 0 if $\theta_t = B$ and 1 if $\theta_t = G$. Again, this is a strong symmetry assumption for the purposes of exposition. The central results would hold with a different payoff structure, and indeed, one of the strengths of this class of models is its flexibility.

There is no physical externality in this structure so individuals have no incentive to manipulate their choice of actions. There is an informational externality in the sense that actions by one individual will affect the process of belief formation and decision-making of other actors. However, payoffs are not inter-dependent in the strong sense of the term. Note that for purposes of simplicity, the payoffs incorporate the constant cost c of Adopting. This could easily be adjusted, but in the context of this model, parsimony is preferred and the choice is not a consequential one for the analysis. Individuals choose to maximize their payoffs, given their beliefs which entails selecting A if they believe $\theta_t = B$ and R if they believe $\theta_t = G$. This is an exceptionally simple payoff structure. It would be relatively easy make the game more complex, but the marginal gain of doing so does not outweigh the additional notation in this case. Moreover, as the model is extended in sections six and seven, the simplicity of the basic form will become a substantial asset.

4.4.7 Solution Concept

The analysis relies on the solution concept of Perfect Bayesian Equilibrium (PBE) (Bikhchandani, Hirshleifer, and Welch 1992). PBE requires that individuals choose optimally given their beliefs and calculate posterior probabilities using a process of Bayesian updating.

4.5 Analysis

The basic analysis of the game is straightforward. We first set an arbitrary and constant signal quality, $q_i = q = .51$. We assume Player 1 has no prior information about the state of the world and so he assigns an anterior probability of $p = 0.50$, assuming each state is equally probable. He observes his private signal $s_1 = \{H, L\}$. Since the signal is informative, if he receives an H signal, player 1 Adopts (A) the mitigation technology, and if he receives an L signal, he rejects (R). By Bayes Rule,

$$Pr(\theta = B|s_1 = H) = \frac{Pr(s = H|\theta = B)Pr(\theta = B)}{Pr(s = H|\theta = B)Pr(\theta = B) + Pr(s = H|\theta = G)Pr(\theta = G)}$$

$$= \frac{(.51)(.50)}{(.51)(.50) + (.49)(.50)}$$

$$= .51$$

Given a signal of H, player 1 adopts because his posterior probability $Pr(\theta = B) = .51$ is greater than the posterior probability that $Pr(\theta = G) = .49$.

The game history for player 2 is either $H_2 = A$ or $H_2 = R$. Because the structure of the game is common knowledge, player 2 is able to perfectly infer the private signal that player 1 received from the game history. Player 1's posterior beliefs become player 2's anterior beliefs, equal to the signal quality, in this case $p = 0.51$. Player 2 observes her private signal and faces two possible cases. Either her signal is consistent with player 1's choice or she receives a contradictory signal (e.g. player 1 adopts and she receives an L signal). If her signal is consistent with player one's action, clearly she takes the identical action. Her priors already suggested the state was more likely and her signal strengthens her belief. If her signal is contradictory, Bayesian updating yields a posterior probability of p=.50 (given that $q_i = q$), and the signals of the two players cancel each other out. Some tie-breaking convention is needed here, so assume player 2 flips a coin to make her decision.[11]

Player 3 faces four possible game histories: $H_3 = AA$, $H_3 = RR$, $H_3 = AR$, $H_3 = RA$. In the latter two cases, in which players 1 and 2 have taken different public actions, player 3 can perfectly infer the signals of each actor. Player one's signal is observable for the same reason it was above. Player 3 can infer player two's signal for the following reason. If player 2 received a signal consistent with player 1's, we know that she would have chosen identically, resulting in one of the former two game histories. The only way that player 2 can select a different public action is by flipping a coin, which she would only do if she received a different private signal than player 1 did. In these cases, because the signal quality is the same for players 1 and 2, the contradictory signals cancel each other out, and player 3's choice setting is identical to player 1's, as is the analysis. He simply follows his private signal.

In the former game histories, in which players 1 and 2 take the same public action, player 3 can still infer player 1's signal perfectly, but cannot be sure about player 2's signal. Player 2 could have chosen consistently because she received the same signal

11. It is possible to allow for abstention or for other tie-breaking decision rules. Essentially, allowing for abstention simply postpones the onset of herd behavior. If player 2 abstains, player three is able to infer her signal perfectly. The following analysis for player i then becomes the analysis for player $i+1$. The fundamental results remain unchanged.

as player 1, or she could have received a signal of L, flipped a coin, and chosen like player 1 for that reason.

If player 3 receives a signal consistent with the actions of players 1 and 2, for example, if $s_3 = L$ given $H_3 = RR$ or $s_3 = H$ signal given $H_3 = AA$, clearly player three chooses identically as well. All the availability information suggests conformity. If player 3 receives an inconsistent signal, for example, if $s_3 = L$ and $H_3 = AA$, then because Bayes' rule can be applied sequentially, the contradictory signals from players 1 and 3 cancel each other out. Each signal is known with certainty and because $q_i = q$ the informational content cancels. The only remaining source of information comes from the observed Adopt action taken by player 2. Player 2's signal cannot be known for sure since she adopts with certainty if $s_2 = H$ and adopts with probability .5 (flips a coin) if $s_2 = L$ (given that $H_2 = A$). However, this means that conditional on her Adopting, the odds that player 2 received a High signal are greater than the odds that she received a Low signal. In essence, what is going on here is that the signals of players 1 and 3 cancel each other out in the calculation. And because it is more likely that player 2 received an H signal, given that she adopted, than an L signal, player 3 updates his belief about θ and finds that the probability that the underlying state is $\theta_t = B$ is greater than fifty percent. So, he adopts as well.

Because player 3 follows the actions of players one and two irrespective of his private signal, we say that his private information is overwhelmed by the public information culled from the game history. It is trivial to show that any rational player will ignore their private information and follow the herd if the previous two individuals have chosen the identical public action, given the signal quality of $q_i = q = 0.51$. The result is known as an informational cascade, herd behavior in which everyone chooses the same action irrespective of their private signal. Note that once a cascade arises, the informational structure is identical for all subsequent actors because the signals that previous actors received cannot be inferred from their publicly observable actions. Because players later in the sequence know that earlier actors Adopt (Reject) irrespective of their private signal, no additional private information is ever revealed. Irrespective of their private signal, later actors will rationally follow the herd. The result is not only a herd of identical behavior, but also an inefficient process of information aggregation. Because all subsequent individuals ignore their signals, no private information is revealed after the cascade has begun; it is lost to the group. Even if the next twenty individuals receive the correct L signal, the cascade will not be broken because there is no way to aggregate that information from individuals to the group. All individuals will Adopt, even though Reject would yield higher payoffs for all actors.

4.5.1 The Probability of Cascades

Bikhchandani, Hirshleifer, and Welch (1998,1992) have shown that the timing of a cascade depends on the sequence of signals and on the amount of noise in the individual signal. A highly informative private signal may delay, though not prevent a cascade. Moreover, the same signals received in a different order will also affect the timing of a cascade. Although two H signals and two L signals constitute the same aggregate information, the sequence HHLL will result in a cascade while the sequence HLHL will not. This highlights the arbitrariness that may result in convergent social behavior. Even when the objective information is identical, a different sequence of signals and the resulting public actions may result in completely different community level behavior. Although the probability of a cascade eventually occurring is actually quite high in most models like this one, when they occur and whether they are good or bad cascades is variable and a central concern.

4.5.2 Good Cascades, Bad Cascades

Both correct and incorrect cascades can arise in this model (Bikhchandani, Hirshleifer, and Welch 1992). An up cascade or a good cascade arises when behavior converges to the proper technology, given the state of the world. In this model, given that $\theta_t = B$, the risk management technology is Adopted. A down cascade or bad cascade arises when behavior converges to the improper technology, given the true state of the world. This highlights the fact that an informational cascade is not necessarily a negative event. As long as individuals are clustering around the correct technology, there is little cause for concern. Indeed, from the perspective of a social planners interested in overall community welfare, precisely what we want is for all individuals to choose identically, as long as all individuals are making the correct decision. Two potential problems present themselves. First, bad cascades can arise, in which the same unwise action is taken by all members of a community. Second, even if individuals cluster around the correct action, we might still be concerned that information aggregation is inefficient. Although a specific case might yield the correct social decision, as policy makers, we might want to encourage institutions that allow for better information aggregation to decrease the odds that bad cascades will arise in the future.

4.5.3 Efficient Aggregation of Information

The cascade literature demonstrates precisely how and why private information is not always efficiently aggregated. Because in many environments, only actions, not signals, are publicly observable, the information from individuals who act after a cascade has begun is lost, rather than shared. The observable actions regime can be compared to a regime that would make all private signals observable (Bikhchandani, Hirshleifer, and Welch 1992). If private signals, not just public actions are observable, the probability that the group will choose the correct action approaches one as the size of the group increases.[12] Cascade models have generally been used to explain why convergent behavior is often observed in social settings. However, in the context of catastrophic risk, the cascade framework suggests that information institutions may play a role in determining which communities respond effectively to catastrophic risk and which do not. In communities faced with similar objective risks, institutions that allow for better information aggregation may help ensure that appropriate strategies are adopted. The cascade model suggests the potential productivity of exploring the role of risk institutions, not just in filtering perceptions of risk, but also in the aggregation of information about management strategies and technologies.[13]

4.5.4 Summary

To this point, several theoretical findings are in hand. First, the cascade model provides one plausible account of why divergent community-level behavior can result from similar private information. Even a modest degree of noise in a private signal can yield persistent herding around different management technologies in different communities. An inability to aggregate information efficiently leads to equilibria in which different groups adopt completely different strategies in response to the same

12. No proof is included, but see Bikhchandani, Hirshleifer, and Welch (1992) for a discussion. The intuition follows the law of large numbers.

13. Interestingly, this argument also implies the potential relevance of network ties and social capital notions from sociology. To the extent that social networks facilitate the aggregation of information, groups with more ties or more extensive networks may fare systematically better than communities with many structural holes.

objective information. Second, group level decisions that appear to be coherent judgments about appropriate courses of action may in fact be the result of an arbitrary series of choices by individuals with poor and potentially even incorrect private information.[14] Nowhere is this more so the case than with respect to catastrophic risk. Even individuals with good information must realize their signals are noisy. Thus far, we have seen that inefficient social behavior can result from very little private information about the probability of disasters. And we have done so through a fairly basic application of models of individual choice from economics and finance.

4.5.4.1 Caveats

One objection to the cascade model focuses on the sequential nature of the structure. On one reading, it is unrealistic to impose this restriction. My response is two-fold. First, the most obvious alternative to the sequential structure is a simultaneous choice structure in which all actors choose at once in the current period, observing the actions of other players only in the next stage of the game. However, the simultaneity assumption is far more restrictive than the sequential one. Second, if we were to choose an intermediate ground, something akin to clustered choice, in which different clusters of individuals choose sequentially, but within a cluster individuals choose simultaneously, the logic of the game would be essentially identical. Subsequent actors would attempt to cull information from the publicly observable actions of previous actors or clusters, and their ability to do so effectively would depend on the same factors as in the cascade model. There is no doubt that the included model

14. As an aside, the cascade model provides us with another reason to question the coherence of community judgments in the same way that social choice theory has historically. Though not a novel insight, the cascade model again highlights that individual rationality can often result in poor social decisions when judgments are aggregated.

is an oversimplified version of the decision-environment; however, the simplification is intentional. The point is to clarify the underlying informational dynamic and attempt to understand the impact of private information, public choices, and cognitive tendencies on patterns of community behavior.

A second objection is that the possibility of information sharing renders the model implausible. The machinery of the cascade model relies on an inability to talk or share the information from private signals with the group. In the real world, simply talking to individuals seems a viable alternative. Though theoretically individuals could choose to share information with all members of a group, empirically the limitations on time and resources make this somewhat unlikely. The model is intended to provide a stylized version of the decision environment that captures the key components of the information problem the actors face. No doubt real citizens can and do share private information with friends, but in part, this dynamic is folded into the idea of private information. The correct parallel in the game form is to allow private information or the quality of private signals to vary across individuals. Though this chapter does not treat such an extension directly, the game form is readily amenable to such adaptations. The key claim is that even if individuals do share some information, there is still a meaningful distinction between the private information they hold after such conversations and the publicly available information culled from the observed actions of others. The cascade model still allows us to capture and analyze this intuition.

4.5.4.2 Extensions

Explicit in the cascade model is an assumption about the way that individuals evaluate risk and process new information. More precisely, the model assumes that individuals update their beliefs rationally according to a Bayesian decision procedure. They begin with anterior beliefs about the probability of an event and then calculate posterior beliefs when they receive new information. The posterior estimate is then used to choose a course of action. There is nothing inherently troubling about this framework. Indeed, experimental work suggests that individuals tend to update in the right direction, though not to the degree a Bayesian procedure implies.

However, in the context of catastrophic risk, we have some additional empirical information about the way probabilities are perceived by individual actors. First, estimates of probability are often biased. In the context of natural disasters, citizens seem to exhibit an availability bias. Moreover, individuals can be overconfident in their estimation. Overconfident individuals tend to think their own information is better than everyone else's because they are too confident in their own ability to evaluate risk. As a result, an overconfident or arrogant actor might not respond rationally to publicly available information. To put it differently, overconfident actors might weight their private information more heavily than information derived from other actors. This is not to say that individuals are always overconfident or always display biases in risk perception, but rather that such phenomenon are not uncommon, and each warrants some exploration. Fortunately, the cascade model is flexible enough to incorporate both of these phenomena.

4.6 Formalizing Availability

The evidence from markets and laboratory experiments suggests that decision-making about catastrophic risk sometimes exhibits an availability bias. When an event has occurred recently, individuals overestimate the probability it will occur again, and when an event has not occurred recently, individuals often underestimate the probability of occurrence. Prior work has elaborated a general theory of availability cascades (Sunstein and Kuran 1999). The point of this section is to clarify the interaction between strategic information environments and cognitive bias by introducing biased actors into the structure of the game. Even a few biased individuals can increase the odds of an incorrect cascade. Loosely speaking, bias can spread, making social outcomes sub-optimal.

Conceptually, one way of understanding the availability bias is that it implies that current beliefs or perceptions of probabilities will be conditioned on events in a previous time period. If the event in question, in this case, a natural disaster, has occurred recently, an individual's probability estimate will be upwardly biased, and if the event has not occurred recently (i.e. the event is *unavailable*) the estimate will be biased downward. Let $\theta_{t-1} = \{G, B\}$ denote whether the state of the world in the previous time period was good or bad, as above.

Next, we require a way to formalize the bias that results from using availability as a heuristic. A function is needed that transforms initial beliefs into biased beliefs. Since all probabilistic beliefs must still be bounded by the $[0, 1]$ interval, the generic bias function would look something like the following:[15]

15. I am grateful to Sven Feldmann for suggesting this formulation and the specific functions used herein.

$$f^{\alpha} : [0,1] \rightarrow [0,1] \tag{4.4}$$

where if the bias is positive

$$f^{+}(x) > x \tag{4.5}$$

and if the bias is negative

$$f^{-}(x) < x \tag{4.6}$$

The function adjusts existing beliefs upward or downward on the unit interval depending on whether the event in question is readily available.[16] Next, let the subscript α represent bias, and let the bias transformation be defined as

$$f : f(x) = x^{\frac{1}{\alpha}} \quad \forall \quad \alpha \in (0, \infty) \tag{4.7}$$

If $0 < \alpha < 1$, the function adjusts beliefs downward. If $\alpha > 1$, the function adjust beliefs upwards. If $\alpha = 1$, then no transformation takes place. There is no bias and no adjustment to beliefs. Note that the subsequent probability estimate is always defined on the [0,1] interval, so no matter how strong the bias is the subsequent beliefs remain properly specified. The bias transformation allows for probability estimates to be adjusted to account for bias.[17] The one cumbersome feature of the function is its asymmetry. However, for the purposes of discussion and analysis, an index function

16. In the informational story I am telling, availability is simply a function of whether or not the event has occurred recently. In other formulations, availability might well be a function of other factors.

17. Note that there are other functions that could be adopted with similar properties. Though this one is parsimonious and effective, suggestions about other functions are welcome. A related model that relies heavily on the Beta function is currently being explored.

for the degree of bias (α) can be defined simply as

$$f(\alpha) = \log(\alpha) \tag{4.8}$$

which is just a more intuitive way to think about bias. If the index value is negative, a downward bias exists. If the index function is positive, an upward bias exists. If the index function is 0 (i.e. log(1)), no bias exists in either direction. Whereas the bias function adjusts beliefs upward or downward, the bias index provides a more intuitive way to discuss the relevant issues. For the remainder of the chapter, I generally speak of upward or downward bias, by which I mean the bias index is positive or negative.

4.6.1 A Biased First Mover

To analyze the effects of bias on the game of technological adoption, we begin by assuming the first individual in the choice sequence exhibits a bias and that the two subsequent actors are rational. Actor 1 either observes a signal consistent with his bias (e.g. $\alpha = +$ and $S_1 = H$), or inconsistent (e.g $\alpha = -$ and $S_1 = H$). If his private signal is consistent with his bias, clearly he chooses an action based on his signal (equivalently based on his bias). If his private signal is inconsistent with his bias, then his choice depends on the magnitude of bias (α) and the quality of his private signal q_i. When the signal is relatively poor (e.g. $q = 0.51$), it is possible for an availability bias to overwhelm the private signal. But when and if this occurs is largely an empirical matter. The theoretical point here is a fairly simple one. If actor 1 is subject to a bias, he may choose Reject despite a High signal or Accept despite a Low signal.

Player 2 faces only two potential game histories: $H_2 = A$ or $H_2 = R$. However, whereas in the rational game she could perfectly infer player 1's private signal, that is no longer possible. If she is not aware that the first actor is biased, she will act as if her inference is correct. If she receives a signal consistent with player 1's action, she will inevitably follow suit, despite the fact that player 1's action might have been based on his bias, rather than his signal. We know that player 3 will ignore his private information if players 1 and 2 choose identically. But, in this case, the consistent game history is not based on accurate probability calculations. We will observe herd behavior based on extremely sparse information. On the other hand, if player 2 receives a signal inconsistent with player 1, she will flip a coin as above. This could be the correct action, but there is also a positive probability that player 1 ignored his private signal, in which case player 2 would follow her own signal (consistent with player 1's) if she had this knowledge. What we start to see in this dynamic is that a biased early actor can throw off the entire choice sequence, but the impact will depend on whether it is common knowledge which actor in the sequence has biased beliefs.

The third actor either sees a convergent game history, in which case he follows the herd, ignoring his own private information, or he observes an divergent game history in which players 1 and 2 took different actions. In the latter case, he follows his own signal. But, if player 1's bias overwhelmed his private information, resulting in the divergent game history, player three will follow his own private signal, rather than the more accurate (in the aggregate) signals of the first two actors. In the former case, we may see herd behavior on the basis of very little information or biased beliefs about the state of the world. In either case, the process of information aggregation has been undermined by a single actor who exhibits an availability bias. The point is not that incorrect cascades will always occur, but rather that the resulting equilibria will be based on an even less efficient process of information aggregation.

Table 4.1: Potential Combinations of Signals and Bias

		Signal	
		High	Low
Bias Index	Upward (+)		
	Downward (-)		

4.6.2 A Biased Second Mover

Suppose the second actor is subject to an availability bias, but all other actors are rational. Player 1 behaves as discussed in the purely rational case. Player 2 faces only two potential histories. Either $H_2^{\alpha} = A$ or $H_2^{\alpha} = R$. In either case, player 2 can infer player 1's signal perfectly. Since there are only four combinations of bias and signals, we can analyze this setting with the basic 2x2 form in Table 4.1.

First, consider player 2's decision if player 1 Adopted. In the upper left corner of Table 4.1, her bias, the game history, and her private signal are all consistent, so clearly she chooses Adopt. In the top right and bottom right corners, her signal conflicts with player 1's signal, and because the signal precisions are identical, her bias is the only remaining source of information. Whereas in the rational game we assumed she would flip a coin, in this case, clearly her existing bias will dictate her strategy. She will play Adopt if the bias is upward (top right) and Reject if the bias is downward (bottom right). In the remaining bottom left cell, her private signal is consistent with player 1's signal, but inconsistent with her existing bias. The available information says Adopt, but she has a downward bias. Here, player 2's action depends on the relative magnitude of the bias (α) with respect to the signal quality (q). However, even for a relatively noisy signal (e.g. $q = 0.6$). Her posterior probability that $\theta_t = B$ would still be well above 80 percent, given her signal and player 1's signal. Though it is possible for an availability bias to be that strong, it seems unlikely to be the case empirically.

Now, consider player 2's choice if player 1 Rejected ($H_2^{\alpha} = R$). In this case, the bottom right corner represents the case where bias, private information, and public information are consistent. Clearly, she plays Reject in this case. On the left hand side of Table 4.1, player 2's signal is inconsistent with player 1's signal. The two signals cancel out (still assuming constant signal quality) and all that is left is her bias. In the upper left corner, the bias is upward, so she Adopts; and, in the bottom left corner, the bias is downward, so she Rejects. In the remaining top right corner, the two signals are consistent, but they contradict her bias. By the same reasoning as above, it seems more likely she will play Reject, but such an argument is conditional upon the magnitude of the upward bias. So, we have a full characterization of the conditions under which player 2, subject to an availability bias, will play Adopt or Reject.

4.6.2.1 The Follower's Dilemma

The question is will a biased second mover affect the decision of player 3, and how might that impact the ultimate equilibrium. Begin with the two game histories in which players 1 and 2 chose different public actions: $H_3 = RA$ and $H_3 = AR$. Though one might be tempted to think that player 2's bias will debilitate player 3's ability to make accurate inferences about the signal she received, that is not the case. Because there was only one cell in Table 4.1 in which player 2 played Reject (Accept), given player 1's decision to Accept (Reject), player 3 can still perfectly infer player 2's signal. And, though player 2's bias increases the chances that she will make a mistake, it does not affect the choice behavior of player 3 for these two game histories. Bias does not spread.

Unfortunately, the same cannot be said when players 1 and 2 take the same action: $H_3 = AA$ and $H_3 = RR$. In these cases, player 3 cannot perfectly infer player 2's private signal. Player 2 chooses Adopt in three of the four cases when player 1 chose Adopt, and Reject in three of the four cases when player 1 played Reject. For each of these alternative histories, either player 3 receives a signal consistent with them (e.g. $S_3 = H$ and $H_3 = AA$) or inconsistent with the histories, (e.g. $S_3 = L$ and $H_3 = AA$). If the signal is consistent, then clearly player 3 simply follows his signal. If his private signal contradicts the game history, we have a more interesting and ambiguous case.

If player 3 is not aware of the bias, which seems most reasonable, then he will follow the game history irrespective of his own private information, as in the original game. Here we get a cascade because the perceived public information overwhelms player 3's private information. The problem is that the information is, in reality, not as informative as it appears. Because player 2 could be conditioning her strategy on θ_{t-1}, in addition to θ_t, the probability of her choosing optimally in the current time period is diminished. Precisely because player 2's action is biased, and because player 3 will ignore his own information if player 2's choice coincides with player 1's action, herding around poor management decisions can more easily result. The probability of a bad cascade arising with a biased second actor is greater than it is with fully rational actors.

4.6.3 A Biased Third Mover

Finally, what if the first two players are rational and the third actor exhibits an availability bias? Again, return to Table 4.1. Suppose both the previous players chose to Adopt, so $H_3^{\alpha} = AA$. In this case, the upper left cell is straightforward. If the history, player 3's private signal, and his bias all suggest adopting, clearly he will adopt. In the top right corner, player 3 would follow the cascade in the rational model anyway and his bias supports that move as well, so he plays Adopt. In the bottom left cell, his private signal is consistent with the game history, but his bias is downward. In this case, his bias (α) would have to be quite large to overwhelm the mixture of public and private information. Whether this occurs is an open empirical question, but all intuition suggests that player 3 will follow the herd and Adopt in this case unless he has an exceptionally powerful bias. In the remaining bottom right corner, player 3's private information and his bias suggest rejecting, while the game history suggests adopting. Here, the determining factor will be the relative size of the bias (α) and the signal quality (q). I return to this case subsequently.

What if player 3's game history is $H_3^{\alpha} = RR$. This case is obviously closely related to the first. The history suggests playing Reject. In the lower right cell of Table 4.1, all information suggests rejecting, so he plays R. In the bottom left corner, a rational player would follow the history and play R, and player 3's bias supports the move anyway, so he plays Reject. In the upper right corner, all information suggests playing Reject, except his availability bias. As above, the magnitude of the bias would need to be enormous to overwhelm the other sources of information. So, player 3 chooses Reject. Finally, the strategy for the upper left corner depends on the relative magnitude of the bias and the signal quality.

In the final two potential game histories, the actions of players 1 and 2 conflict. One chose adopt, while the other chose reject. Recall from the original game that player 3 could perfectly infer player 1's signal no matter what, and perfectly infer player 2's signal when she played a strategy different than player 1's, which is the case we have here. Because signal quality does not vary across individuals, the information from players 1 and 2 cancels. As a result, the analysis for the biased third actor proceeds just as the analysis for a biased first mover does.

4.6.4 Discussion and Implications

With this analysis in hand, we can develop some basic intuitions about how biased actors will behave in a simple game of technological adoption. We have a number of cases where a biased mover will not meaningfully affect the equilibrium of the game, several cases where bias alone dictates the strategy chosen, and a handful of cases that are ambiguous on their face. We would need to know more about the relationship between bias and private information to rigorously analyze them. The challenge now is to characterize these cases and tease out the implications.

When private information is consistent with the game history, an availability bias will not influence the equilibrium of the game. A mixture of private and public information can easily overwhelm whatever previous bias exists. Yet, when an observed game history (i.e. public information) pulls in one direction and both personal bias and private information pull in the other, the effects of bias may be important. While a rational actor would give adequate weight to the publicly available information, a biased actor might not, increasing the odds of a personal mistake. Alternatively, when game histories are inconsistent; that is, when public information is ambiguous or uninformative, there can be a tension between private information and personal bias. When a rational actor would simply follow his/her "good" signal, the biased actor may not.

While this increases the odds of an individual mistake, the more important effect is to undermine the process of information aggregation that even a coarse action set like this one allows. The rational actor that follows a biased player may make incorrect inferences from the observed public actions. As a result, the correct calculus of subsequent actors' decision procedures may yield incorrect results. When biased actors appear early in a choice sequence or on the heels of an inconsistent game history (e.g. $H_3 = AR$), they can increase the probability of a cascade in the direction of their bias. Because in this case, their bias is a function only of the previous state of the world θ_{t-1}, not the current state of the world θ_t, such an effect increases the odds of an incorrect cascade. Speaking informally, in a model of sequential choice, bias can spread, undermining the potential for efficient information aggregation. As a result, the potential for costly individual mistakes may give rise to socially detrimental herding around poor management technologies.

4.7 Overconfidence

Though availability received more empirical support in chapter 3, overconfidence still constitutes an interesting phenomenon in this case. Though ultimately, I think availability is more powerful explanation of behavior in this arena, the methodological point remains the same. Findings about empirical decision-making can be productively integrated with simple models of rational choice to enhance our understanding both of our models and of human behavior.

4.7.1 *The Nature of Overconfidence*

Most evidence about overconfidence has been developed in the calibration literature (Alpert and Raiffa 1982; Fischoff, Slovic, and Lichtenstein 1977). However, empirical applications have noted overconfidence in a range of professional fields, among lay decision-makers, and experts.[18] To reiterate, people tend to be overconfident when answering questions of moderate to extreme difficulty (Odean 1997; Yates 1990) and be too optimistic about future events. In the case of risk evaluation, overconfidence implies that decision-makers do not update their beliefs adequately in response to new information. Decision-makers weight their own information too heavily and are too confident that their initial decisions are correct. The empirical evidence on disaster management is mixed on this front. Citizens are generally unresponsive to changes in the informational environment. Informational campaigns designed to increase mitigation or management behavior have had little impact. One interpretation is that people fail to update their beliefs based on this new information because they are too confident that their prior decisions were correct. There is some potential evidence that overconfidence plays a role in the risk management arena, although the scope and precise nature is unclear.

While experimental findings of overconfidence abound (Kagel and Roth 1995), the insights are just now being introduced into rational actor models. For example, Odean (1997) showed that overconfidence can help explain patterns of stock trading in the market. In this section, I want to demonstrate that community members who are overconfident can help prevent bad cascades and enhance the probability of good cascades. Following the work of Bernardo and Welch (1999), I argue that in the catastrophic risk context, where the potential for incorrect cascades is large

18. For a discussion, see Odean (1997) or Lichtenstein, Fischoff, and Phillips (1982).

and the ramifications even larger, a community that has a healthy share of overconfident individuals may fare better than a community with all rational actors. Because overconfident actors may fail to fully update their beliefs given new information, overconfidence may actually help drive more efficient information aggregation. Although more efficient aggregation will not prevent cascades, by delaying their onset, it will result in an increased probability of communities herding around the proper management technology. Creating informational campaigns or regulatory institutions that take advantage of this fact could decrease overall social losses.

4.7.2 Formalizing Overconfidence

The most straightforward way to formalize overconfidence follows Bernardo and Welch (1999) who evaluate the impact of overconfident entrepreneurs in an evolutionary model of firm competition. By adopting a bit of notation from them and with the core insight from the cascade model in hand, we can begin to untangle the role of overconfidence in decisions about catastrophic risk.

Let S_n be the number of H signals less the number of L signals that can be inferred by any individual from the actions of the first n actors. $S_n = S_{(n-1)} + 1$ if everyone can infer that the n^{th} actor's signal was H, $S_n = S_{(n-1)} - 1$ if everyone can infer that the n^{th} actor's signal was L, and $S_n = S_{(n-1)}$ if the n^{th} individual's signal cannot be inferred. In the rational model above, an actor adopts if $S_n \geq 1$, which incorporates two cases. Either $S_{(n-1)} \geq 0$ and the n^{th} individual observes H or $S_{(n-1)} \geq 2$ and the n^{th} individual observes L. In the latter, the n^{th} individual ignores her signal, follows the herd, and we have a cascade. Stated more generally, cascades among perfectly rational actors when signal precisions are identical, occur when $S_n = \pm 2$. If $|S_n| \geq 2$, a cascade will occur with certainty.

The notation provides a ready-made way to understand the dynamics of overconfidence in this decision structure. Recall that overconfident individuals believe their own information is better than it actually is, by definition. For a given signal quality q, an overconfident actor thinks that the actual quality is $q' > q$. As a result when he updates his beliefs about θ, he will give too much weight to his own private information and not enough weight to the public information from game history. The three ideal types are the maverick who ignores public information entirely ($q < q' = 1$), the rational actor who takes account of both ($q' = q$), and what might be considered an actor with esteem problems who ignores his private information in lieu of whatever public information is available ($q > q' = 0$)

Unlike rational actors who will follow the herd if $|S_n| \geq 2$, actors who are overconfident may not follow the herd because they think their own private information is stronger than it actually is. Generically, we can say that overconfident actors will follow their own signal if $|S_{(n-1)}| < k$ and follow the herd if $|S_{(n-1)}| \geq k$, where k is a critical point increasing monotonically with q' (Bernardo and Welch 1999). The basic intuition here is that as an actor is more and more overconfident, he believes that his private information is increasingly better than everyone else's. More public information is required to outweigh the overconfident actor's private signal. As a result, it takes a longer sequence of identical actions to overwhelm the actor's private information. A rational individual will herd if $|S_n| \geq 2$ precisely because she is aware that the quality of her signal is the same quality as the actors who chose before her. An overconfident individual requires that S_n be greater in order for him to follow the herd. More generally, k and $-k$ will be absorbing states resulting in cascades, as above (Bernardo and Welch 1999).

4.7.3 Analyzing the Implications

Introducing overconfident actors into the model has one main implication. Overconfidence delays the onset of cascades and in the process allows more information to be aggregated before herding starts. Cascades still occur; however, because overconfident actors will not follow the herd when rational actors would, they allow their private signals to be viewed by the community. While cascades will arise even with overconfident actors, as the difference between $\pm k$ and ± 2 increases, so too will the time before a cascade occurs. Having overconfident actors in the sequence delays the onset of a cascade, and as a result, allows for a more efficient process of information aggregation.

Recall that one problem with informational cascades from a social planner perspective is the strong possibility of a bad cascade, in which individuals herd around an inappropriate management technology. With a noisy signal, the probability of a bad cascade nears 50 percent. While the cascade framework helps explain cross-community heterogeneity with respect to risk behavior, from a policy perspective, we should be concerned with how bad cascades can be avoided. Again, the model highlights the central role of information and information institutions.

4.7.4 Caveats

Overconfidence is a fairly robust finding from behavioral economics. However, applying the finding in a discussion of cascades generally and natural disaster strategies specifically, warrants a few caveats. First, the evidence presented in the previous chapter did provide particularly strong support for the role of overconfidence in decisions about disaster risk. Second, in order for overconfidence to delay the onset of cascades and provide social benefits, all actors must know which community members are overconfident. For example, if the fourth actor views a game history $H_4 = AAR$, he only relies on his own signal if he knows that the third actor is overconfident. While in many contexts this is a reasonable assumption, it is not clear how well it applies to managing catastrophic risk. Third, overconfidence implies mistakes at the individual level. By definition, overconfident actors ignore available information that is technically correct. As a result, they will make more mistakes than rational actors, which is precisely why there is a social benefit. From an evolutionary economics standpoint, it is not clear overconfidence would persist. Still, the point is a simple one: understanding the implications of empirical decision-making on rational actor models is an important step in the development of theory. However, each application requires an inquiry into the reasonableness of the analysis.

4.8 Cascades and Catastrophic Risk

The discussion began with an empirical puzzle: communities facing identical objective risks respond with remarkable divergence when choosing risk management strategies. By combining formal analysis with key empirical findings about the way people evaluate risk, a viable explanation of this heterogeneity was advanced. When faced with uncertain technologies and imperfect private information, rational actors will look to the actions of others as a way of gathering information. When they do so, private information may fail to be efficiently aggregated and herd behavior can quickly result. When this process takes place simultaneously in different communities with the same aggregate information, one group may exhibit widespread adoption of a risk management strategy and the other may exhibit widespread rejection. Moreover, this herd behavior can be remarkably persistent, despite the poor informational foundation.[19]

The cascade model provides a plausible and intuitively appealing account of group decision-making that has been documented in a wide variety of contexts. Though the case for the accuracy of cascade models may be strong generally, in the case of catastrophic risk, it is even stronger. Empirical surveys have shown that individual decisions about mitigation, hazard insurance, and other self-protective behavior are often strongly influenced by the actions of friends or neighbors facing similar choices. When faced with large and ambiguous risks, it is perfectly rational for individuals to gather information by observing the choices of others.

At the same time, when actors use availability as a heuristic to form beliefs or exhibit overconfidence, the aggregation of information may be affected. The basic implication of the cascade model is that factors supporting the aggregation of private information will help cause good cascades and avoid bad cascades. Overconfidence is one such factor and local institutions that are able to take advantage of this fact should serve communities better than those that do not. By the same token, factors that further undermine the process of accurate information aggregation, like the availability bias, may push communities toward non-managing herds.

19. Note that this is a debatable point in the literature. Scholars who developed the model of informational cascades argue that cascades are fragile because the introduction of any new public information can easily halt the cascade. I would argue that new public information competes with existing private information. If so, the new information would have to be quite powerful to overwhelm the anterior probability, which when a cascade occurs is somewhere on the order of 80-90%.

In each of the rational, biased, and overconfident cases, the role of information institutions is important. Communities that have an effective infrastructure for information transmission and aggregation should consistently fare better in dealing with disaster risk than communities that do not. When an individual fails to purchase insurance and his home is destroyed by a hurricane, it is unfortunate. Yet, when entire communities fail to manage risk, there are far-reaching social ramifications, both for other citizens and for the State. This social reality, which is best characterized not by inaction, but by heterogeneous action, presents a common, but rarely analyzed case for legislators. Chapter 6 asks how this social reality affects the decision-environment of politicians trying to formulate policy. The chapter suggests heterogeneity in the risk behavior of citizens has clear constraining implications for politicians devising institutional arrangements.

However, before turning to the interaction of institutional choice and the patterns of community behavior that the data suggest, some empirical testing of the cascade model is required. Although the motivation for adopting the model was driven by survey findings, the model's accuracy cannot simply be assumed. In most applications of the cascade model, observed herd behavior is the starting point and the cascade model is one possible explanation. In this case though, the cascade model was adopted because it was a parsimonious and reasonable approximation of the decision environment. As a result, we can derive predictions from the model, devise an empirical testing strategy, and offer evidence about the model's accuracy in the disaster context. Developing and implementing an empirical testing strategy for the cascade model are the core tasks for the following chapter.

CHAPTER 5

HERD BEHAVIOR AND HOMOGENEITY

5.1 Introduction

The previous chapter elaborated a theoretical model of individual choice about managing natural disaster risk. In essence, the cascade model of individual behavior notes that rational individuals will often cluster around an identical, but potentially sub-optimal strategy for risk management. Because the informational content of publicly observable actions taken by friends and neighbors will generally outweigh all but exceptionally good private information, local herds can easily result in the model. Cognitive biases may exacerbate the challenges of information aggregation or actually facilitate better social decision-making by preventing the onset of cascades. This account provides an explanation of why we observe local homogeneity with global heterogeneity in risk behavior. While the previous chapter was almost entirely theoretical, geared towards model exposition and demonstration, the task for this chapter is more empirical. Naturally, building a compelling case for the cascade model requires empirical testing despite the substantial challenges of this turn.

The empirical challenges stem largely from two sources. First, it is easy to misinterpret the predictions of the model. Care and precision about what the model actually predicts is critical. In most applications, the cascade framework has been used to offer a potential explanation of herd behavior. The starting point is an empirical phenomenon of herding in a context where there is no apparent rationale or benefit to homogeneous behavior. The cascade model provides one potential explanation, which has been applied quite broadly. However, in the natural disaster context we start from a slightly different point of departure. The empirical finding of local homogeneity and global heterogeneity in combination with previous survey work suggesting that individuals use friends and neighbors as information sources, motivated the technological adoption or cascade model. The model provided a number of helpful insights and an easy way to formalize the relationship between heuristics, cognitive biases, and strategic interaction. Yet, testing the accuracy of the cascade model requires some additional theoretical work. We need to develop predictions above and beyond those that motivated the initial adoption of the cascade model since anything else would be tautological. As discussed in greater detail below, this chapter focuses on one primary additional prediction. The cascade model actually focuses on the level of variation in social behavior, rather than the (mean) level of behavior. In the catastrophic risk context, the cascade model predicts that the variance of risk management behavior should be low, but has very little to say about whether the level of insurance coverage (i.e. risk management activity) should be high or low in a given community. This is a tricky point to grasp, and indeed, it is relatively uncommon to focus on variance in most econometric models. However, because the cascade model has clear predictions about variance, while only ambiguous ones about the mean, a variance model necessarily constitutes the core of the empirical testing strategy.

The second challenge of empirical testing stems from the nature of the available data. A first-best solution would rely on individual level data that could not only demonstrate group-level homogeneity or herding, but also that the information signaling rationale was driving decisions. Ideally, we would like to document the process of decision-making from this starting point, showing that we either observe or fail to observe the existence of cascades across an entire sample of communities, as individuals in a choice sequence act. Of course, such data are virtually impossible to obtain outside of a laboratory context. A second-best approach would be to work with community level data on risk management behavior together with survey data that documented a cascade-like rationale in the responses of participants in some communities, but not in others. Even if these data were available, surveys come with their own respective pitfalls. Presumably, there are social incentives that discourage admitting that financial decisions are driven solely by the actions of others, even if there is a reasonable informational justification for such behavior. Getting respondents to admit to a herding rationale might be difficult if not impossible. Even in this case then, we would likely be driven to rely on aggregate patterns of social behavior, which are essentially the data used in this chapter. This chapter relies on county-level data on risk management decisions, demographics, and natural hazard losses. However, it is important to keep in mind that both this chapter and the previous one are rooted in the insights of previous survey work on hazard related behavior. The survey findings from previous work are what motivated the cascade model in the first place. The community-level data constitute a reasonable middle ground for further testing the theoretical framework. The question then becomes what types of aggregate behavioral patterns does the cascade model predict? The task of this chapter is briefly to clarify the answer to this question and then turn to strategies for empirical testing.

5.1.1 Structure and Organization

Section two develops the theoretical implications of the cascade model for patterns of risk management behavior and identifies a series of empirical tests. Section three provides an exposition of the statistical methodology required to perform these tests. Though the methodology is not overly complicated, the nature of the cascade hypothesis requires emphasizing parts of regression equations ordinarily ignored or under-emphasized. Section four presents the primary findings and discussion. Finally, section five highlights the weaknesses of the current analysis, notes remaining issues to be treated in subsequent research, and provides an evaluation of the current evidence.

5.2 Implications and Predictions

Though the cascade model provides a helpful general insight about the potential micro level dynamics of macro-level phenomena, offering evidence that communities are actually herding requires more than introducing a plausible model, no matter how interesting the dynamics. Precise predictions need to be identified and an appropriate empirical testing strategy devised.

The informational cascade model predicts that communities will often herd around risk management technologies on the basis of little actual information. Importantly though, the model has little to say about whether communities will herd around high levels of risk management or low levels of risk management. In the simplified form elaborated in the previous chapter, the model has empirical implications not so much for the level of intra-group risk management, but for the level of intra-group variation in risk management that we should observe. That is, the cascade model has only weak predictions about the mean level of risk management within communities, but strong predictions about the variance of risk management within communities. Where informational cascades occur, variance should be low because individuals are herding around the same risk management strategy. Most people are behaving in the same way, either buying hazard insurance or not doing so. If cascades are not occurring then there should be larger variance in the way individuals respond, since bearing catastrophic risk will be unattractive to some citizens and relatively attractive to others. All else being equal, including the actual level of risk exposure, we would expect lower levels of internal community variance when cascades are occurring than when there is no cascading.

This is a clear prediction, but testing requires some reference point. We need to know when cascades are more and less likely to occur. The key here is that the underlying dynamic of a cascade is informational. Cascades arise because of the way that information is gleaned from the actions of others. The question then is what type of informational environment is more likely to give rise to cascades. One way to get at this question is to return to the survey finding that motivated the initial adoption of the cascade model. Individuals often look to the behavior of their friends and neighbors as informational cues about whether they should purchase hazard insurance or invest in other risk mitigating measures (Kunreuther 1978). A seemingly robust finding from economics, psychology, and sociology is that individuals are more likely to take informational cues of this sort from individuals who are like themselves. As a result, there should be a clear link between demographic homogeneity within a group or community and the propensity for herd behavior. As the level of demographic homogeneity increases, the informational environment is more favorable to the formation of cascades because—all else equal—there are more similar individuals from which to take cues. By this logic, intra-community demographic homogeneity should be positively related to the existence of cascades.

With these two observations in hand, we can begin crafting an empirical test. If demographic homogeneity is positively associated with the existence of cascades, and the existence of cascades should be associated with low levels of risk management variance, then the variance of risk management behavior should be a positive function of the level of demographic homogeneity. As demographic homogeneity increases, cascades are more likely to occur, and as a result variance should be lower. The variance based logic allows for straightforward testing and has at least an intuitive appeal.

5.3 Methodology

As it turns out, modeling the variance rather than the mean is relatively straightforward in the likelihood framework of statistical inference (King 1989). To formulate the model, we proceed as we ordinarily would, first specifying a stochastic component and then specifying systematic components for the mean as well as the variance. For the sake of illustration, I rely on a normal distribution:

$$Y_i \sim f_{Normal}(y_i|\mu_i, \sigma_i^2) \tag{5.1}$$

Most regression models simply view the variance component as a nuisance parameter, estimated only because the researcher is interested in some other parameter like the mean or regression coefficients (King 1989). For example, when specifying the systematic component, we often set

$$\mu_i = f(X, \boldsymbol{\beta}) \tag{5.2}$$

while leaving the variance constant: $\sigma_i^2 = \sigma^2$. The expectation of the dependent variable is a function of a set of explanatory variables (X). The task then is simply to estimate the relationship between those explanatory variables and the mean, which usually looks something like

$$\mu_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \tag{5.3}$$

However, from a likelihood perspective there is nothing distinctive about one parameter of a distribution as opposed to another. For that matter, the same is true from a

Bayesian perspective. Though the variance is often an ancillary or nuisance parameter, in many cases it has substantive importance and sometimes it is of more interest than the mean parameter (King 1989, 66). Both the mean (μ_i) and the variance (σ_i^2) are just parameters that can be estimated with exactly the same methods as long as there is adequate data. As King notes, "[i]ndeed, building a likelihood function with any number of parameters is easy mathematically, and, if sufficient data exist, is statistically unproblematic as well" (King 1989, 66). We can simply specify a systematic component for the variance:

$$\sigma_i^2 = g(Z, \gamma) \tag{5.4}$$

where the set of exogenous variables Z may or may not include the X variables in the function for the mean, and estimate the equation directly by maximum likelihood methods. The model now has two systematic components, a mean and a variance function. However, in selecting the functional form for $g(\cdot)$, we require a function that is strictly non-negative since variance can never be negative. One such form is

$$\sigma_i^2 = \exp(\alpha_0 + \alpha Z_{1i} + \alpha_2 Z_{2i}) \tag{5.5}$$

in which case we have specified the variance as a function of a constant and two explanatory variables, and where the exp($\cdot$) function is used so that the variance is never negative (Brehm and Gronke 2001). This poses no problems for estimation, but does require post-estimation processing of the regression coefficients.[1] In the following discussion, the variance is parameterized by intra-community demographic homogeneity. For example, Z_1 is the level of racial homogeneity in the county while Z_2 is the level of economic homogeneity. In this way, we can use demographic measures

1. For a more sophisticated and extended discussion of estimating variance functions, see Davidian and Carroll (1987).

as indicators of the likelihood of cascades, and then attempt to predict the level of variance from the indicators.

To estimate the general model, we have to specify a parameterization for both the mean and the variance. As crude indicators of homogeneity, I rely on census variables that summarize factors like racial make-up and economic diversity.[2] Though imperfect, these measures of homogeneity seem to be relatively robust and capture an important intuition about the conditions under which informational cascades are most likely to arise. The dependent variable in the equation for the mean is the number of flood insurance policies per household purchased in the county during the year of observation. The mean is a function of the level of flood losses, education, median income and, indicators of racial make-up included to test the possibility that different economic or racial groups respond to risk differently for reasons discussed below. Again, though the equation for the mean is usually of primary interest for scholars, the cascade model has no strong predictions about the absolute level of risk management behavior in a community. It predicts only that intra-community variance should be lower when cascades arise. While I present the findings for the mean equation, it is the variance findings that are emphasized.

5.3.1 Estimation

The paper takes two approaches to estimation. First, both the variance and mean equations can be estimated directly using maximum likelihood methods, as noted above. Second, Markov Chain Monte Carlo (MCMC) methods can be used for parameter estimation as well. MCMC methods have received increasing attention not

2. A number of different indicators of homogeneity were attempted. No parameterization changed the results substantially.

just in political science, but throughout the social sciences as they take advantage of the recent gains in computing power, making very difficult higher dimension problems tractable. My own exposition draws heavily on Jackman (2000a) and Jackman (2000b). While a full exposition of MCMC methods is beyond the scope of this chapter, I do want to explain some basic features of the method and clarify where MCMC differs from MLE.[3]

Both likelihood and MCMC methods rely on probability models to link observed data $\mathbf{y}$ with unknown parameters $\boldsymbol{\theta}$ via some probability model that the researcher either knows or posits. Generically, we usually write such models as $y \sim f(\mathbf{y}|\boldsymbol{\theta})$ and perhaps the most common example is normal data: $y_i \sim N(\mu, \sigma^2), \forall i = i, 2, ..., n$. When μ is replaced with a systematic component $(\mathbf{x}_i\boldsymbol{\beta})$ the model is simply ordinary least squares regression. The likelihood function summarizes the information about $\boldsymbol{\theta}$, our parameters of interest, in $\mathbf{y}$, the data that we have observed. By relying on measures of the shape of the likelihood function, we can make statistical inferences about the various parameters in which we are interested. Probably the most common inference we want to make is about whether the relationship between the dependent variable and one of the independent variables is significantly different than zero, but of course there are many other hypotheses that could be tested, and the likelihood framework provides an exceptionally powerful and flexible way to do so.

Both frequentists who use likelihood methods and Bayesians, who were early advocates of MCMC methods, rely heavily on the likelihood function for making statistical inferences. However, whereas frequentists rely on characterizations of the likelihood function for inference, Bayesians want to evaluate features of the posterior distribution of the parameter vector $(\boldsymbol{\theta})$. To see the relationship between a likelihood and

3. For those without methodological interests, the following discussion can be skipped without a significant loss of coherence.

a Bayesian setup, note that Bayes' rule can be written to characterize the posterior density, $p(\boldsymbol{\theta}|\mathbf{y})$ as $p(\boldsymbol{\theta}|\mathbf{y}) \propto p(\boldsymbol{\theta})\mathcal{L}(\boldsymbol{\theta}|\mathbf{y})$. This is the Bayesian mantra: the posterior is proportional to the prior times the likelihood. When the prior is diffuse, the likelihood function dominates, and ML and Bayesian parameter estimates converge. For example, the parameter vector might contain a regression coefficient in a least squares regression model. Whereas the frequentist would present the point estimate which itself is the result of a direct (usually iterated) maximization algorithm, and a standard error (usually drawn from an assumption of asymptotic normality), the Bayesian would characterize the shape of the posterior distribution for the coefficient. Today, usually the method by which the posterior distribution is identified is via the simulation methods of MCMC.

The basic intuition of MCMC is that we can divide our data into things that we can observe (e.g. the given realization of the data) and things that we cannot observe (generally parameters or missing data). By specifying a joint distribution of all the "stuff" in the model, we can express any parameter of interest as a conditional distribution on the data and all the other parameters except the one of interest. Using the information we do have, we can form a temporary estimate for the given parameter and then express the next parameter conditional on all the other stuff in the model plus our new estimate for the first parameter. After all the other parameters have been updated, we can turn back to the original parameter of interest and form a successively better approximation. As described, this is a generic iterative procedure. MCMC methods generate a sample of parameter estimates at each iteration from the appropriate probability distribution (Jackman 2000b).

The MCMC sequence will converge to the posterior distribution under fairly general conditions, and the key here is that there is no important distinction between parameters like regression coefficients, nuisance parameters, or even missing data. All these parameters are just non-observed "stuff," which can be stacked into a vector $\boldsymbol{\theta}$. Once the relationship between the observed and un-observed data has been specified, most applications proceed by relying on the Gibbs sampler. Gibbs sampling essentially partitions the vector $\boldsymbol{\theta}$ into subvectors $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ..., \boldsymbol{\theta}_d)$, expressing the full joint posterior density for $\boldsymbol{\theta}$ as series of conditional (lower dimensional) densities. The sampling scheme is described by Jackman (2000b):

> Iteration t of the Gibbs sampler starts with $\boldsymbol{\theta} = (\boldsymbol{\theta}_1^{(t)}, \boldsymbol{\theta}_2^{(t)}, ..., \boldsymbol{\theta}_d^{(t)})$ and makes the transition to $\boldsymbol{\theta}^{(t+1)}$ via the following scheme:
>
> 1. Sample $\boldsymbol{\theta}_1^{(t+1)}$ from $p(\boldsymbol{\theta}_1 | \boldsymbol{\theta}_2^{(t)}, \boldsymbol{\theta}_3^{(t)}, ..., \boldsymbol{\theta}_d^{(t)}, Y)$
> 2. Sample $\boldsymbol{\theta}_2^{(t+1)}$ from $p(\boldsymbol{\theta}_2 | \boldsymbol{\theta}_1^{(t+1)}, \boldsymbol{\theta}_3^{(t)}, ..., \boldsymbol{\theta}_d^{(t)}, Y)$
>
> $\vdots \qquad \vdots$
>
> d. Sample $\boldsymbol{\theta}_d^{(t+1)}$ from $p(\boldsymbol{\theta}_d | \boldsymbol{\theta}_1^{(t+1)}, \boldsymbol{\theta}_2^{(t+1)}, ..., \boldsymbol{\theta}_{d-1}^{(t+1)}, Y)$

The sequence of sampled vectors from this scheme forms a Markov Chain, which converges to the target posterior density as the number of samples approaches to infinity (Jackman 2000b). We can then store the samples and use various statistics to summarize the sequence for the purpose of inference. All this can be a bit confusing, but essentially we proceed simply by writing down the probability model (just as we would in a likelihood framework), choosing some starting values for the simulation which in this case will be arbitrary and vague (i.e. diffuse or uninformative priors), let the sampling algorithm run for a series of iterations, check the sequence for convergence using various diagnostics, and then characterize the posterior distribution of the parameter vector for statistical inference. The Monte Carlo principle tells us that as long as we are willing to draw enough samples, we can obtain an arbitrarily precise estimate of the posterior distribution (Jackman 2000a). Subject to some limitations on computing power and the researcher's patience, we can gain estimates with highly desirable properties.

For those who find themselves uncomfortable with this method, recall that the MCMC and MLE estimates will converge for relatively simple problems. However, for difficult problems with which MLE has trouble, MCMC will often proceed without difficulty. Note also the flexibility. MCMC methods treat any component of the parameter vector identically. The given parameter, whether it is a regression coefficient, a mean parameter, a variance parameter, or any other parameter of a given distribution we might specify, is re-expressed conditionally on the other parameters in the vector, and a sample is drawn for the given iteration. In the same way that we estimate regression coefficients for the mean effects we can estimate coefficients for the variance effects.[4]

In the context of this paper, the benefit of the MCMC method is three-fold. First, it provides a second-check on the direct maximization estimates. Variance models can be unstable and direct maximization algorithms can sometimes struggle. MCMC provides a check on the likelihood estimates. Second, it allows us to obtain confidence intervals for our coefficient estimates without recourse to heroic assumptions about asymptotic conditions. Third, making use of the Gibbs sampler allows for visual inspection of the sampling sequence and thus makes for easier visualization of the underlying statistical machinery. Whereas the presentation of a coefficient estimate and a standard error conveys key information, much data is also lost.[5] Finally, as

4. This is not a distinction between likelihood and Bayesian analysis, but the machinery of MCMC makes this somewhat more transparent.

5. In truth, this is a criticism of common presentation of statistical findings, rather than of likelihood per se, but nonetheless MCMC forces us to be more explicit in the presentation of findings.

MCMC methods become more common and prominent in the social sciences, being able to compare estimates and findings using different statistical frameworks and techniques provides a check for robustness and can help inform future work. Both the ML and MCMC estimates are presented.[6]

5.3.2 Data

The data are county level observations for 1990.[7] Each observation contains the number of flood insurance policies purchased during the year, an estimate of flood related losses, and a series of demographic variables indicating education, economic and racial diversity, the number of households in the county, and the number of building permits for new construction issued. The flood related data were provided by the Federal Insurance Administration at the Federal Emergency Management Agency (FEMA), while the demographic variables were drawn from census data.[8]

5.3.2.1 Measures

As measures of intra-community homogeneity, I rely on two fairly crude, but commonly used measures that emphasize economic and racial variation. The idea is to capture the degree of similarity or difference that exists among the individuals in a given community. Are the individuals predominantly similar to each other or is there

---

6. Simulations were performed using WinBUGS, version 1.3 (Spiegelhalter, Thomas, Best, and Gilks 2000).

7. The model was estimated using data for both 1990 and 1997. The results were largely similar for each year. Only the results for 1990 are discussed herein. Technically, a pooled cross section time series approach is feasible with these data, but there are some additional methodological challenges associated with such an approach. Future work is planned to treat these issues directly.

8. The census data are contained in the *USA Counties* CD-ROM distributed by the U.S. Department of the Census.

a wide range of types? If they are predominantly similar, then the environment is ripe for cascades to rise. If they are largely dissimilar, it is not that cascades can never arise, but that the informational environment is more hostile to their presence. The indicator of economic heterogeneity is calculated as the ratio of mean household income to median household income in the county.[9] The measure is not perfect, but it does capture the degree of spread in the distribution. The racial homogeneity measure is given by:

$$RH_i = -(1 - \sum p_j^2) \tag{5.6}$$

where p_j is the proportion of the county population made up of a given racial group and j : {White, Black, Asian, American Indian, Other} according to the 1990 census categories.[10] Bear in mind that there is no theoretical framework on the table that suggests race or income should predict risk management behavior. Though one could conceivable construct such a theory— perhaps more plausibly for income than for race—I have no such theory in mind. The theoretical model under consideration predicts a link between community homogeneity and a propensity for informational cascades.

At this point, I want to anticipate a quite reasonable objection. Mainly, if different racial groups always manage risk differently, then the community homogeneity indicator will be associated with decreased variance, but only because different racial

9. An alternative formulation of economic heterogeneity uses gini coefficients to summarize variation. Both measures capture the same intuition; however, the ratio of mean to median income is slightly more intuitive and familiar to readers outside of economics, so I rely on it herein.

10. Note that in the 1990 census, *Hispanic* remained a classification of "origin" rather than race. This will change in the 2000 census. As a result, the racial homogeneity measure is not without its problems. However, it remains the standard measure in the literature.

groups respond to catastrophic risk differently. An increased variance will be observed, but only as an artifact of the reality that different economic or racial groups respond to risk differently. The crux of this objection is that we might observe the predicted variance relationship, but not for the reason I have offered. This is, of course, entirely possible, but if the objection is correct, it implies that we should observe direct effects of the proportion of different racial groups in counties on the mean level of risk management behavior. That is, we should find evidence of a direct relationship between race and risk management. As an empirical matter, this turns out not to be the case. While racial homogeneity does yield decreased variance, there is no statistically significant relationship between race and the level of risk management.[11] Thus, the finding cannot be explained away by the assertion that different racial groups have a propensity to respond to risk differently.

The equation for the mean level of risk management activity is specified using a mixture of economic and demographic data. As in chapter 3, one question is whether the level of risk exposure is associated with increased investment in risk management. At the state level, a clear association was identified. The county-level data offer a further way to test that association at a lower level of analysis. Unfortunately, it is far more challenging to recover the flows of Federal disaster relief figures to specific counties and municipalities. As a result using disaster relief expenditures as an indicator of historical risk is not possible. However, whereas figures on flood losses were quite noisy at the state level, the county level data on flood losses are substantially better. Thus, figures on county level flood losses can be used as a rough indicator of risk exposure. In addition to the expected positive relationship between flood losses and the number of flood insurance policies purchased, the county-level

11. I return to this point more fully at the in the discussion of the main findings.

data also allow for more direct tests of hypotheses about economic well-being and the propensity to insure. A number of previous studies have found that income level is positively associated with the propensity to insure. Because low-income populations are likely to have less disposable income in the current period, they may be less willing to invest in insurance instruments whose payoff is uncertain. I would suggest that there are reasonable theoretical reasons to predict either a positive or a negative relationship on this point. While wealthy individuals have more disposable income, they are also better situated to self-insure and bear the risk of future losses, rather than paying a premium to avoid them. Because no theoretical framework developed in this project provides strong predictions one way or the other on this issue, I abstain from offering a strong prediction but present the results nonetheless. Finally, to rule out the possibility that consistent differences in risk management behavior across racial groups is driving the variance equation, I include indicators of the proportion of the county population made up of each of the census racial categories.[12] Though the mean equation is not my primary interest, the findings may be of some relevance for policymakers or academics.

5.3.3 Summary

Before turning to the empirical findings, it is worth pausing to be clear about the hypotheses. The central hypothesis is that the level of intra-group homogeneity will be negatively related to the variance of intra-group risk management behavior. When cascades occur there will be less variation because individuals will tend to herd around a single level or type of activity. Informational conditions that favor the formation

12. To avoid collinearity, the "other" and "American Indian" category are excluded from the model.

of cascades should be associated with lower levels of intra-community variance. The analysis adopts measures of economic and racial homogeneity as indicators of informational conditions. Because individuals tend to rely on informational cues from people who are similar to themselves, as the similarity of a group increases, so too does the propensity for cascades to arise, all else being equal.

5.4 Findings and Discussion

The maximum likelihood and MCMC estimates of the variance model are presented in Table 5.1. The dependent variable is the number of flood insurance policies purchased in the county per household.[13] Maximum likelihood estimates are presented on the left hand side while the MCMC estimates are presented on the right hand side of the table. The key findings are found in the variance equation.

The two exogenous variables are the indicators of intra-community homogeneity. As the indices rise, they indicate increasingly homogeneous conditions in the community. Both the measures are bounded by zero and negative one. When the community is relatively racially homogenous, consisting almost exclusively of a single race, the measure tends towards zero and as the level of racial diversity increases the measure tends towards -1. The same is true of the indicator of economic homogeneity. The economic homogeneity indicator decreases as the level of economic diversity rises.[14]

13. The model could be formulated using per capita flood insurance policies, per household flood insurance policies, a logged version of either of these two indicators, or simply by including the raw number of flood insurance policies purchased on the left hand side of the regression equation and using the number of households as an independent variable. Each of these specifications was attempted, and though naturally the size of the coefficients changed, neither statistical significance nor the substantive interpretation were altered.

14. Note that these measures are usually indicators of heterogeneity rather than homogeneity and are bounded by the $[0, 1]$ interval, rather than the $[0, -1]$ interval. For the

We are interested in the effect on variance as the measures increase towards the homogenous end of the spectrum. Both the indicators of demographic homogeneity are negative and statistically significant in the variance portion of the model just as the cascade framework predicts. As the level of community homogeneity increases, the variance of risk management behavior decreases. More homogeneous communities are associated with less variance in the way that individuals manage disaster risk. Thus, as informational conditions grow increasingly favorable to the formation of cascades, the variability of risk management decisions should and does in fact decrease.

Substantively, both measures of homogeneity have roughly similar effects, though the impact of economic homogeneity is clearly larger. Recall that because we parameterized the variance using the $\exp(\cdot)$ function, some post-estimation processing of the coefficients is needed. To illustrate, the effect of economic homogeneity is calculated by $= \exp(.907 - 1.57) - \exp(.907) = -4.29\%$. Communities that are more economically homogenous exhibit roughly four percent lower variance in risk management behavior.[15] Similarly, the effect of racial heterogeneity is to decrease variance by just less than two percent. Though at first glance this looks to be a modest effect, over the entire range of the homogeneity indicators, the effect is actually quite substantial. It is also reassuring that both the MCMC and ML estimates yield virtually identical estimates of the coefficients in both the variance and the mean equation. Despite some

purposes of discussion, it is easier to discuss an increase in homogeneity rather than a decrease in heterogeneity so the variables are transformed by subtracting each value from 0. The transformation only changes the sign of the two exogenous variables in the variance equation. The substantive interpretation and all the other effects remain identical.

15. In the MCMC analysis, the X matrix is centered to help with convergence and decrease correlation within a sequence. Centering does not affect the regression coefficients.

Table 5.1: Maximum Likelihood and MCMC Estimates of Risk Management

	Variance Equation		
	MLE	MCMC	Effect
Economic Homogeneity	−1.59	-1.57	4.29
	(.334)	—	
	—	[-2.23, -.935]	
Racial Homogeneity	−1.12	-1.16	1.7
	(.229)	—	
	—	[-1.60, -.705]	
Constant	.901	.907	
	(.035)	—	
	—	[.841,.975]	
	Mean Equation		
	MLE	MCMC	
Flood Loss (log)	.429	.430	
	(.044)	—	
	—	[.344, .516]	
Education	−.011	-.01	
	(.006)	—	
	—	[-.021, .001]	
Mean Income (log)	−.292	-.293	
	(.051)	—	
	—	[-.389, -.187]	
Pct White	−.579	-.588	
	(.677)	—	
	—	[-1.99, .687]	
Pct Black	−.214	-.228	
	(.712)	—	
	—	[-1.65, 1.12]	
Pct Asian	−3.93	-3.91	
	(1.48)	—	
	—	[.919 , 6.76]	
Constant	−6.30	-6.30	
	(.04)	—	
	—	[-6.38, -6.22]	
N=1649			
Log Likelihood = −3101.35			Wald=165.4

The dependent variable is the per household number of flood insurance policies purchased in a community in 1990 (log). Standard errors are in parentheses for the maximum likelihood estimates. For the Gibbs sampler, the mean of the last 2,000 samples is reported. The 95% confidence interval is reported in brackets.

potential problems of instability with variance models, these results appear strong and robust.

To get a sense of the MCMC analysis, I include some graphical summaries of the procedure. First, Figure 5.1 contains the Gelman and Rubin Shrink Factors, a test statistic used to diagnose convergence of the MCMC sequence. The shrink factors quickly fall toward one, indicating the sequence has likely converged. The same is true for the parameters in the mean equation as well, although the plots are not included.

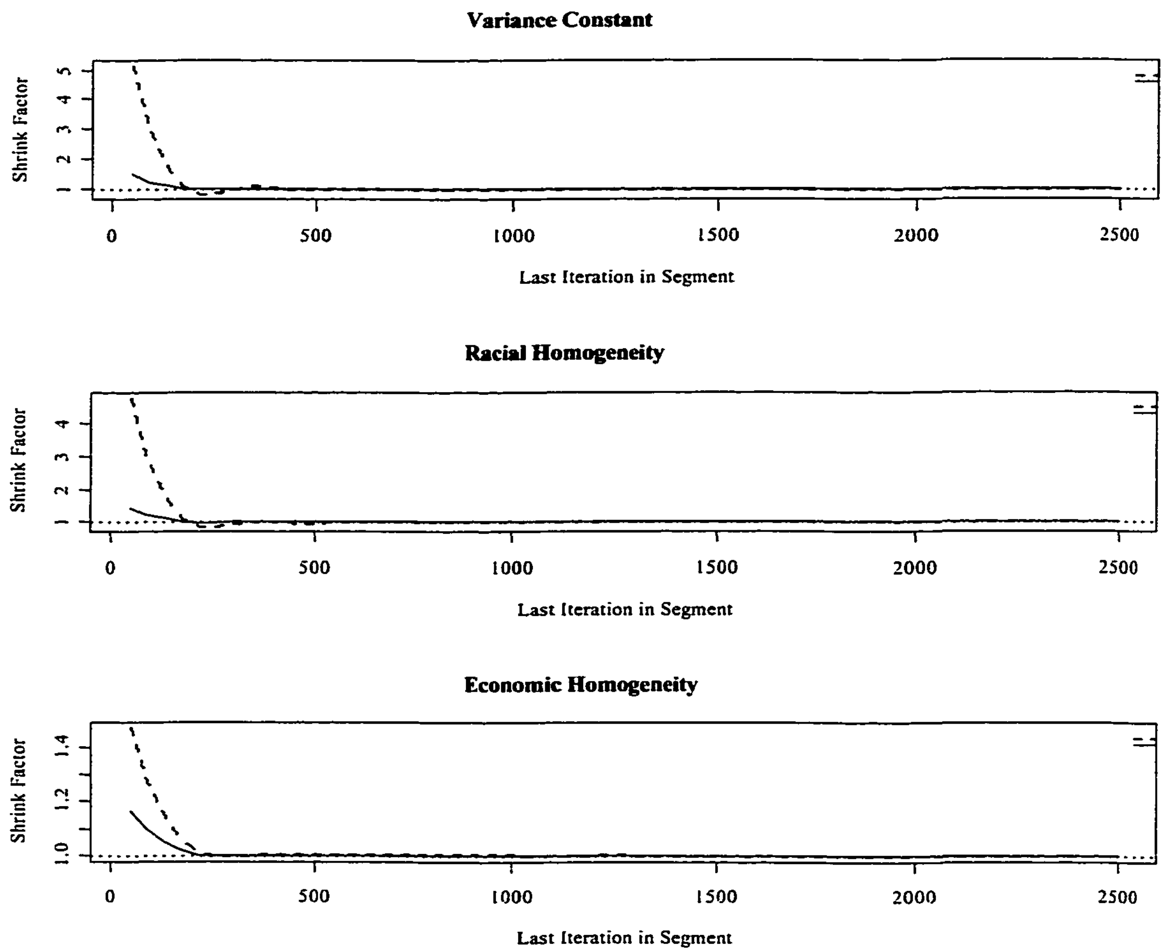
Figures 5.2 and 5.3 contain the densities and traces of the parameter histories of the Gibbs sampler. The density plots show the region in which the parameter is most likely to be located, as summarized in Table 5.1. The densities look approximately normal. The spread around the constant is clearly smaller, but neither of the plots is particularly lumpy and both are uni-modal.

The trace plots look stationary, suggesting that correlation across samples is not a serious problem, and most iterations maintain parameter estimates in the same neighborhood. All and all, the output supports the stability of the estimates of the model. The output in these figures then, simply reassures us that the results identified in Table 5.1 are reasonable.

Importantly, the findings about homogeneity and variance are not driven by the differential response to natural hazard risk by different racial groups. In the mean model, the percentages of the population made up different races (e.g. percentage of the county population made up of Whites) are not statistically significant in the presented model, nor were they in any of the attempted alternative specifications. Race is simply not a good predictor of risk management behavior at least at the community level.[16] Moreover, according to the informational story I have been telling,

16. Though see the discussion of the "Asian" variable below.

Figure 5.1: Gelman and Rubin Shrink Factors for Variance Equation



The Gelman and Rubin test statistic is calculated over the course of the iterations and plotted as a trace plot. The dotted line represents the 97.5% distribution while the solid line represents the median. The shrink factors all quickly fall toward 1 for the given parameters, suggesting that the MCMC sequence has converged on the posterior density (Jackman 2000b).

Figure 5.2: Gibbs Sampler Output of Coefficient Densities in Variance Equation

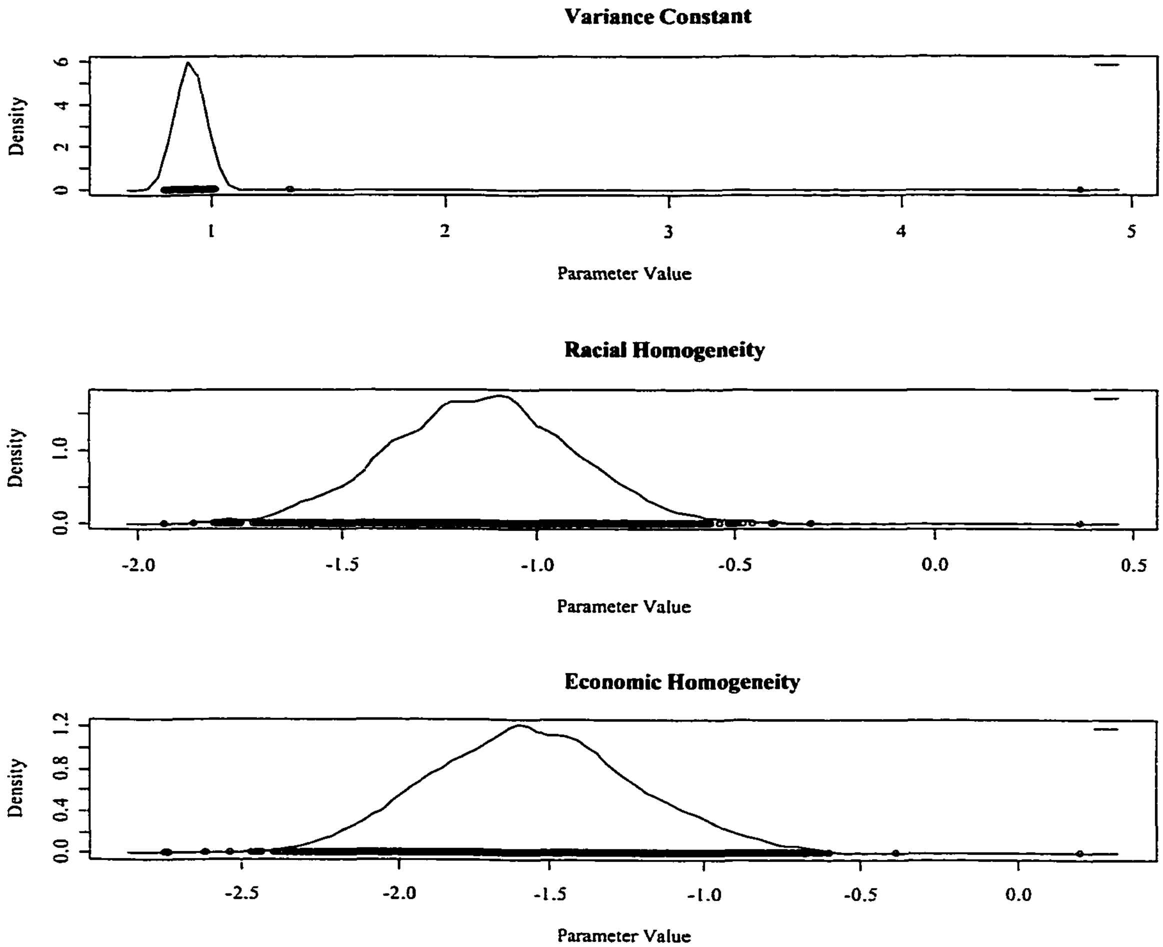
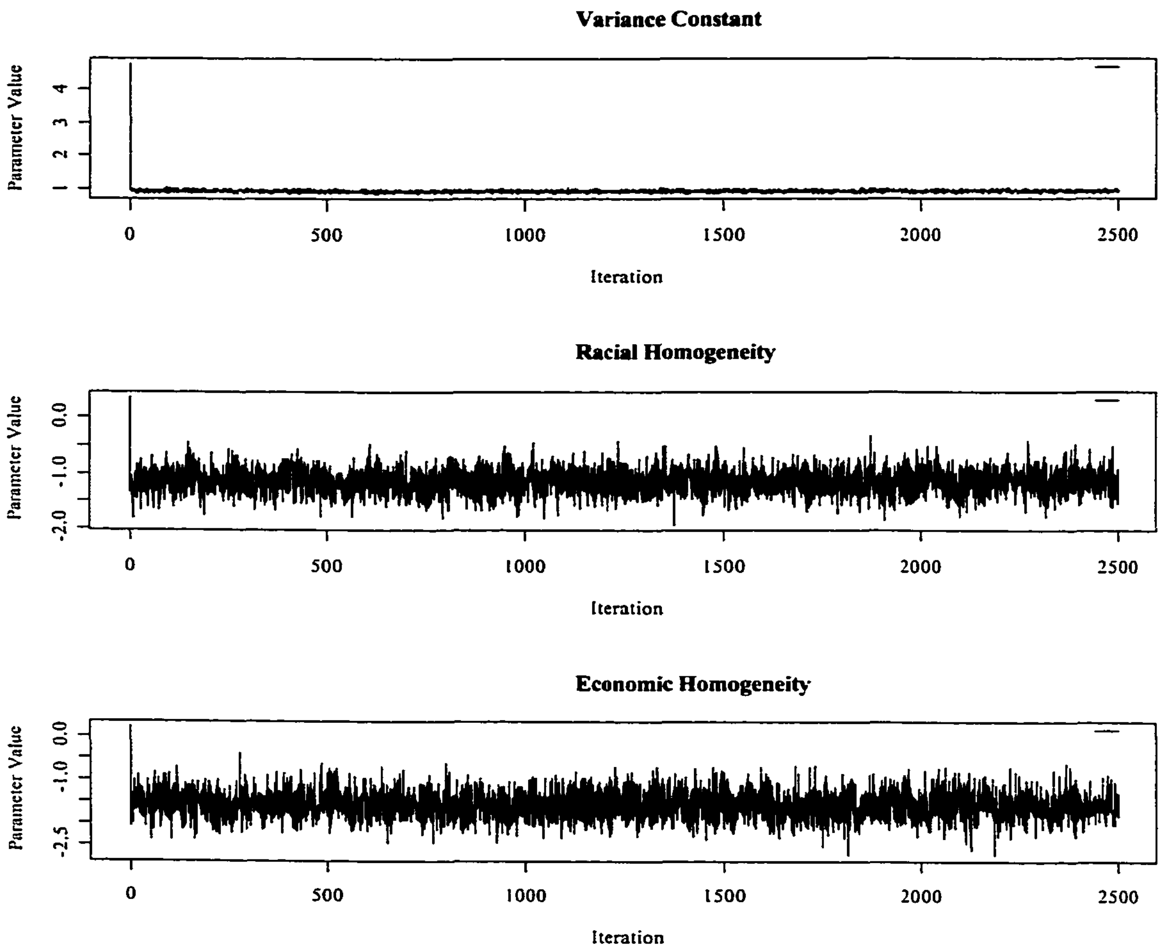


Figure 5.3: Trace Plot of Parameters in Variance Equation.



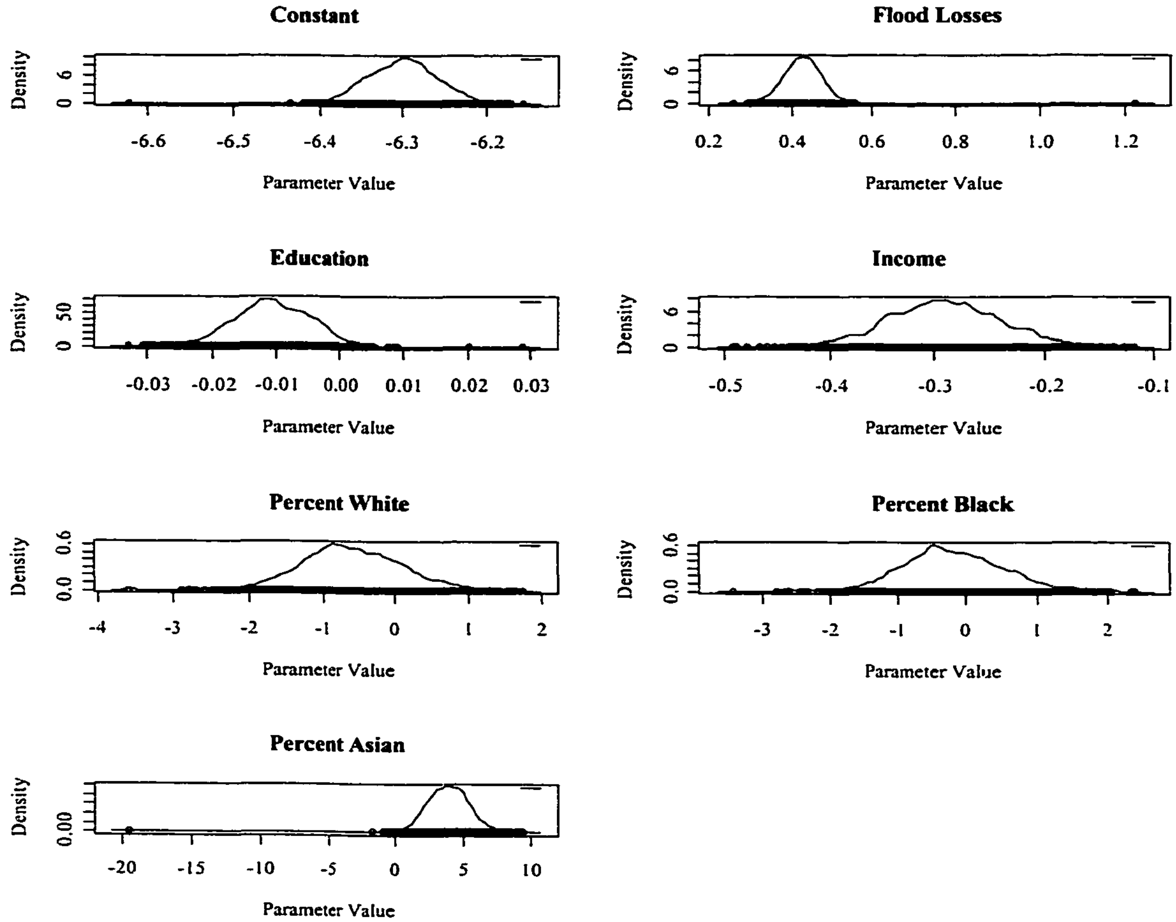
there is no reason it should be. Members of the same group in one community might herd around extensive risk management activity, but herd around virtually no risk management activity in another community. The issue is how easy it is for cascades to form in different groups. When communities are more homogenous, measured either racially, economically, or presumably by a host of other potential indicators, cascades are more likely to occur. As a result, the model predicts and the findings support the proposition: increased community homogeneity decreases the variance of risk management activity. Though the analysis presented here is preliminary, it offers confirmation of the central empirical prediction of the cascade model.

A few results from the mean model that echo the earlier findings are worth noting as well. First, the level of flood losses is a strong and robust predictor of the demand for flood insurance. There are two ways to think about this effect. First, the losses variable at least partially summarizes the level of flood risk, since on average, losses tend to be higher in communities where the level of risk exposure is higher. In this sense, larger proportions of county populations insure against floods when there is a greater level of flood risk. An alternative way to conceive of the variable is in a more longitudinal sense. It is possible that individuals only purchase insurance after a major flood event, as some prior work has suggested. With additional longitudinal data one could discern whether the effect of the loss variable is the result primarily of cross-sectional differences in risk exposure or more longitudinal within-community variation in the level of flood losses. With the currently assembled data, the only viable interpretation is the former one, and it dovetails nicely on the earlier findings in chapter 3. It is reassuring both from a policy perspective and from a methodological perspective that higher levels of losses are associated with more risk management. It suggests the data and the other inferences are reasonable. Second, as noted above, none of the racial make-up variables are statistically significant except the "Asian" variable.[17] Finally, note that the per capita income variable is statistically significant, but has a relatively modest effect substantively. Moreover, the coefficient is negative, indicating that as wealth rises there is actually less investment in hazard insurance. Perhaps this is because wealthier households are better equipped to self-insure. At very least the model does not support previous assertions that wealthy people are more likely to rely on financial instruments like insurance. The densities from the Gibbs sampler for the mean model are presented in Figure 5.4. Again the densities look uni-modal and approximately normal. However, most of the race parameters cannot be meaningfully distinguished from zero, which is why the effects are not statistically significant.

On the whole, the model offers a first layer of general support for the cascade framework. The dominant theoretical prediction is that cascades should yield lower levels of intra-community variance. Using indicators that summarize the favorability of environmental conditions for the formation of cascades, the statistical analysis shows that communities in which cascades are likely to form consistently and robustly display lower variance. More rigorous testing is certainly needed, not just in the disaster risk context, but also in other arenas where the cascade model has been proffered. However, the variance model approach allows for the direct implications of the cascade framework to be tested.

17. I have no particular explanation for the statistical significance of this coefficient, but it does not appear to be substantively important. I am in the midst of exploring the issue.

Figure 5.4: Gibbs Sampler Output of Coefficient Densities in Mean Equation



5.5 Conclusions, Caveats, and Implications

The previous chapter began with one puzzle and one observation. The puzzle was that even after accounting for the level of objective risk exposure that communities face, there is still substantial heterogeneity in the way that communities respond to disaster risk. Individuals facing similar risk respond with widely divergent strategies for risk management. Some individuals invest in extensive measures while others virtually ignore the threat of catastrophic losses. The simple observation was derived from previous surveys of residents living in hazard-prone areas: individuals often look to the behavior of friends and neighbors as a way of gathering information about the usefulness of hazard insurance (Kunreuther 1978). From these two basic starting points, the informational cascade model was developed and the implications of relevant cognitive biases on social equilibria explored. Though the model was consistent with previous work, no new empirical evidence was offered to support the cascade model's validity. This key task for the current chapter was to develop a meaningful statistical methodology to test the model using actual hazard insurance data.

Unlike most models of social phenomena, the cascade model has only weak predictions about the mean level of investment in risk management. Rather, its strong predictions have to do with the variance of risk management behavior. Cascades result in herd behavior around a particular action, but they can result around virtually any action in the choice set. When a cascade occurs, it is not that we expect everyone to invest in insurance, but rather than we expect everyone (most people) to behave similarly, irrespective of whether investment is high or low. We expect little intra-group variation.

Because the substantive implications of the cascade model are about intra-group variability, a heterogeneous regression model was used to test the hypotheses. By allowing the researcher to parameterize the variance, hypothesis tests about the relationship between exogenous variables and variance can be performed as easily as hypothesis tests about the relationship between exogenous variables and the mean, as is the convention. These results are preliminary, but they also contain fairly strong confirmation of the hypothesis. Informational conditions that favor cascades are associated with less variance in risk management behavior. Thus, not only does the cascade model provide a plausible explanation of why communities facing similar levels of actual risk exposure respond so differently, but this first cut of empirical analysis moves the model from the realm of plausibility to the realm of probability.

A number of caveats are warranted as well. First, the model was tested using a single year of cross-sectional data. Theoretically, using multiple years would allow not only for efficiency gains, but also for the exploration of longitudinal trends within counties, states, and regions. In the same way that variance was parameterized cross-sectionally, it is possible to extend the statistical methodology to Time Series Cross Section data, though not without introducing some additional complications.[18] Future research that takes advantage of this opportunity could offer an even more compelling case for the cascade model. Second, better indicators of objective risk exposure would make the model substantially stronger. Ideally, having information about the amount of geographic area inhabited in high risk flood zones within each county would offer a better indicator of risk exposure.[19] Third, though I believe the variance approach is the most reasonable way to test the cascade hypothesis, other

18. For a related, though not identical model see Brehm and Gronke (2001).

19. The data have just been acquired and will be integrated into the analysis at a later date. Financial constraints made the acquisition of these data difficult.

methods are potentially relevant. By using methods from spatial statistics, it might be possible to test for contagion effects across communities. Though the theoretical framework of this project has focused on intra-community variation, community borders are often fuzzy and there is no compelling reason why the propensity for cascades to spread would stop at the county line. A positive and statistically significant spatial trend might offer some additional support for the hypothesis. Though these alternative approaches could be productive, none of them provides as comprehensive an opportunity to test predictions as the variance model does.

The past two chapters argued that the cascade model offers a novel, compelling, and flexible way to model social behavior generally and decisions about disaster risk specifically. On its own, the point is important, but if the cascade model is even loosely correct, then it has critical implications for risk regulation and disaster policy. On the one hand, scholarship that tries to understand the development of domestic disaster institutions without an eye towards herd behavior will miss important constraints on the political choices of legislators and interest groups. Policy decisions are often partially a function of citizen behavior, and modeling political decisions with an inaccurate or incomplete view of citizen decision-making may hinder the positive task at hand. Thus, to craft a meaningful account of risk regulation, we need to understand the dynamics of citizen choice. The cascade model provides another critical piece of the disaster risk puzzle. On the other hand, for those interested in constructing legislative policies that protect citizens and minimize either aggregate social risk exposure or overall economic losses, the cascade dynamic is an equally important building block. Social or economic incentives stemming from government policies may have little impact if informational cascades are driving citizen choice. Policies and institutions that acknowledge and take advantage of the cascade dynamic may result in more efficient, equitable, and cost-effective government institutions. The following chapter takes the main cascade finding as given, teases out implications for government policy, and models the development of Federal disaster policy as a function of the external constraints imposed by this type of citizen decision-making and the changing political dynamics of the disaster policy arena.

CHAPTER 6

DISASTERS, DELEGATION AND INSTITUTIONAL DESIGN

6.1 Introduction

The past several chapters have discussed both theories and data about the way individuals perceive and manage disaster risk and the way such behavior creates patterns of community level risk management activity. With this discussion in the background, I want now to turn to the structure of federal disaster policy. To reiterate an earlier point, unlike most treatments of disaster policy that assume these institutions are exogenous and then ask about their impact on citizen behavior, this chapter seeks to endogenize the institutional environment. By focusing explicitly on how citizen behavior constrains legislative action and on the internal political dynamics with the legislature, my story of institutional evolution suggests a rather different interpretation than the current literature.

6.2 Policy History

Between 1940 and 1995, the federal government undertook a wholesale reconstruction of the way it deals with natural disasters and catastrophic risk. An ad hoc ex post relief regime that had existed for well over a century gave way to a bureaucratically administered system of relief and risk management. Prior to this reorganization, disaster relief packages had provided pork to constituents for which representatives could take credit, and logrolling allowed other members to gain political capital by trading votes with representatives from disaster prone states. For example, after the western blizzards in 1949, representatives requested relief and Congress appropriated direct relief funds to aid in the recovery of communities:

> Mr. Chairman, I cannot too strongly urge the quick and complete approval of the proposed appropriation of another $500,000 for assistance

> in the storm-stricken States of the West and Middle West, including Nebraska. ... The present peril of snow and cold inevitably merges into the peril of floods—floods that can scarce fail to exceed the floods of 1944 and 1946 in destructiveness and danger to life and property. ... Paul Revere warned that "The British are coming." I remind you that the floods are coming.[1]

In this early time period of legislation, relief was relatively infrequent and always the result of disaster-specific legislation. During the transition from this early phase of policy, the ad hoc relief regime was slowly replaced by an institutionalized system of disaster management. A permanent federal role took shape in the Disaster Relief Act of 1950, was further solidified by the National Flood Insurance Program Act of 1968 and the Disaster Relief Act of 1970 with amendments in 1974. The Federal Emergency Management Agency (FEMA) was established in association with President Carter's Reorganization Plan No.3 in 1978. Administrative responsibilities were transferred from a host of other federal agencies under Executive Orders 12127 and 12148. Throughout this period, the federal role in managing natural disasters expanded, and primary responsibility was slowly delegated to the bureaucracy. One puzzle is why Congress would give up such an effective tool for distributing pork to constituents. It is relatively rare that Congress wants to delegate policies that distribute benefits to a targeted constituency (Epstein and O'Halloran 1999). Moreover, Congress delegated discretionary authority to the executive to administer relief. Why give the President an additional tool of political power?

1. Statement of Hon. Karl Stefan, A Representative in Congress from the State of Nebraska before the Subcommittee of the Committee on Appropriations, House of Representatives, Eighty-First Congress, First Session, on Additional Disaster Relief in Storm-Stricken Areas, February 1, 1949.

At the same time, the oversight structure adopted by Congress was remarkably extensive for what is, essentially a distributive program.[2] Conventional wisdom suggests that Congress prefers fire alarm to police patrol oversight, especially when a natural monitoring coalition exists. Yet, in disaster policy, Congress adapted police patrol oversight mechanisms that have the FEMA reporting to nearly two-thirds of all standing committees in Congress. Not only are rule-making and oversight procedures stringent for FEMA, but budgeting procedures also provide an extra layer of legislative control. Though FEMA receives an annual appropriation for operations, most of its budget, including funds for disaster relief, is provided by supplemental appropriation measures. Though the obvious justification for a supplemental budgeting procedure is that the frequency and severity of catastrophic events will vary from year to year, the effect is to create an additional layer of political control over agency decision-making.

After transitioning from an ad hoc legislative regime to an institutionalized system (Phase I to Phase II), the legislative structure underwent another transition in the 1980's (Phase II to Phase III). The relatively modest initial system of relief slowly increased in scope and depth, ultimately resulting in a multi-billion dollar program. For a program that citizens and the government agree is inequitable, one might ask why such a system evolved. Once institutionalized, why did the structure develop the way it did, from a small and explicitly supplemental federal policy to the behemoth federal program that it is today?

2. Terming the disaster relief regime as distributive is not entirely fair. According to most classification schemes disaster policy contains a mix of distributive and informational (i.e. high expertise) issues. Still, the general point holds. While there is a strong potential for agencies to develop expertise in this arena, so too would there be a similar potential for Congressional committees to do so.

Explaining these two transitions is the core task of this chapter. Part of the approach is inherently interpretive, as it relies on a mix of evidence from the Congressional Record, testimony at legislative hearings, roll-call votes and trends in appropriations. My hope is that by relying on rationalist intuitions, we can make sense of the observed institutional structure that developed to regulate catastrophic risk in the United States. Previous chapters have discussed some of the major historical developments in the area of natural disasters and catastrophic risk. They introduced the collection of institutions that regulate catastrophic risk in the United States and highlighted the distributive effects of catastrophic risk policy. Such work, drawn together from a host of primary and secondary sources, sets the stage for offering a positive account of the regulatory environment. This chapter surveys the dominant existing theories, clarifies the weaknesses of current approaches, and constructs an alternative account.

Existing theories fall mainly into two categories. First, scholars who study natural disasters have often argued that governmental policy is the result of largely arbitrary reforms, coming on the heels of particularly catastrophic events. A devastating flood or hurricane often brings consideration of policy reforms. Because public attention is short lived, such a process results in piecemeal and incremental policy evolution, with little attention to overarching social goals.[3] A second body of work tries to understand disaster policy as a specific example of more general policies on risk and social insurance. For example, Moss (1999) argues that changes in disaster policy are consistent with broad changes in social approaches to managing risk more generally.[4]

3. For examples of this view, see May (1985), Birkland (1997), or Popkin (1990).

4. For example, the creation of the Federal Deposit Insurance Corporation (FDIC) or unemployment insurance constitute similar approaches to federal management of risk that is particularly devastating at the individual level.

By tracing changes in the general approach of the federal government to managing risk in the twentieth century, Moss suggests that changes in disaster policy are best understood as pieces of this background social change.

Against these theories, I argue that the process of policy development cannot be understood without careful attention to internal political dynamics within Congress on the one hand, and the patterns of citizen disaster behavior on the other. The central thesis is as follows. In the early period of disaster legislation, politicians were faced with a changing distribution of disaster related benefits. Benefits were becoming increasingly concentrated among a handful of legislators; most legislators were receiving a shrinking piece of the economic pie. As a general proposition, either logrolls or vote-trading could remedy this situation. However, the way citizens deal with disaster risk made these strategies untenable. An as alternative mechanism, legislators chose to delegate policy responsibility to the bureaucracy. The act of delegation and institutionalization created incentives for interest groups to become more involved in the disaster policy arena. As more social groups began rent seeking, the level of spending and the scope of benefits both increased dramatically.

6.3 Path-Dependence and Incremental Reform

The most popular explanation of domestic disaster policy is that innovations were the result of arbitrary and piecemeal responses to specific disasters, rather than overarching ideological goals or interest group agendas (May 1985; Popkin 1990). Historically, Congressional hearings have been held in the aftermath of many major disasters, and reform efforts are often initiated, if not adopted (Birkland 1997). For example, major flood events inevitably bring reconsideration of the National Flood Insurance

Program, as the Midwestern floods in the early 1990's yielded the National Flood Insurance Reform Act of 1994. Birkland (1997) argues that natural disasters function as focusing events that create media attention and exert public pressure on politicians who respond with hearings and reforms. May (1985) notes that during periods between disasters, the disaster risk arena consists of "policies without publics," leaving policy evaluation for those times when it is most affected by emotional outcries and intense pressure for action.

> From this writer's perspective, as one who has been involved directly in both the use and evolution of disaster programs and policies, May seems to be right. A good deal of what is current law and practice did evolve from specific disasters, discussions among a few participants at a particular meeting or conference, limited testimony at congressional hearings, and sometimes, interpretation of regulations made by one or two persons on an emergency basis (Popkin 1990, 120).

On this view, the structure of risk regulation is simply the result of incremental and arbitrary policy adjustments to a standing disaster relief policy initiated in the 1950's. There is obviously some truth to this line of argument. Major restructuring of the disaster policy does generally occur after a major natural disaster, and there is no doubt that catastrophes do serve as a focusing events (Birkland 1997).

The problem with this view is that it gives us little purchase on the question of institutional selection. Assuming a policy window exists after a disaster, why is one institutional framework selected over another? What sorts of political opportunities are created and maintained by the legislative process? Disaster policy has too many distributive implications to be the arbitrary result of bureaucratic policy makers and the timing of natural disasters. Moreover, the players involved in legislative hearings and reform initiatives are a fairly constant group. Surely, there is at least the specter of interests trying to gain from this process. Similarly, though this view helps a bit with the timing of reform, it gives inadequate attention to the goals of legislators and bureaucratic actors. More serious inquiry into the nature of citizen decision-making, interest group pressure, and political choice is needed.

6.4 Risk Management and Social Change

Unlike the incremental reform approach, Moss (1999) has argued that the evolution of disaster policy can be explained by understanding contextual changes in the nation's approach to managing risk in the past century. By understanding the link between catastrophic risk policy and changes in the social approach to risk more generally, the structure of policy appears somewhat more coherent. Note that Moss is explicitly referring to phases in the evolution of broader risk management policies, and trying to locate the specific evolution of disaster relief policies in that rubric.

> Until about 1900, most risk-management policies provided security for businesspeople against risks that were thought to discourage investment and trade [Phase I management policies]....Beginning mainly after 1900, a new set of risk-management policies emerged, offering security to the American worker against a variety of industrial hazards.... Social insurance legislation and countercyclic fiscal policy stand out as the primary policy innovations of Phase II. Phase III commenced around 1960 and involved an extension of risk-management policy to protect not only business and labor but also citizens more generally. The expansion of federal disaster relief after 1960 represents one of the many changes associated with Phase III..... The transitions from Phase I to Phase II to Phase III were, in my view, primarily a consequence of the rapid rise in income that industrialization generated (Moss 1999, 222).[5]

5. It is worth nothing that the phases Moss refers to do not precisely correspond to the phases identified in the introduction. His analysis starts with background phases in the approach to risk management and then turns to disaster policy. My analysis is rooted in the transitions of approaches of disaster policy themselves. My apologies for the resulting confusion.

Not only were such policies more in play politically, but Moss also argues that distinct pressures made the latter half of the 20th century a particularly attractive time to expand government programs in these ways. One reason has to do with the nature of disaster risk (Moss 1999, 325). Policies directed at low probability high consequence events were particularly popular during this timespan.[6] Simultaneously, policies created to safeguard individual welfare supposedly created increasing public expectations about the role of government: "Americans increasingly expected protection against an ever-widening array of hazards and, at the same time, were becoming more and more comfortable with federal insurance and other forms of public risk management" (Moss 1999, 326). Rising expectations, increased income, and a background expansion of federal programs to safeguard citizens, all contributed to the development and rise of disaster relief policies. Background historical trends coupled with the nature of catastrophic risk itself helped yield an institutionalized system of disaster relief, or so the argument goes.

No doubt the evolution of risk management institutions specifically, and the changing role of the federal government more generally, played some role in the evolution of disaster policy in the United States. However, Moss's account, like the story of idiosyncratic incrementalism above, obviates the role of interest groups in this process and relegates strategic political action to a secondary if not tertiary role. Political economists should be skeptical of this view. Strategic action, both by politicians and interests drives much policy in this country. To ignore that possibility in this arena seems unnecessary and unwise. More careful attention needs to be paid to the precise political dynamics involved in the transitions from one policy regime to the next and

6. For example, limited liability for corporations, workers' compensation, and unemployment insurance all target events that have a low probability of occurring for an individual, but a serious consequence if they do occur.

to the structures that constitute the essential transitions. The question is not just why disaster management policy emerged (though this is clearly a critical question and one for which we have only a partial answer), but why such policy emerged when it did and why it evolved in the specific structure that we observe. Who stood to benefit from a bureaucratically administered system and what sort of enacting coalition emerged to support such a move?

Moreover, much of the Moss argument rests on the claim that rising public expectations for disaster relief drove politicians to routinely provide aid. This is an intuitively pleasing claim because it is essentially a self-fulfilling prophecy. If citizens believe the government will provide aid, then they will not adopt self-protective technologies, and the government, faced with desperate citizens and public pressure, will provide extensive aid after natural disasters. This is a perfectly reasonable argument about why an observed social equilibrium of ex post relief and no ex ante self-protection is sustained,[7] but the argument cannot explain why disaster relief institutions evolved initially. Given a social equilibrium in which there is no government relief provided, failing to manage catastrophic risk is not an optimal strategy unless individuals are strongly risk seeking with respect to large losses. Thus, as an explanation of the initial decision to provide government relief, the explanation falters. Moreover, the transition from ad hoc relief to an institutional aid structure cannot be explained by this logic. Ad hoc relief supports this equilibrium as well as institutionalized policy.

At the same time, the rise of programs intended to protect individual citizens against various risks began in the late 1920's. Why did somewhere between thirty and fifty years elapse before the structure of disaster relief was transformed? The

7. In the language of game theory, the respective strategies of citizens and the government are mutual best replies. Equivalently, the outcome is a Nash equilibrium.

answer cannot be that disaster policy was not on the table. Ad hoc appropriations were not uncommon during this time period, and the country's experiences with floods, drought, and earthquakes were quite vivid. Major disasters (e.g. hurricanes in 1926 and floods in 1927) were common during this time period. Deposit insurance was introduced in the aftermath of the Great Depression and crop insurance in 1938 (Goodwin and Smith 1995). Why was federal flood insurance not implemented until 1968? Indeed, federal flood insurance proposals were considered some twenty years earlier in 1949 and actually passed into law in 1956, though appropriations were withheld in the subsequent Congress.[8] If the same historical forces were at play, why does the timing of the introduction of disaster relief institutions differ so substantially from the development of other social insurance and individual hazard protection programs? What changed during the 1950's and 1960's that created a legislative coalition for such legislation when none existed previously? A general story about social trends in risk management cannot answer these questions. Indeed, they are distinctively political questions. The Moss argument is helpful for understanding the historical backdrop against which disaster policy is cast. However, puzzles remain about the political dynamics, the specific institutional structure of disaster relief policy, and the interaction between citizen decision-making and strategic political action.

8. The flood insurance legislation was passed by both houses and signed into law by the President. However, the appropriations committee in the subsequent session refused to provide any funds for the agencies created to administer the policy, and as a result the program never went into operation. The process was so quickly forgotten that in 1967-68, when the NFIP was being considered again, it was not until the legislative process was almost complete that one legislator recalled the previous legislation. See the 1965 Hearing before the Subcommittee on Small Business of the Committee on Banking, House of Representatives, 89th Congress, first session on H.R. 7397 A bill to authorize a study of methods of helping to provide financial assistance to victims of future Natural Disasters and S.408 An Act to Authorize a Study of Methods of helping to provide financial assistance to Natural Disasters, June 24, 1965.

6.5 From Ad Hoc Relief to Institutionalization

I want now to focus on the first transition in the policy history from a disaster-specific approach to providing disaster relief to the institutionalized and bureaucratically administered system of disaster management. At its core, this transition involves a decision about whether to produce disaster legislation via the mechanisms of casework or by bureaucratic administration. Prior to this transition, disaster policy was always disaster specific. A disaster would strike and then legislators might introduce specific legislation to deal with the resulting destruction. When the transition from ad hoc ex post legislation to an institutionalized system of relief is complete, primary responsibility has been delegated to various administrative agencies. Because of the nature of the transition in question, the literature on delegation and oversight from political science is quite relevant. This literature began as an effort to clarify whether Congressional delegation negatively impacted overall policy goals (Lowi 1979; Fiorina 1982; Ogul 1976; Niskanen 1971). Though the delegation as abdication hypothesis dominated in the early literature, work in the 1980's challenged that conventional wisdom by studying the various mechanisms that Congress could use to control the bureaucracy and the conditions under which legislators might prefer delegation to casework (Epstein and O'Halloran 1984; McCubbins and Schwartz 1984; McCubbins, Noll, and Weingast 1987; Moe 1985). What emerged was a better, though by no means complete, theory of delegation and oversight mechanisms as potential strategies for legislators facing a mixture of internal and external constraints (Kiewiet and McCubbins 1991).

In general, politicians might prefer delegation to casework for four types of reasons. First, legislators might delegate with constituent relations in mind. For example, Fiorina (1977) argued that legislators may benefit by exposing constituents to the regulatory process. If the regulatory process goes awry, politicians can "rescue" constituents, better positioning themselves to take contributions from grateful constituents. A second collection of theories suggests that economic firms or other constituent organizations might prefer the uncertainty associated with bureaucratic regulation to the legislative process (Fiorina 1986; Fiorina 1982; McCubbins 1985). For example, interests dissatisfied with the current legislative equilibrium may well prefer the uncertainty of a future bureaucratic decision to the currently available legislative outcome. As a result, interests might actually lobby for delegation because it allows for the possibility of a better outcome.

The third group of explanations argues that delegation allows politicians the best of both worlds (Wilson 1974; Arnold 1990). It allows unpopular policy to be made by the bureaucracy, while ensuring that concentrated interests will be able to maintain influence over the bureaucratic process by exerting political power. By this reasoning, legislators delegate to avoid the blame for poor policy and simultaneously ensure that interest groups will maintain access to the political process. Finally, Moe (1985) has highlighted the problem of "legislative drift" (Moe 1990). Future legislative coalitions may have different policy preferences than those of the current Congress, and therefore might undo previous legislative outcomes. To protect their policies from legislative drift, legislators may prefer to delegate authority to the bureaucracy in an effort to insulate their policies from changes in the political tide.

For the most part, these theories highlight reasons that politicians might prefer delegation to casework. By contrast, theories from the Congressional dominance school tend to emphasize the negative implications of delegation by highlighting the principal-agent problem associated with bureaucratic administration. The basic problem of oversight is that delegation requires giving primary policy responsibility to an agent (bureaucracy) whose interests may conflict with the principal (legislature). This threat of "bureaucratic drift" implies that delegation entails risk. Legislative control over policy outcomes is imperfect, but two types of controls might mitigate this problem. Ex ante controls dictate the procedures by which policy will be constructed, whereas ongoing controls check agency actions on a more regular basis by relying on ex post sanctions like budget restrictions (Calvert, Moran, and Weingast 1987), reauthorization hold-up, etc. McCubbins and Schwartz (1984) argue that a relatively uninformed Congress can best control the bureaucracy by relying on "fire alarm" oversight mechanisms. Interest groups who have expertise in a particular policy area and knowledge of how bureaucratic action affects their interests, have incentives to alert legislators when the bureaucracy goes awry. Fire alarm mechanisms provide a cheap, and relatively efficient way of monitoring bureaucratic action, especially since in equilibrium, the bureaucracy never steps out of line and no sanctions are required (Epstein and O'Halloran 1999, 24). McCubbins, Noll, and Weingast (1987,1989) highlight how administrative procedures function as mechanisms by which Congress can control bureaucratic action.

Formal models and case studies indicate that the threat of both legislative drift and bureaucratic drift are factors in decisions about institutional structure. The question becomes how we are to make sense of which concerns will dominate the legislative process at different points. Epstein and O'Halloran (1999) have tried to unify the questions of delegation and oversight into an overarching theory of transaction-cost politics. Their essential insight is that Congress will decide whether to internalize (casework) or contract (delegate) based on which alternative minimizes the overall average political transaction costs. Their model predicts that decisions about delegation and institutional structure will be a function of the degree of difference between policy preferences of the committee medians and floor medians, between Congressional preferences and Executive preferences, and whether the policy issue is primarily informational or distributive. Since they briefly consider disaster relief directly, the application provides a helpful transition.

Epstein and O'Halloran (1999) argue that delegation in disaster policy allows politicians to avoid being blamed for mistakes in a policy arena in which there is no credit for getting things right:

> Emergency disaster relief is another case and point; there is no upside for getting things right, only a downside for making a mistake. In both areas, Congress has delegated to the bureaucracy on the assumption that, without executive branch expertise, outcomes would be even worse (Epstein and O'Halloran 1999, 23).

Yet, there are quite clearly potential political benefits from doling out disaster relief. Indeed, politicians are often said to like disaster relief even more than the recipients (Rauch 1992). In effect, Epstein and O'Halloran (1999) argue that disaster policy is an informational issue where agency expertise develops, with low levels of preference conflicts between Congress and the bureaucracy. This is, of course, partially true; but, it ignores the reality that disaster policy is as much distributive as informational and that committees develop issue expertise as well. Preference differences between committee medians and floor medians, or between committee medians and the executive ideal point, should encourage and discourage delegation respectively. Yet, it is not at all clear that committee preferences were historically outliers in this area. The two dominant committees were Public Works and Banking; neither represents such a radical divergence from the floor so as to warrant changing regimes. Moreover, though it is true that the level of legislative-executive conflict on this issue is generally modest, increasing the possibility of delegation somewhat, why were such extensive oversight provisions adopted if preferences were essentially convergent?

The rest of the literature is no more helpful on this point. Indeed, it is highlighted precisely because legislative action seems to contradict so much of what is conventional wisdom. Legislative drift seems unlikely to be the dominant concern since politicians in almost every Congress since the 1920's have enjoyed bringing constituents benefits. Nor does the threat of bureaucratic drift seem particularly prominent.

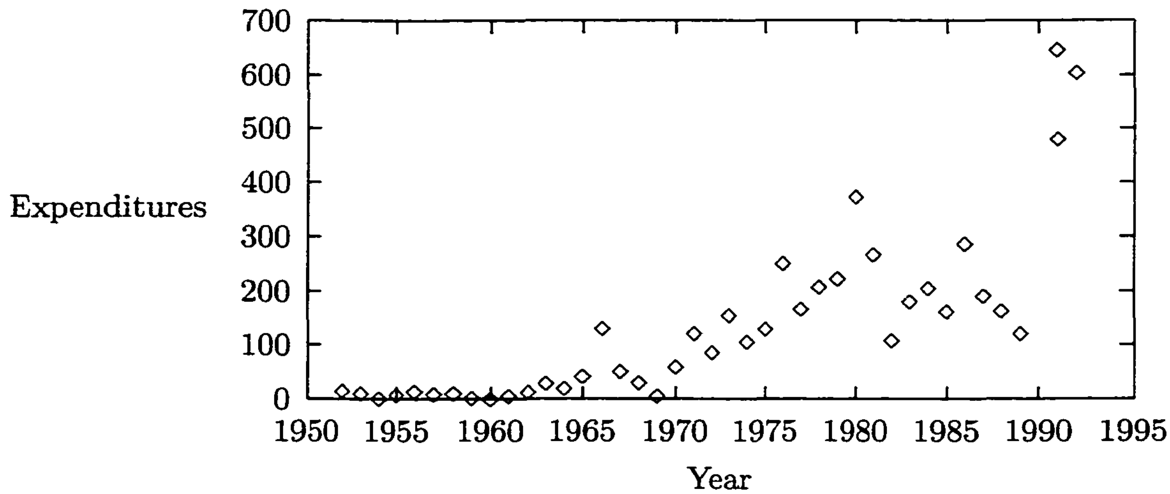
The point is not that the transaction cost approach is incorrect. On the contrary, for one with rationalist intuitions it is almost correct by definition. To suggest that politicians will take a given action when the benefits of doing so outweigh the costs is likely right, but it begs the question. What types of costs will tend to dominate in different policy areas at different points in time. How will such costs change over time and dictate strategic political choices by legislators? Epstein and O'Halloran (1999) offer helpful general propositions that build on the idea of unidimensional preference conflicts, but ultimately the factors they emphasize fare poorly in the case of risk policy. Moreover, their model ignores the external constraints that the public may put on legislators. In few places are such constraints clearer than the setting of disaster policy. Indeed, their notion of political transaction costs is fairly rigid. I suggest that changes in the transaction costs legislators face do determine decisions about institutional structure. However, in disaster policy, such costs are partially external, deriving from legislators' interactions with the public, and partially internal, deriving from their interactions with fellow legislators.

In essence, my argument is that two factors drove this transition. First, legislators were facing a changing distribution of disaster-related benefits. The first step in my argument is to demonstrate that these distributive changes existed. Second, the range of legislative strategies for dealing with these distributive challenges was limited by the behavioral patterns of citizen decision-making, highlighted in the previous chapters. Any strategy that involved withholding disaster relief, even on a short-term basis, was virtually impossible to implement. This meant that both extensive logrolls and elaborate vote trading schemes were less viable. Against this backdrop, delegation to the bureaucracy was one of few alternatives available to legislators that at once resolved the distributive challenges they faced, while still acknowledging the strategic dilemmas on the table.

6.5.1 Delegation and Distribution

Though rising costs are often noted as a justification for switching legislative regimes, overall expenditures on disaster relief were not increasing at a particularly severe rate. In constant dollars, spending did clearly increase starting at about 1970 as Figure 6.1 shows, but overall spending was still relatively modest relative to most other policy programs. While it is true that the bureaucracy might have a relative institutional advantage for cost-control, a similar relative advantage exists for all sorts of issues that continue to be addressed with casework. It seems unlikely that fiscal restraint could be the sole or perhaps even the primary political motivation in this case. In point of fact, the most regular involvement of Congress in the affairs of FEMA and previously the Office of Emergency Protection (OEP) is observed when bureaucratic actors tried to impose cost-control mechanisms on disaster relief policy. If cost-control was the dominant issue, it seems more likely than not that Congress would tend to support such reforms, rather than oppose them. However, I want not to overstate the case. There is little doubt that a sub-set of legislators was concerned with rising disaster-related costs (May 1985). Nonetheless, there is an important distributive sub-text to the overall increase in expenditures.

Figure 6.1: Federal Disaster Relief Expenditures 1950-1995



From a distributive perspective, legislators care not just about how much money gets spent, but also about who gets benefits. One way to conceptualize the distribution of disaster relief is to inquire about the relative concentration or dispersion of disaster relief spending. To the extent that the concentration of relief is high, only a few states receive the vast majority of overall expenditures. To the extent that relief is more evenly dispersed, many, if not most states receive their fair share. Using simple measures from the industrial organization literature, we can create an annual index of disaster relief concentration (dispersion) and explore changes in the index over time.

Concentration ratios are used in economics to study the degree of competition in industries. The ratios are calculated by summing the amount of business done by the top three, four, or five firms in the industry, and dividing that figure by the overall volume of business done in the industry. The ratios vary between zero and one, where one indicates a perfect monopoly and zero indicates perfect competition.[9] Thus, when the top few firms account for most of the overall business, the ratio nears one and very little competition is thought to exist. As such, concentration ratios can also provide a helpful tool for understanding the distribution of disaster relief across states. The parallel to a four-firm concentration ratio is simply a four-state concentration ratio, where the total dollar value of the relief received by the states receiving the most relief is summed and divided by the overall disaster relief given during that year.[10]

Figure 6.2 is a plot of annual four-state disaster relief ratios, plotted over time with a lowess curve tracing the trend in the data.[11] What should be obvious is that prior to approximately 1980, concentration is increasing at a relatively constant rate. The top handful of states is receiving a growing proportion of overall relief, which implies that the vast majority of states are receiving a shrinking piece of the pie. The top four states receive somewhere between twenty and forty percent of all disaster relief spending.

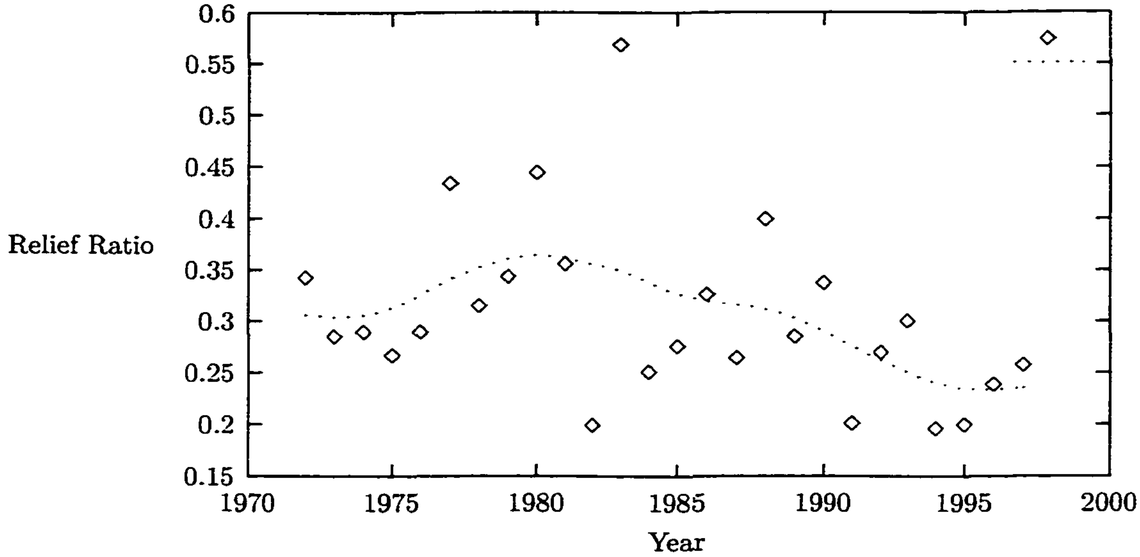
---

9. If the concentration ratio is denoted O_i to signify an Oligopoly effect, then dispersion is generally computed simply as $1 - O_i$.

10. In keeping with the economics literature, I exclude the top relief receiving state in each year. Concentration ratios can often be responsive to particularly large deviations. In the disaster relief context, a single state may receive a large amount of relief in a given year precisely because they had a particularly devastating disaster. Including that state in the relief ratio obviates the trend we are really after. Thus, both for theoretical reasons and for consistency reasons, the top annual recipient of disaster relief is excluded and the ratios are calculated using the second to fifth largest aid recipients.

11. Five firm and three firm ratios were also computed. The trend in the data is essentially identical. Thus, I rely on four-firm ratios throughout.

Figure 6.2: Four-State Disaster Relief Concentration Ratios, 1972-1997



The switch in the trend comes roughly at the time FEMA takes over primary policy responsibilities. Though the graph obviously cannot demonstrate the motivation of legislators, it can show the clear effect of bureaucratic administration on the structure of disaster relief. In the 1980's and 1990's, disaster relief spending continues to rise. What changes is the distribution of relief dollars. The top handful of states receiving disaster relief was getting an increasing proportion of overall expenditures. Irrespective of how concentration (dispersion) is measured, it is clearly increasing (decreasing) throughout the 1970's. This change in the distribution of political benefits exposes some of the underlying political dynamics.

As an example, consider the supplemental appropriations bill passed in 1972 that dealt primarily with the aftermath of Hurricane Agnes. As part of the legislation, the loan forgiveness portion (grant) of aid from the U.S. Small Business Association was doubled, the interest rate lowered to 1%, and the eligibility requirements extended a year backward and forward. Extending the time period back by one year had the effect of qualifying losses from a recent California earthquake, an incredibly costly quake that was still in the headlines because of reports of widespread fraud in applications for federal relief.[12] The bill itself was a $1.3 billion appropriation that was expected to last only six months.

While support for giving aid, in and of itself, was relatively strong, the votes in both the House and the Senate on the retroactive loan provisions were actually quite contentious. The bill passed the House easily, but the vote on a proposed amendment to remove the retroactive loan provisions failed by only two votes. In the Senate, the vote to limit the retroactive feature of the legislation failed 26-61, while the ultimate legislation passed 49-38.[13] As politicians grew more adept at extracting gains for their constituents, not just from their own relief bills, but also from the relief bills of others, the overall concentration of legislative benefits rose. Using retroactive provisions, states that received relief once were able to receive benefits repeatedly. Whereas in earlier time periods, small relief bills were passed quickly with little consideration, debate, or delay, as time goes on, the legislative process became more contentious.

Years later, there is anecdotal evidence of a similar phenomenon with respect to disaster relief for farmers. Though disaster relief was a terrific boon to farmers historically, in the late 1980's and 1990's, it became much less beneficial for the average individual recipient. As Rauch (1992) notes, "For farm lobbyists, the aid bills are Chinese fire drills. Political pressures typically turn the disaster-aid bills into

12. See Hearings before subcommittees of the Committee on Appropriations, United States Senate, Ninety-Second Congress, Second Session on H.R. 16254: An Act Making Certain Disaster Relief Supplemental Appropriations for the Fiscal Year 1973 and for other purposes. For a discussion of loan fraud in California, see the exchange between Senator Hollings and Mr. Knebel, a representative of the US Small Business Association at page 52 therein.

13. See roll call votes numbers 746-747 on H.R. 15692 on August 4, 1972.

what a farm lobbyist called a 'political feeding frenzy'." The president of the Kansas Farm Bureau, Doyle D. Rahjes, noted that per farmer aid has decreased, even as the overall relief has grown. "'You wind up spreading whatever money you've got, and usually it comes to such a small amount that it doesn't help much"' (Rauch 1992). Even politicians shared the sentiment as Representative Glenn English, D-Oklahoma said: "These days you ride in with pennies where you used to bring dollars, and everyone starts throwing rocks."[14] Obviously this more contemporary story does not contribute to my causal case for the earlier time period, but it does help illustrate the more general phenomenon in question. When the benefits from expenditures are consistently concentrated among a few states, then the average per-state (constituency) benefits will be smaller. As the concentration increases, the average per state benefits will decrease; and, a changing distribution of benefits matters in politics. Reform, of one sort or another, grew more likely. For reasons discussed below, bureaucratic administration became a more desirable institutional arrangement.

6.5.2 Costs, Benefits, and Coalitions

The changing trend in overall disaster relief concentration has clear implications for the underlying political dynamics. If the choice between case work and delegation is a trade-off between costs and benefits, and we assume that the benefits of casework must have been substantial enough to outweigh the costs when casework was the regime of choice, then the decision to delegate necessitates a change in either the costs or benefits of the institutional regime. What is generally highlighted in the literature on disaster policy are the rising costs of producing disaster relief via casework; but these costs are, almost without fail, conceived of simply as expenditures. On this reading,

14. Interview cited in Rauch (1992).

bureaucratic administration was adopted because it would be cheaper. In reality, bureaucratic administration was not cheaper. The mean level of spending after 1980 was over three times that of mean spending prior to 1980, even excluding years in the 1950's when spending was extremely low.

This point is helpful, but it ignores the most critical piece of the puzzle. Not only were costs on the rise, but benefits to the average legislator were also decreasing. Thus, a bureaucratically administered regime was becoming more attractive relative to the casework regime. A focus only on costs obviates the benefits portion of the cost-benefit ratio. Analyzing concentration ratios shows that the benefits of dealing with disaster relief via casework were falling for the majority of legislators. Thus, the casework cost-benefit ratio was rising as well, making casework less attractive, and all else equal, delegation more attractive.

The key issue here is why, if legislators were upset with the growing concentration of benefits, they did not simply stop passing relief bills. Alternatively, why not generate logrolls or trade votes so that the political benefits not received from disaster relief could be obtained elsewhere. The answer to this question centers on the interaction between citizen disaster behavior and political choice.

Various portions of this project have detailed the fact that individuals in high risk communities sometimes do not engage in adequate risk management. Some communities do invest time and resources planning for potential environmental hazards, but many do not. Noll and Krier (1990) have argued that cognitive biases in the way citizens evaluate risk may yield over- or under-demand for legislative intervention. Earlier in the project, I argued that citizens do, in fact, exhibit biases in the way they evaluate disaster risk, and that the result is a demand for legislation very much in keeping with the Noll and Krier argument. Even if one disagrees with my analysis, the empirical trend of some portion of the population managing risk while some portion ignores it, has the same implication for the formation of government policy. Because some citizens will be consistently exposed, but unprotected from catastrophic risk, there are always citizens in need when disasters strike. Resisting the intense demand for relief both from constituents in need and from the public at large is exceptionally difficult.

In cases like these, politicians may choose to *lash themselves to the mast* to resist the cries for relief after a disaster strikes, as in the story of Ulysses and the Sirens (Elster 1984; Noll and Krier 1990; Thaler 2000). With the knowledge that citizen demand for legislative intervention may be biased, politicians may adopt ex ante measures of self-restraint to resist acting in the face of intense public pressure. Different institutional arrangements maximize or minimize the level of political insulation.

The basic structure of the sirens problem is that an actor cannot trust himself to resist alluring temptation in the future. For politicians, the sirens' song is sung by citizens in need after a catastrophe. Intense public pressure is hard to resist. The key is that the strategic interaction in the Sirens metaphor is not between citizens and the State—though many commentators focus on this interaction—but rather between politicians in the current period and future incarnations of politicians' selves. The typical way out of a Sirens' dilemma is some mechanism of precommitment. In Ulysses' case this meant being lashed to the mast so he could not give in to the Sirens' call, while his shipmates had their ears filled with wax so that they could not hear the Sirens' song, thereby avoiding temptation. By constraining a future-period self, the lash to the mast strategy allows long-term goals to be achieved in the face of short-term temptation.

The problem is that either a logroll or a vote-trade requires a credible threat that legislation will be withheld if no bargain is reached. However, the structure of the game is common knowledge to both legislators and citizens. Why would a legislator from a disaster-prone state expend political capital on logrolls when public pressure alone is adequate to ensure that relief bills pass? Because of the intense public pressure to provide ex post relief both from those affected by natural disasters and from sympathetic citizens, withholding relief is too costly politically. No strategy that requires a credible threat of withholding relief is likely to be particularly effective in legislative negotiations. In this sense, neither logrolls nor simply abstaining from relief provision are viable solutions to the typical legislator's dilemma. In this sense, the reality of citizen response to catastrophic risk provides a critical constraint on legislative strategy.

In the face of this challenge, legislators required a strategy that allowed them to alter the distributive dynamics of disaster policy without relying on the threat of withholding aid. Delegation not only provides a solution, but the bureaucracy is also better situated to withstand intense demands for legislative action. The new institutional arrangement increased the likelihood that regulators could *strike when the iron is cold*, rather than reforming policy when emotions are running high.

Though concerns about distribution are unlikely to explain the behavior of politicians receiving the lion's share of federal relief dollars, they are a powerful explanation of the behavior a majority of legislators who were receiving decreasing benefits under the casework regime. Delegation to the bureaucracy was thus one of the few viable policy alternatives that served as an adequate instrument of precommitment and that responded to the changing distributive dynamics of disaster policy. On this reading, the institutional choice of bureaucratic administration was at once a reply to internal legislative dynamics, and at the same time, a function of external constraints imposed by the way citizens deal with catastrophic risk. Both the underlying political dynamic within Congress and the structure of interaction between citizens and politicians contribute to our understanding of catastrophic risk policy.

6.6 From Institutionalization to Largesse

With a theory of the transition from ad hoc legislation to institutionalization in hand, we can proceed to the question of the second transition from a relatively modest relief regime to the extensive and costly system that exists today. My argument draws on insights from the economics of regulation literature and focuses on the unintended consequences of institutionalization.

Economic models of regulation highlight the propensity of firms to seek rents from government policy and institutions (Becker 1983; Peltzman 1985). Though organized interests are often noted in discussions of disaster policy, rarely are they emphasized as driving forces in the creation or maintenance of government policy. Political economists are attuned to the reality that different forms of government policy have implications for firms or groups trying to extract gains from the political process. Because ex post relief payments amount to a transfer from non-affected taxpayers to citizens in disaster-prone regions, disaster policy has obvious and important distributive implications. In agreeing to share or spread risk, the government assumes an uncertain cost, which if realized, will be passed on to taxpayers. This unoriginal observation highlights the fact that disaster policies, like most distributive or re-distributive government programs, are likely to be couched in highly politicized terms. Given this empirical reality, the relative inattention given to the role of organized interest groups in the evolution of risk institutions is particularly surprising.

This section argues that the institutionalization of disaster relief created incentives for existing organizations to try to extract rents from the political process. By reducing uncertainty about the long-term benefits of rent-seeking, institutionalization encouraged political participation. The influx of groups into the disaster relief arena yielded a larger relief structure with greater payoffs to those receiving benefits. As a result, relief programs were gradually expanded to more and more constituents, at an ever-increasing overall cost.

6.6.1 Rising Tides, Rising Costs

In 1952, the federal government spent $16 million on disaster relief. In 1995, the expense was $606 million (constant dollars). In current dollars, the 1999 disaster relief expenditures topped $2.4 billion, and that excludes loan obligations by the U.S. Small Business Administration, mitigation programs, and expenditures on the National Flood Insurance Program.[15] There is little debate in the literature about whether the relief regime has grown tremendously in the past half century. Again, witness Figure 6.1, a plot of overall federal disaster relief expenditures from 1952-1993 in real dollars.

The trend in the data is straightforward. A fairly constant state of affairs is evident until the early 1970's when expenditures begin to rise. At that point, they increase steadily, culminating in the extravagant expenditures of the mid 1990's. What is debated in the literature is the underlying phenomenon that explains the trend. Two potential theories might be relevant. First, a theory of budget-maximizing bureaucrats could explain such an increase. If bureaucrats were concerned mainly with

15. U.S. Census Bureau. Table 1. Federal Government Grants and other Payments to State and Local Governments, by Agency and for Selected Programs, by State and Outlying Area: Fiscal Year 1999.

increasing their budgetary allowance, then we would expect an overall increase in spending. Though plausible in the abstract, the specific context of disaster relief appropriations undermines the theory's validity. FEMA receives an annual appropriation, but the majority of relief expenditures are granted through supplemental appropriation bills, in which FEMA is required to give fairly extensive justification of the need for funds, making bureaucratic budget maximization a much more difficult proposition.[16] Second, a theory of incremental change suggests that budgeting appropriations will tend to be small adjustments from the previous year of funding. If every year, program funding increased slightly, over time we should observe a substantial increase. However, Figure 6.1 clearly shows that the rate of change increases at some point in the 1970's. Whereas the growth rate was fairly small in the 1950's and 1960's, throughout the late 1970's, the slope increases dramatically. Path dependence or incrementalism fails to explain why we would observe this change. Against, these theories, I want to suggest a fairly standard story of interest group mobilization. Social actors sought to extract rents from a developing policy arena, and the mix of delegation and institutionalization provided the perfect opportunity to do so.

In classic models of economic regulation, the extraction of rents tends to be straightforward, either resulting in direct payments or lower levels of regulation than would otherwise be observed (Becker 1983; Peltzman 1985). When firms are being regulated, regulatory capture may allow them to set higher prices or maintain market control. Beyond the basic benefits of financial payments, catastrophic risk provides a slightly less obvious case. Still, disaster policy offers two major types of rents to interests. The first consists of direct or indirect financial payments. The earliest forms, of course, were direct payments to help with clean-up and reconstruction costs

16. Before FEMA was created, other administrative agencies that administered disaster related funds were subject to largely the same budgeting procedures.

(Landis 1998) and virtually all structural mitigation programs (e.g. dams) were financial boons to local constituencies. Modern disaster policy, whether in the form of ex ante subsidies for insurance or ex post relief payments remains essentially a direct financial payment to individuals or organizations.[17]

Second, like financial payments, the allocation of risk itself is a valuable asset. What might loosely be called *risk-rents* can be extracted in a number of forms. The entire disaster relief structure can be understood as an exercise in risk-shifting. Consistently providing ex post relief effectively shifts the risk of catastrophic losses from individual citizens, economic firms, or community associations to the federal government. Additionally, the State might more explicitly assume certain types or levels of risk from private actors. For example, in the past few years, insurance associations have lobbied the government to provide a form of public reinsurance to limit the exposure of member firms offering hazard insurance.[18] Finally, regulation of land-use, construction practices, and real estate sales may be understood as a type of risk-rent as well. The implementation (or lack thereof) of strict property use regulations for property in high risk zones creates gains (losses) for the owners of such property and their respective associations. When FEMA tried to prohibit the provision of flood insurance for structures located below a certain elevation and within a certain distance from the shore, in order to decrease costs, groups like the Clearwater Beach Association were furious. They insisted the move would destroy

---

17. Whether better organized constituencies are able to extract greater payments than poorly organized ones is an open question. Evidence on the politicization of the Presidential Disaster Declaration process is mixed (May 1985; Platt 1999).

18. State guarantee funds popular in the 1980's were an almost identical form of risk-rent. States agreed to guarantee insurance policies beyond a certain level of risk, using a mixture of private contributions and public funds. The guarantee funds were exhausted when underground storage tanks began leaking, resulting in litigation and enormous payments from the funds. See Viscusi (1996).

the value of their property, and demanded that FEMA not implement the rule. Said, C.M. (Bud) Schauerte, representing the Clearwater Beach Association:

> The Association is convinced that certain provisions of Title IV under S.1405, if enacted into law, would adversely impact Florida homeowners and small business more severely than any state or territory which participates in the National Flood Insurance Program (NFIP). ... Title IV, if it becomes law, would selectively deny flood insurance and thereby devalue homes and real estate on all the nation's coastlines. ... Title IV also would restrict or deny the freedom to build or rebuild homes and small businesses on privately owned land.[19]

The point here is simply to note that rents extracted by social actors who we might loosely think of as *risk-entrepreneurs*, may take forms less obvious than traditional financial payments or regulatory forbearance. Nonetheless, the regulation of catastrophic risk can provide equally desirable benefits.

6.6.2 The Effect of Institutionalization

Even if one disagrees with my account of the transition from the ad hoc legislative regime to the institutionalized structure, it should still be clear that institutionalization creates incentives for social actors. Institutionalization reduces uncertainty about the long-term gains of rent-seeking. When legislation is produced on an ad hoc basis, the resources spent on rent-seeking might yield only a one time return. Actors might get rents in one time period, and fail to do so in another, decreasing the average per-period returns on rent-seeking activity. Compare that regime with an institutionalized system, where once a benefit is gained, it is unlikely that it will be taken away. FEMA hardly ever tries to eliminate a benefit for a constituency, and

19. Statement of C.M. (Bud) Schauerte, Clearwater Beach Association before the Senate Banking/Housing and Urban Affairs. National Flood Insurance Reform Act of 1993. September 14, 1993.

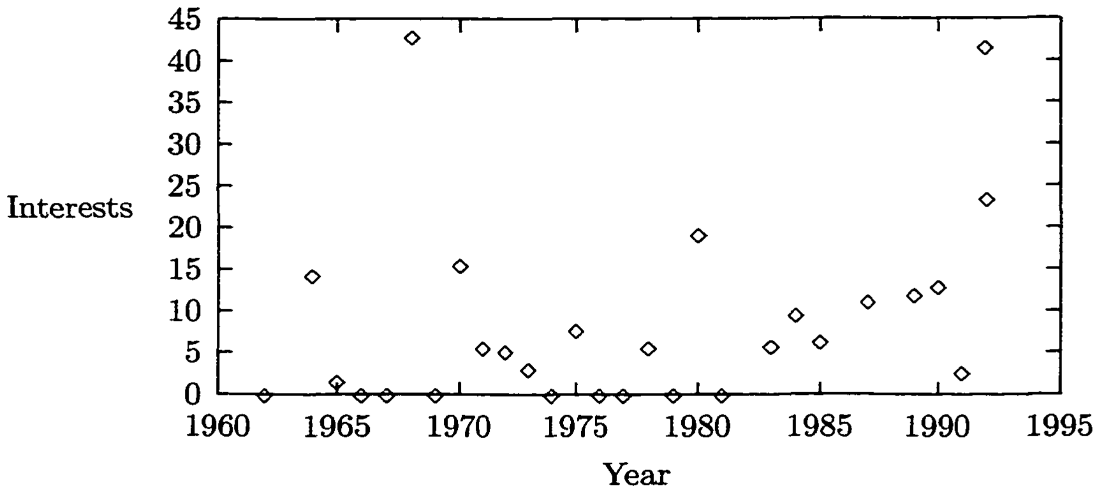
on the few occasions when it has tried to do so, Congress promptly stepped in to prevent it. All else being equal, the long-term returns on rent-seeking activity under an institutionalized system of risk management will be greater than those under an ad hoc legislative regime. If the argument is correct, then three empirical predictions result. First, there should be an increase in the participation of interest groups and private sector representatives in the legislative or administrative process over time. Second, there should be evidence of an expansion of targeted benefits to constituencies. And third, we should see efforts by affected groups to protect the gains they have extracted. There is at least moderate evidence of all these corollaries, and their collective validity lends credence to the central hypothesis.

6.6.2.1 Tracing Rent-Seeking Behavior

If greater rent-seeking activity underlies the increase in programs and expenditures, at very least we should observe an increase in rent-seeking activity over time. One crude way to test this claim is to examine the proportion of testimony at legislative hearings given by representatives of industry and interest groups. If organized interests are trying to influence this policy arena, we should see an increase in the proportion of testimony over time. Figure 6.3 contains a plot of the proportion of overall witnesses made up of interest group representatives at Congressional hearings on earthquake and hurricane disaster related legislation (Birkland 1997).

Though the relationship is somewhat noisy, there is a clear increase over time. The two big outliers at the top of the plot correspond to the creation of the National Flood Insurance Program in 1968 and the National Flood Insurance Program Reform Act of 1993, both of which resulted in extensive participation from the insurance industry. Because of the larger than usual potential gains or losses at stake in these years,

Figure 6.3: Percentage of Legislative Testimony Given by Interest Groups



industry participation skyrocketed. Removing the outliers, a positive and statistically significant association exists between interest group participation and overall relief expenditures. For the moment, the evidence is generally supportive of the hypothesis. The proportion of interest group testimony at Congressional hearings increases over time, suggesting more rent-seeking activity, and this increase is positively associated with a rise in federal disaster expenditures.

6.6.2.2 Targeted Benefits

In addition to the overall level of participation by interest groups in the disaster relief policy process, we should also be able to find efforts of lobbying by specific interests to extract group-specific gains. Efforts by the Earthquake Project in the 1980-1990's provide a helpful illustration.

In the 1980's, the insurance industry became concerned about the prospect of a catastrophic earthquake that would threaten the solvency of the industry. Early in

1986, a coalition known as the "Earthquake Project" was formed to lobby for federal backstopping of industry losses (Kirschten 1990). The insurers sought a mandatory nationwide purchase requirement and a federal relief fund to cover excess losses. As part of the effort, the coalition, supported by about 300 firms, engaged the services of David A. Jewell and Associates Inc., a Washington D.C. public relations firm, the Seattle law firm of Preston, Thorgrimson, Ellison & Holman to devise and implement a legislative strategy; and former Rep. Lloyd Meeds (D.-Wash., 1965-79) to direct the lobbying effort (Kirschten 1990). Though it is plausible the insurance industry went to these steps on a whim, a more reasonable view is that given the historical success of social actors in extracting risk rents from the disaster policy process, the insurance industry thought it could succeed. Indeed, by requiring mandatory insurance purchases for homes throughout the country and convincing the federal government to create a backup fund, the industry would have succeeded in creating a mandatory captive market, while simultaneously minimizing the risk the industry itself had to bear.[20] The coalition succeeded in burying a scientific report that FEMA commissioned after the 1990 Loma Prieta earthquake in California, while its own report was put front and center in a media campaign. The reports disagreed as to the impact of a big quake not on the insurance industry, but as to the overall impact on the U.S. economy (i.e. whether federal intervention was warranted) (Starobin 1992). Although the bills in the early 1990's were not ultimately passed, similar measures continue to be considered, and the entire incident serves as clear evidence of rent-seeking activity by organized interests.

20. The regulation of insurance companies in the United States has a particularly convoluted structure. Most insurance regulation is done at the state level, which historically has added an additional complication to the formulation of federal policy. For a discussion of the regulatory framework, see Meier (1988).

6.6.2.3 Protecting Rents

We have seen an increase in the participation of interest groups in the legislative process, as well as interests seeking targeted legislative benefits. A final piece of supporting evidence can be found in concrete cases of organized interests trying to protect the rents they succeeded in extracting. A transparent example of such activity can be found in the efforts to block FEMA's proposed regulatory changes in 1986.

On April 18, 1986, FEMA proposed regulatory changes to the Disaster Relief Act of 1974 (PL 93-288). The proposed regulations were an explicit attempt to limit the level of federal expenditures, which had been steadily increasing. Substantively, FEMA sought to increase the proportion of costs paid for by the states (from 25% to 50%), reduce the scope of disasters that would qualify for federal assistance, and restrict the distribution of relief funds so that certain types of structures and land would not be covered (Howard and Oberstar 1987).[21] It is worth noting that FEMA's effort to restructure its rules was a response to a 1981 GAO request that FEMA adopt more consistent methods for disaster declaration and relief payments, and pressure to meet the 1986 budget restrictions. FEMA developed a "capability indicator" that essentially indexed a community's ability to pay for disaster recovery that drew on per capita income, tax base, level of losses, etc. It was estimated that the new method would have made 61 of the previous 111 disaster declarations ineligible for federal relief. On many counts, the proposal was perfectly reasonable. It would have been fiscally responsible, better distinguish between genuine and political requests for relief, and encourag local risk management, both by government officials and citizens. However, not surprisingly, there was a backlash. As James Dougherty, Chairman of

21. For example, levee, irrigation and reclamation districts would have been prohibited from receiving federal assistance.

the Board of Supervisors for the County of Ventura, California put it: "The Board ... earnestly seeks your support in preventing the adoption of regulations by the Federal Emergency Management Agency which would effectively gut the disaster assistance program established by Public Law 93-288, the Disaster Relief Act of 1974."[22]

On July 23, 1986, the House subcommittee on Investigations and Oversight of the Committee on Public Works and Transportation held a hearing on FEMA's proposed regulations. Three separate panels decried the regulations. First, non-committee representatives from virtually every region testified against the regulations. Then, state emergency management officials testified about how devastating the proposed rule changes would be, and local officials told of how hard they were working to control disaster risks and how counterproductive the new rules would be. Some of the harshest criticism came from Trent Lott, who somehow managed to claim that the country's ability to respond to a natural disaster had actually *deteriorated* since 1969 (Howard and Oberstar 1987, 10). The NGA, of course, opposed the new rules saying they would, "undermine the intent or purpose that the Congress had when it passed the law in 1974 which was to 'broaden the scope of disaster relief.'"[23]

Both the House and the Senate quickly passed legislation. H.R. 5488, introduced by Chairman James J. Howard of the House Public Works committee, established a 75/25 split of Federal/non-Federal disaster relief costs and prohibited FEMA's adoption of the proposed regulations. The bill was passed by a voice vote under

22. Letter from James Dougherty to Honorable Robert J. Lagomarsino, United States Representative, July 1, 1986.

23. Statement of Mr. Lacy E. Suiter, Director, Tennessee Emergency Management Association on behalf of the National Governors' Association. Statement for the Subcommittee on Investigations and Oversight of the Public Works and Transportation Committee. U.S. House of Representatives on the Federal Emergency Management Agency. July 23, 1986.

suspension of the rules on September 30. The Senate responded with a comprehensive amendment to the Disaster Relief Act of 1974. And, the House appropriations committee included language that restricted the use of FEMA funds to activities that did not implement the proposed regulations. It is worth noting that despite these sanctions, FEMA's budget was increased substantially. Congress's intent was not lost on FEMA, which formally withdrew the proposed regulations from the Federal Register in November 1986 (Howard and Oberstar 1987, 17). Once again, the point is a simple one. Not only did organized interests succeed in expanding the scope and level of disaster relief programs, but they also managed to entrench their gains.

The proposed regulatory changes in the 1980's are just one example of many. Proposed changes to the National Flood Insurance Program received no less vocal condemnation by affected interests. Consider the statement of Dr. Peter Fallon of the North Beach Civic Association before the Senate Banking committee:

> We feel the NFIP has been a very successful program and agree that it needs some fine tuning. ... Make no mistake. If this bill is passed with its highly controversial and scientifically unreliable erosion zones, it will be a disaster for our tax base. ... We feel that the intrusion, no, the violation of our property rights by the Federal government mapping these 30-60 year zones will guarantee significant and time delaying litigation.[24]

Note also the recognition by interest groups that administrative procedures are critical instruments of political control. As the National Association of Realtors put it:

---

24. Statement of Dr. Peter Fallon of the North Beach Civic Association before the Senate Banking/Housing and Urban Affairs. National Flood Insurance Reform Act of 1993. September 14, 1993.

> Our second major concern with the previous bills was that they allowed FEMA to designate entire communities as "erosion prone" without holding public hearings or giving affected property owners the right to public comment or an appeal of this decision.[25]

At this hearing, the National Association of Realtors was ready to support the bill (S.1405) because the current version had integrated extensive procedural requirements, ensured that zoning was kept as a local responsibility, and removed many of the land-use restrictions that had been present in the previous versions.

What these excerpts are intended to demonstrate is that historically, social actors have been fully aware of the gains to be had from the institutions of disaster relief and catastrophic risk management. The inability of FEMA to produce effective and equitable regulations that would likely have lowered aggregate social risk exposes the power of entrenched interests in this policy arena. Not only have interests been successful in establishing greater benefits, but they have also been effective at keeping them.

6.6.3 Overview

This section sought to explain why the structure of disaster relief ballooned from its relatively modest initial size in the 1950's, to the substantial system of relief and risk management that exists today. By relying on general quantitative trends in the participation of interest groups in the legislative process and a more qualitative presentation of legislative hearings, I have tried to argue that this second transition was primarily a function of increased participation by organized interests. Institutionalization reduced uncertainty about the long term gains of lobbying efforts and created

25. Statement of Pat Campbell-White, National Association of Realtors before the Senate Banking/Housing and Urban Affairs. National Flood Insurance Reform Act of 1993. September 14, 1993.

an incentive for both public and private interests to seek rents. Empirical evidence about increased industry participation in legislative hearings, examples of sustained lobbying efforts by industry coalitions to extract preliminary rents, and cases of effective mobilization to protect extracted rents all supports the basic proposition. Rent seeking by organized interests played a critical, if not central role in the expansion of disaster relief benefits and expenditures.

6.7 Conclusion

This chapter began with a simple question. Why did the institutions of disaster risk regulation evolve in the way that they did? I have argued that the initial transition toward bureaucratization was the result of a growing concentration of disaster relief benefits and steadfast external constraints from citizen behavior, which itself was partially driven by the existence of cognitive bias. The chosen political strategy of delegation, while perfectly rational, had unintended consequences. Institutionalizing disaster relief created incentives for organized interests to seek rents. Because politicians had inadequately insulated disaster policy, the tandem of interests and legislators slowly increased the breadth and depth of benefits. The collection of institutions that regulate catastrophic risk in the United States, though puzzling at first glance, makes quite reasonable sense when understood as the result of this interaction between strategic political actors, citizen behavior, and interest group activity.

CHAPTER 7

BIAS AND BEHAVIOR: CONCLUSIONS AND IMPLICATIONS

7.1 From Whence We Came

This project began with a fundamentally political question: why do we deal with disaster risk the way that we do in the United States? Providing a compelling answer to this question necessitated using tools and insights from throughout the social sciences, but especially economics and psychology. Thus, though the question about institutional arrangements is one for political science, the methods used have been varied. Unlike much work on disasters that has sought to understand the incentives created by various approaches to risk regulation, I sought to endogenize the institutions of disaster management by asking about the incentives and strategic environment that gave rise to and continued to drive natural disaster policy. This process of endogenization took a somewhat circuitous path through conceptual models of individual decision-making, quantitative evidence about risk perception and risk response, game theoretic models of social choice, and historical analysis of legislative policy. Though the methodological tools and theoretical building blocks utilized were diverse, there was a straightforward analytical progression to the project. Each stage of the analysis contributed a key insight that served as building block for the remainder of the project.

The project began with a review of the dominant approaches to risk and uncertainty. We saw that the conventional wisdom about the way individuals respond to disaster risk and legislative policy was troubled by theoretical holes or inconsistent with the empirical data. Against this backdrop of theoretical inadequacy, I suggested the potential productivity of jointly analyzing rationalist and cognitive factors. Because individuals are often thought to have trouble evaluating disaster risk, and because beliefs play such a critical role in games of information, more attention needed to be focused on understanding how these respective pieces of the risk puzzle fit together. Throughout the next several chapters, I tried to show that it is possible to simultaneously construct meaningful empirical tests for cognitive tendencies and rational decision-making. Moreover, it is possible to expand the range of actors in game theoretic forms without sacrificing the core methodology or insight. Focusing on the impact of more psychologically realistic actors in games allowed us to clarify the conditions under which bias matters and those under which individual bias is largely irrelevant. By avoiding the pitfall of arguing against the viability of an entire school of thought, it became possible to elucidate the relative roles of cognitive and rationalist factors in the process of social choice.

The analysis demonstrated that some citizens do exhibit biases in the way they evaluate risk, but that the import of such findings is that bias can spread through communities as individuals make decisions about uncertain risk management technologies. The cascade model helped explain why we see local homogeneity but global heterogeneity in response the same level of risk exposure. As I tried to show in the previous chapter, these patterns of behavior are more than just an observational curiosity. If the cascade model is correct, individuals will not always rationally respond to selective incentives created by government policy. As such, the cascade pattern places distinctive constraints on the behavior of legislators. One way of thinking about this point is that cascade behavior restricts the legislative choice set.

The reality of social heterogeneity dictates that some portion of the citizenry will almost certainly be unprotected when disaster strikes and that some people will be under-responsive to changing social incentives. Historically, politicians grappled not only with this problem of citizen behavior, but also with changing distributive dynamics within Congress. These distributive changes created an inter-temporal commitment problem, which legislators attempted to resolve by delegating to the bureaucracy. This was not a bad strategy, but it created new incentives for interest groups, who were far more responsive than ordinary citizens. The previous chapter argued that the institutional arrangement we observe today is largely the result of this tension between the external constraints imposed by citizen behavior—itself partially driven by cognitive bias—and the internal strategic problems that legislators faced. Thus, at numerous levels, strategic and cognitive factors worked to drive the reality of modern disaster risk.

7.2 Strategy and Cognition

The phrase *Strategy and Cognition* was intended to focus attention on the potential interaction between strategic or rationalist issues on the one hand and cognitive or perceptual issues on the other. To be fair, though, there has been an ambiguity in the way this phrase has been used throughout the project. Because strategy and cognition matter in slightly different ways at each level of analysis, some clarification may be warranted. Essentially, I have used strategy and cognition as a conceptual term in four ways. First, from a methodological perspective, I have tried to show that one can adopt theoretical assumptions from both schools of thought, while still relying on quantitative analysis for empirical testing and formal analysis to tease out the dynamics of decision-making. Chapters 3 and 4 are both examples of this integrated approach. Thus, there is a basic methodological punch-line that has surfaced periodically throughout the project.

Substantively, I have tried to show that analyzing strategy and cognition together matters for individuals, groups, and institutions, though in a slightly different way for each. For individuals deciding whether or how to manage disaster risk, chapter 3 showed that both rationalist and cognitive factors are important. As one example, although citizens were responsive to changes in the level of risk exposure in their environment, both their beliefs and their management decisions were also responsive to the historical variability of disaster risk. In this case, rationalist and cognitive factors appear to coexist. Both are important, and the existence of one does not negate the existence of the other.

At the group level, chapter 4 demonstrated that individual level bias can, but does not always, have a significant impact on the decisions that fellow citizens make about risk management. Bias can spread through a group, making it less likely that social choices about risk management will be optimal, but some cognitive tendencies may actually help a group choose optimally. For example, when a community contains a few overconfident citizens, the process of information aggregation will be *more* efficient than with a group of all rational actors. At this level of analysis, we see the full range of potential interaction between strategy and cognition. Psychologically realistic actors can enhance, debilitate, or have virtually no impact on the process of social choice. Of course, our selection of cognitive effects should be rooted in empirical analysis. The data suggested that availability was a more important effect for disaster risk than overconfidence. However, in other cases, different findings would surely dominate. The key is to ground the emphasis on a particular cognitive finding in actual data, and then rely on a game form that is appropriate and realistic to explore the interaction.

At the institutional level, the focus on strategy and cognition was slightly more complex, but no less critical. In one sense, the pattern of citizen disaster behavior, which itself was a function of cognitive factors, produced cyclical demands for legislative intervention. Just as Noll and Krier (1990) suggested over a decade ago, prior to a major event, there is often an under-demand for legislative action and after a major event, there is often an over-demand for legislative intervention. Historically, this cognitive part of the equation had two effects, both roughly relating to strategy. First, it affected distributive politics within Congress as discussed in chapter 6. Second, it altered the bargaining game between legislators. Commitment problems in Congress that could ordinarily be resolved with log-rolls or bargains required a new institutional solution, which delegation provided. Institutionally then, we saw that cognitively driven behavior by citizens altered the strategic environment faced by legislators, and indeed, the strategies legislators ultimately selected. As it turns out, these were not trivial effects. The shift in institutional arrangement had a profound impact on the environment for rent-seeking and the ultimate structure of disaster policy. At the institutional level, we see almost a meta-interaction between strategy and cognition.

In sum, the project has tried to demonstrate that an emphasis on strategy and cognition can produce substantively important insights at each level of analysis, and in the process, enhance our understanding of risk and risk policy in the United States. With diverse methods, an integrated theoretical framework, and a reliance on multiple data sources, I have tried to show that the regulation of catastrophic risk is driven by the way strategic and cognitive factors interact and co-exist, not just for citizens but also for the State.

7.3 Future Research

The project has raised a handful of issues that warrant some future attention. First, though behavioral economics has finally taken hold within mainstream economics, it continues to have virtually no influence on the discipline of political science. Short of a few sporadic treatments and a seminal paper by Quattrone and Tversky (1988), the discipline has largely ignored recent developments. For a field so dominated by tools from economics, this is somewhat surprising. Nonetheless, tremendous opportunity exists for the application of ideas from behavioral economics to substantive problems in political science. In particular, since so much work on American politics relies on rational choice or game theoretic methodology, an exploration not just of the distinctions and differences between cognitive and rationalist models, but also of the systematic interaction between strategic environment and cognitive factors is surely at least potentially productive.

A second direction for research is the exploration of variance models in more widespread applications. In law, these models are an essentially untapped resource despite the fact that many substantive problems in law are really about the variance parameter of a distribution, rather than the mean. For example, classic models of deterrence emphasize the effect of the probability of detection and the severity of punishment as roughly equal determinants of behavior. As either factor increases, the level of unlawful behavior should decrease. Yet, more than likely, there is a variance effect here as well. As either factor increases (decreases), the variance of behavior should and could decrease (increase) as well. Punitive damages are another example. One facet of this substantive issue is the variability of damage awards, but rarely, if ever, are parameterized variance models used. Even in political science, where such models have received occasional use (e.g. Brehm and Gronke (2001) or Franklin (1991)), they are still largely underutilized. The theoretical underpinnings of many substantive problems have an important variance component which remains almost entirely ignored (King 1989).

Finally, though I have tried to offer an integrated model of citizen choice about disaster risk, I have maintained a somewhat more narrow conception of political choice.

One obvious direction for further research is to construct a model of legislative behavior that analyzes the interaction between rationalist and cognitive factors in a more individualist way than I have done. With the wealth of informational models of legislative behavior that exist, one could easily explore the impact of more psychologically realistic actors in these game forms. In one sense, although the broad questions considered by this project are about legislative action, most of the emphasis has been on citizen behavior. This bottom heavy approach could be supplemented with greater emphasis on modeling political decision-making.

7.4 Normative Implications

Throughout this project my emphasis has obviously been on positive questions. Nonetheless, my attempts to abstain from the normative quagmire that is modern disaster policy have been only partially successful. There are after all normative implications of the project and to suggest otherwise is to shirk intellectual responsibility. However, exploring the normative aspects of risk regulation warrants a book unto itself, so in this venue, I want simply to highlight a few particularly relevant concerns. On the one hand, this project has ramifications for the way that we understand the institutions of disaster management in the United States. The particular reconstruction that I have given to our institutional arrangement has inevitable normative undertones. On the other hand, if the model of human behavior I have presented is accurate, as I believe it is, then there are implications for policy reform as well.

7.4.1 Reconstructing Institutions

In the United States, natural disaster policy is frequently criticized by both academics and the popular press. The policies are often portrayed as either the result of bureaucratic ineptitude or political malfeasance. Moreover, it is not uncommon to hear the words ineffective, inefficient, or inequitable either immediately before or after the "natural disaster policy." That said, my analysis demonstrates that when creating and reforming natural disaster policy, legislators were grappling with various strategic problems. They were facing a changing distribution of disaster relief benefits and persistent biases in the demand for legislative intervention that constrained their ability to select institutional responses. The institutional strategy they selected, though ultimately ineffective, was a perfectly plausible reply to the challenges they faced at the time. In one sense then, the analysis suggests a more favorable or at least less sinister interpretation of the modern disaster policy. At the same time, it reminds us that changes in institutional regimes create incentives for social actors. In the disaster arena, institutionalizing disaster policy and locating primary administrative responsibility in the bureaucracy, resulted in a rise of interest group activity. Thus, the analysis also highlights the darker side of disaster policy. Whether intentional or not, political choices made by legislators encouraged interest groups to become more involved in the policy arena, which ultimately increased overall expenditures without an obvious corresponding rise in social benefits. Many active components of disaster policy benefit targeted constituencies without either providing broader benefits or decreasing risk exposure. This is not a novel observation, but it is important both to provide empirical evidence to document the claim and to locate the claim in the context of a more general story about the genesis and evolution of U.S. disaster policy.

In this way, the project could adjust the normative content that we attach to certain institutions. Though I have little interest in either legitimizing or delegitimizing government policies, it is possible to use this work to do some of either.

7.4.2 Potential Policy Implications

The analysis also suggests a few directions for modest policy reforms. First, the cascade model points out the importance of emphasizing not just the production of information about natural disaster risk, but also the process of information dissemination itself. Government institutions—whether local, state, or federal—that take advantage of the process of information transmission evidenced in the cascade model may fare better at decreasing social risk exposure. Second, the analysis in chapter 3 highlights the possibility that individuals might mis-perceive the risk domain in which they are operating. For example, individuals might think they are in a high probability domain when in fact they are in a low probability domain. Because individuals exhibit different behavior when they are dealing with high and low probability risks or gains and losses, policies intended to create selective incentives may not have the desired effect if these factors are ignored. At very least, the project suggests focusing on risk domains when creating and reforming policy. Better still would be to allow for the possibility that individuals might misperceive the domain in which they are operating. Third, the project highlights the importance of looking at both cognitive and rational factors together when creating policy. Joint analysis may yield insights about human behavior that would otherwise be lost as legislation and policy is crafted. Finally, it is also clear that greater emphasis on empirical and historical data, rather than theoretical assertions is required when crafting legislative reforms. Too much policy has been based on too little data. Careful and rigorous consideration of empirical evidence is a prerequisite not just for meaningful scholarly insights, but also for the construction of effective and innovative government policy.

7.5 Conclusion

Images of disaster are commonplace in the United States. Even characters in literature are transfixed by the images of destruction and devastation.

> That night, a Friday, we gathered in front of the set, as was the custom and the rule, with take-out Chinese. There were floods, earthquakes, mud slides, erupting volcanoes. We'd never before been so attentive to our duty, our Friday assembly. ... We were otherwise silent, watching houses slide into the ocean, whole villages crackle and ignite in a mass of advancing lava. Every disaster made us wish for more, for something bigger, grander, more sweeping.[1]

Yet, this fascination is not a modern one. To wit, much of the Bible is an ancient record of the trials and tribulations of dealing with disaster risk. But, neither ancient nor modern records of natural disasters are particularly encouraging. Death and destruction seem to inevitably result. This project has tried to paint a somewhat more temperate portrait of disaster risk. Though it remains true that many citizens are largely unprotected from the wrath of nature, much variation exists as well. Many citizens and communities have gone to great lengths to protect themselves from the risk of floods, hurricanes, or earthquakes; and we should not lose sight of this fact. As the range of risks has expanded and the level of risk risen, so too has the variety and utilization of risk management strategies. Moreover, the efforts of the State, though perhaps not always as effective as we might like, have grown equally extensive. My hope is that this project contributes to the ongoing scholarly research agenda; and,

1. Delillo (1984, 61)

that in combination with insights from throughout the social sciences, this body of research might enhance our approach to dealing with the ever-present threat of natural disasters.

APPENDIX: PANEL CORRECTED STANDARD ERRORS

This appendix provides an overview of estimating Panel Corrected Standard Errors (PCSE's). When errors are spherical, the error variance matrix is given by

$$\mathbf{\Omega} = \sigma^2 \mathbf{I} \tag{A.1}$$

and OLS provides optimal estimates. However, panel data may exhibit heteroskedasticity, where

$$\mathrm{Var}(\epsilon_{i,t}^2) = \sigma_i^2 \tag{A.2}$$

be contemporaneously correlated across units within the same time period, such that

$$\mathrm{E}(\epsilon_{i,t}\epsilon_{j,t}) = \sigma_{ij} \tag{A.3}$$

$$\mathrm{E}(\epsilon_{i,t}\epsilon_{j,t'}) = 0 \quad \forall t \neq t \tag{A.4}$$

or be serially correlated where

$$\epsilon_{i,t} = \rho\epsilon_{i,t-1} + \nu_{i,t} \tag{A.5}$$

where $\nu_{i,t}$ are independent, identically distributed zero-mean random variables (Beck and Katz 1996). It will often be the case, that including a lagged dependent variable on the RHS of the equation will eliminate serial correlation, as it does in this case. Thus, we can estimate the equation

$$y_{i,t} = \phi y_{i,t-1} + x_{i,t}\beta + \epsilon_{i,t} \tag{A.6}$$

Because OLS provides consistent estimates of the coefficients, we simply require an estimate for $\mathbf{\Omega}$. PCSE's are calculated using the OLS residuals from an equation in which the errors are temporally independent (as in equation (10)), so $\mathbf{\Omega}$ takes the form

$$\mathbf{\Omega} = \mathbf{\Sigma} \otimes \mathbf{I_T} \tag{A.7}$$

where Σ is the N $\times$ N matrix of error variances and contemporaneous covariances (with σ_i^2 along the diagonal and σ_{ij} on the off diagonal) and $\otimes$ is the Kronecker product. Letting $\mathbf{E}$ denote the T $\times$ N matrix of the OLS residuals, $\frac{\mathrm{E'E}}{T}$ is a consistent estimate of $\mathbf{\Sigma}$ (Beck and Katz 1996). To get the PCSE's we simply take the square root of the diagonal elements of the matrix given by

$$(\mathbf{X'X})^{-1}\left(\frac{\mathbf{E'E}}{T} \otimes \mathbf{I}_T\right)\mathbf{X}(\mathbf{X'X})^{-1} \tag{A.8}$$

The exposition here is entirely due to Beck and Katz (1996), which also contains a more detailed derivation. The basic logic is that we know the panel structure of the data yields the form $\mathbf{\Omega} = \mathbf{\Sigma} \otimes \mathbf{I}_T$ so in order to estimate $\mathbf{\Omega}$ we need to identify an estimate of $\mathbf{\Sigma}$, which again is the N $\times$ N contemporaneous error covariance matrix. By stacking the errors where $\epsilon_\mathbf{t}$ is the vector of unit errors at time t, $\mathbf{\Sigma} = \mathrm{E}(\epsilon_\mathbf{t}\epsilon_{\mathbf{t}'})$. Though we do not observe $\epsilon_\mathbf{t}$, we do observe $\mathbf{e_t}$. And, therefore we can identify a consistent estimate of $\mathbf{\Sigma}$ by

$$\hat{\mathbf{\Sigma}} = \mathrm{T}^{-1}\sum_{t=1}^{T}\mathbf{e}_t\mathbf{e'}_t = \mathrm{T}^{-1}\mathbf{E'E} \tag{A.9}$$

PCSE's are consistent estimates of the standard errors of $\hat{\beta}$ and have excellent finite sample properties (Beck and Katz 1996; Beck and Katz 1995).

REFERENCES

1994. "The Earthquake: Mapping the Devastation; The Damage: First the Earthquake, then Aftershocks and Fires." *New York Times* Sectoin A:16.

Alexander, David. 1997. "The Study of Natural Disasters, 1977-1997." *Disasters* 21(4):281–304.

Alpert, Marc and Howard Raiffa. 1982. "A Progress Report on the Training of Probability Assessors." In *Judgment Under Uncertainty*, eds. Daniel Kahneman, Paul Slovic, and Amos Tversky, Cambridge: Cambridge University Press.

Anderson, Lisa R. and Charles A. Holt. 1996. "Classroom Games: Informational Cascades." *Journal of Economic Perspectives* 10(4):187–193.

—. 1997. "Informational Cascades in the Laboratory." *American Economic Review* 87(5):850–862.

Arnold, Douglas. 1990. *The Logic of Congressional Action.* New Haven, CT: Yale University Press.

Arrow, Kenneth. 1996. "The Theory of Risk Bearing: Small and Great Risks." *Journal of Risk and Uncertainty* 12(2/3):103–111.

Asgary, Ali and K.G. Willis. 1997. "Household Behavior in Response to Earthquake Risk: An Assessment of Alternative Theories." *Disasters* 21(4):354–365.

Banerjee, Abhijit V. 1992. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics* 107(3):797–818.

Beck, Nathaniel and Jonathan N. Katz. 1995. "What to do (and what not to do) with Time-Series Cross-Section Data." *American Political Science Review* 89(3):634–647.

—. 1996. "Nuisance vs. Substance: Specifying and Estimating Time-Series-Cross-Section Models." *Political Analysis* 6:1–34.

Becker, Gary S. 1983. "A theory of competition among pressure groups for political influence." *Quarterly Journal of Economics* 98:371–399.

Bernardo, Antonio and Ivo Welch. 1999. "On the Evolution of Overconfidence and Entrepreneurs."

Bertrand and Mark J. Machina, eds. 1994. *Models and Experiments in Risk and Rationality.* Boston: Kluwer Academic Publishers.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy* 100(5):992–1026.

Birkland, Thomas A. 1997. *After Disaster: Agenda Setting, Public Policy, and Focusing Events.* Georgetown University Press.

Brehm, John and Paul Gronke. 2001. "History, Heterogeneity, and Presidential Approval: A Modified ARCH Approach." *Electoral Studies* (Forthcoming).

Breyer, Stephen. 1993. *Breaking the Vicious Circle: Toward Effective Risk Regulation.* Cambridge, MA: Harvard University Press.

Brown, Ronald H., D. James Baker, and Elbert W. Friday. 1994. *The Great Flood of 1993.* Tech. Rep. Natural Disaster Survey Report, National Oceanic and Atmospheric Administration U.S. Department of Commerce.

Browne, Mark J. and RE Hoyt. 2000. "The Demand for Flood Insurance." *Journal of Risk and Uncertainty* 20(3):291–306.

Burby, Raymond, Beverly A. Cigler, Steven P. French, Edward J. Kaiswer, Jack Kartez, Dale Roenigk, Dana Weist, and Dale Whittington. 1991. *Sharing Environmental Risks: How to Control Goverments' Losses in Natural Disasters.* Boulder: Westview Press.

Calvert, Randall, Mark Moran, and Barry Weingast. 1987. "Congressional Influence over Policy Making: The Case of the FTC." In *Congress: Structure and policy*, eds. Mathew McCubbins and Terry Sullivan, Cambridge: Cambridge University Press.

Camerer, Colin F. and Howard Kunreuther. 1989. "Decision Processes for Low Probability Events: Policy Implications." *Journal of Policy Analysis and Management* 8(4):565–592.

Chamley, Christopher and Douglas Gale. 1994. "Informational revelation and Strategic Delay in a Model of Investment." *Econometrica* 32(5):1065–1085.

Cheit, Ross E. 1990. *Setting safety standards: Regulation in the public and private sectors.* Berkeley, CA: University of California Press.

Dacy, Douglas C. and Howard Kunreuther. 1969. *The Economics of Natural Disasters.* New York: The Free Press.

Davidian, M. and R. J. Carroll. 1987. "Variance Function Estimation." *Journal of the American Statistical Association* 82(400):1079–1091.

Davis, Mike. 1999. *Ecology of Fear: Los Angeles and the Imagination of Disaster.* New York: Random House.

Delillo, Don. 1984. *White Noise.* New York: Penguin Books.

Dong, Weimin, Haresh Shah, and Felix Wong. 1996. "A Rational Appraoch to the Pricing of Catastrophe Insurance." *Journal of Risk and Uncertainty* 12(2/3):208–213.

Douglas, Mary. 1985. *Risk Acceptability According to the Social Sciences.* New York: Russell Sage Foundation.

Douglas, Mary and Aaron Wildavsky. 1982. *Risk and Culture: An Essay on the Selection of Technological and Environmental Dangers.* Berkeley: University of California Press.

Ellsberg, Daniel. 1961. "Risk, Ambiguity and the Savage Axioms." *Quarterly Journal of Economics* 75:643–669.

Elster, Jon. 1984. *Ulysses and the Sirens.* Cambridge: Cambridge University Press.

Epstein, David and Sharyn O'Halloran. 1984. "Administrative Procedures, Information, and Agency Discretion." *American Journal of Political Science* 38:697–692.

—. 1999. *Delegating Powers: A Transaction Cost Politics Approach to Policy Making under Separate Powers.* Cambridge: Cambridge University Press.

Epstein, Richard. 1996. "Catastrophic Responses to Catastrophic Risk." *Journal of Risk and Uncertainty* 12(2/3):287–308.

de Finetti, Bruno. 1972. *Probability, Induction and Statistics: The Art of Guessing.* New York: John Wiley & Sons.

Fiorina, Morris. 1977. *Congress: The Keystone of the Washington Establishment.* New Haven, CT: Yale University Press.

—. 1982. "Legislative Choice of Regulatory Forms: Legal process or Administrative Process?" *Public Choice* 39:33–71.

—. 1986. "Legislator Uncertainty, Legislative Control, and the Delegation of Legislative Power." *Journal of Law, Economics and Organization* 2:33–51.

Fischer, Michael J. 1996. "Union Carbide's Bhopal Incident: A Retrospective." *Journal of Risk and Uncertainty* 12(2/3):257–269.

Fischoff, Baruch, Paul Slovic, and Sarah Lichtenstein. 1977. "Knowing with Certainty: the Appropriateness of Extreme Confidence." *Journal of Experimental Psychology* 3:553–564.

Franklin, Charles H. 1991. "Eschewing Obfuscation? Campaigns and the Perception of U.S. Senate Incumbents." *American Political Science Review* 85(4):1193–1214.

Freeman, Paul K. and Howard Kunreuther. 1997. *Managing Environmental Risk Through Insurance.* Boston, MA: Kluwer Academic Publishers.

Froot, Kenneth A., ed. 1999. *The Financing of Catastrophic Risk.* Chicago and London: University of Chicago Press.

GAO. 1990a. *Flood Insurance: Information on Financial Aspects of the National Flood Insurnace Program.* Tech. Rep. GAO/T-RCED-99-280, Government Accounting Office, Washington D.C.

—. 1990b. *Flood Insurance: Information on the Mandatory Purchase Requirement.* Tech. Rep. GAO/RCED-90-141FS, United States General Accounting Office, Washington D.C.

Goodwin, Barry K. and Vincent H. Smith. 1995. *The Economics of Crop Insurance and Disaster Aid.* Washington D.C.: The AEI Press.

Green, Donald P. and Ian Shapiro. 1994. *Pathologies of Rational Choice Theory: A Critique of Applications in Political Science.* New Haven: Yale University Press.

Gujarati, Damodar N. 1995. *Basic Econometrics.* New York: McGraw-Hill, Inc.

Hammond, Kenneth R. 1996. *Human Judgment and Social Policy.* New York: Oxford University Press.

—. 2000. "Coherence and Correspondence Theories in Judgment and Decision Making." In *Judgment and Decision Making: An Interdisciplinary Reader*, eds. Terry Connolly, Hal R. Arkes, and Kenneth R. Hammond, Cambridge: Camgridge University Press.

Heimer, Carol A. 1988. "Social Structure, Psychology, and the Estimation of Risk." *American Review of Sociology* 14:491–519.

Hirshleifer, Jack. 1987. *Economic Behavior in Adversity.* Chicago: University of Chicago Press.

Hogarth, Robin M. and Hillel J. Einhorn. 1990. "Venture Theory: A Model of Decision Weights." *Management Science* 36:780–803.

Hogarth, Robin M. and Howard Kunreuther. 1985. "Ambiguity and Insurance Decisions." *The American Economic Review* 75(2):386–390.

Hogarth, Robin M. and Melvin W. Reder, eds. 1987. *Rational Choice: the Contrast between Economics and Psychology.* Chicago: University of Chicago Press.

Honaker, James, Anne Joseph, Gary King, Kenneth Scheve, and Naunihal Singh. 1999. *Amelia: A Program for missing Data.* Cambridge, MA: Harvard University, http://GKing.Harvard.edu.

Howard, James J. and James L. Oberstar. 1987. *The Federal Emergency Management Agency's Proposed Disaster Relief Regulations:Report of the Subcommittee on Investigations and Oversight of the Committee on Public*

Works and Transportation. Tech. Rep. 100-303, House of Representatives, Washington D.C.

Hsee, Christopher. 1996. "The evaluability hypothesis: An explanation for preference reversals between joint and separate evaluations of alternatives." *Organizational Behavior and Human Decision Processes* 67:247–257.

Hsee, C.K, George F. Loewenstein, S. Blount, and M.H. Bazerman. 1999. "Preference reversals between joint and separate evaluation of options: A review and theoretical analysis." *Psychological Bulletin* 125:576–590.

IRC. 1994. "Coastal Exposure and Community Protection: Hurricane Andrew's Legacy."

—. 1995. "Public Attitude Monitor 1995."

—. 1999. "Public Attitude Monitor 1999: Perceptions of the Risk of Natural Disaster."

Jackman, Simon. 2000a. "Estimation and Inference via Bayesian Simulation: An Introduction to Markov Chain Monte Carlo." *American Journal of Political Science* 44(2):375–404.

—. 2000b. "'Missing Data' Problems: Unifying Social Science Statistics via Bayesian Simulation." *Political Analysis* 8(4):307–322.

Johnson, Eric J., John Hershey, Jacqueline Meszaros, and Howard Kunreuther. 1993. "Framing, Probability Distortions, and Insurance Decisions." *Journal of Risk and Uncertainty* 7:31–51.

Jolls, Christine, Cass R. Sunstein, and Richard Thaler. 1998. "A Behavioral Approach to Law and Economics." *Stanford University Law Review* 50(5):1471–1550.

Kagel, John H. and Alvin E. Roth, eds. 1995. *Handbook of Experimental Economics.* Princeton: Princeton University Press.

Kahneman, Daniel. 1994. "New Challenges to the Rationality Assumption." *Journal of Institutional and Theoretical Economics* 150(1):18–36.

Kahneman, Daniel, Paul Slovic, and Amos Tversky, eds. 1982. *Judgment Under Uncertainty.* Cambridge: Cambridge University Press.

Kahneman, Daniel and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision Under Risk." *Econometrica* 47:263–291.

Kahneman, Daniel and Amos Tversky, eds. 2000. *Choice, Values, and Frames.* Cambridge and New York: Russell Sage Foundation and Cambridge University Press.

Kante, Edward J. 1996. "Difficulties in Making Implicit Government Risk-Bearing Partnerships Explicit." *Journal of Risk and Uncertainty* 12(2/3):189–199.

Kiewiet, D. Roderick and Mathew D. McCubbins. 1991. *The Logic of Delegation: Congressional Parties and the Appropriations process.* Chicago and London: University of Chicago Press.

King, Gary. 1989. *Unifying Political Methodology.* Ann Arbor: University of Michigan Press.

King, Gary, James Honaker, Anne Joseph, and Kenneth Scheve. 1998. "Listwise Deletion is Evil: What to Do About Missing Data in Political Science.", paper Presented at the Annual meetings of the American Political Science Association, Boston.

Kirschten, Dick. 1990. "Hyping the Big Quake." *The National Journal* 22(1):11.

Kmenta, Jan. 1986. *Elements of Econometrics.* New York: Macmillan.

Kreps, David M. 1990. *A Course in Microeconomic Theory.* Princeton: Princeton University Press.

Kunreuther, Howard. 1978. *Disaster Insurance Protection: Public Policy Lessons.* New York: John Wiley and Sons.

—. 1996. "Mitigating Disaster Losses Through Insurance." *Journal of Risk and Uncertainty* 12(2/3):171–187.

Kunreuther, Howard and Ian Hogarth. 1995. "Decision Making Under Ignorance: Arguing With Yourself." *Journal of Risk and Uncertainty* 10:15–36.

Kunreuther, Howard, Robin Hogarth, and Jacqueline Meszaros. 1993. "Insurere Ambiguity and Market Failure." *Journal of Risk and Uncertainty* 7:71–87.

Kunreuther, Howard, Nathan Novemsky, and Daiel Kahneman. 2000. "Making Low Probabilities Useful."

Kunreuther, Howard and Richard J. Sr. Roth, eds. 1998. *Paying the Price: The Status and Role of Insurance Against Natural Disasters in the United States.* Washington D.C.: Joseph Henry Press.

Landis, Michele L. 1998. "Let me Next Time Be "Tried by Fire": Disater Relief and the Origins of the American Welfare State 1789-1874." *Northwestern University Law Review* 92:967.

Lee, In Ho. 1993. "On the Convergence of Informational Cascades." *Journal of Economic Theory* 61:395–411.

Levmore, Saul. 1996. "Coalitions and Quakes: Disaster Relief and its Prevention." *University of Chicago Law School Roundtable* 3(1).

Lichtenstein, Sarah, Baruch Fischoff, and Lawrence D. Phillips. 1982. "Calibration of Probabilities: The state of the art to 1980." In *Judgement Under Uncertainty*, eds. Daniel Kahneman, Paul Slovic, and Amos Tversky, Cambridge: Cambridge University Press.

Lohmann, Susanne and Hugo Hopenhayn. 1998. "Delegation and the Regulation of Risk." *Games and Economic Behavior* 23:222–246.

Lowenstein, George and Jon Elster, eds. 1992. *Choice Over Time*. New York: Russell Sage Foundation.

Lowi, Theodore. 1979. *The End of Liberalism: The Second Republic of the United States*. New York: W.W. Norton.

Margolis, Howard. 1996. *Dealing With Risk: Why the Public and the Experts Disagree on Environmental Issues*. Chicago: University of Chicago Press.

May, Peter J. 1985. *Recovering from Catastrophe: Federal Disaster Relief Policy and Politics*. Westport, CT: Greenwood Press.

May, Peter J., Raymond J. Burby, Neil J. Ericksen, John W. Handmer, Jennifer E. Dixon, Sarah Michaels, and D. Ingle Smith. 1996. *Environmental Management and Governance: Intergovernmental approaches to hazards and sustainability*. London and New York: Routledge.

McClelland, Gary H., Gary H. Schulze, and Don L. Coursey. 1993. "Insurance for Low-Probability Hazards: A bimodal Response to Unlikely Events." *Journal of Risk and Uncertainty* 7:95–116.

McCubbins, Mathew. 1985. "The Legislative Design of Regulatory Structure." *American Journal of Political Science* 29:721–748.

McCubbins, Mathew and Thomas Schwartz. 1984. "Congressional Oversight Overlooked: Police Patrols versus Fire Alarms." *American Journal of Political Science* 28:165–79.

McCubbins, Mathew D., Roger G. Noll, and Barry Weingast. 1987. "Administrative procedures as instruments of political control." *Journal of Law, Economics and Organization* 3:243–277.

—. 1989. "Structure and Process, Politics and Policy: Administrative Arrangements and the Political Control of Agencies." *Virginia Law Review* 75(2):431–482.

Meier, Kenneth J. 1988. *The Political Economy of Regulation: The Case of Insurance*. Buffalo, NY: State University of New York Press.

Mileti, Dennis S. 1999. *Disasters by design*. Washington D.C.: Joseph Henry Press.

Moe, Terry. 1985. "The Politics of Bureaucratic Structure." In *Can the Government Govern?*, eds. John Chubb and Paul Peterson, Washington, D.C.: Brookings Institution.

—. 1990. "Political Institutions: The Neglected Side of the Story." *Journal of Law, Economics and Organization* 6:213–253.

Moss, David A. 1999. "Courting Disaster? The Transformation of Federal Disaster Policy since 1803." In *The Financing of Catastrophic Risk*, ed. Kenneth A. Froot, Chicago and London: University of Chicago Press.

Mukerji, Sujoy. 1998. "Ambiguity Aversion and Incompleteness of Contractual Form." *The American Economic Review* 88(5):1207–1231.

Niskanen, William A. 1971. *Bureaucracy and Representative Government.* Chicago: Aldine-Atherton.

Noble, Kennth B. 1996. "California to Get More in Quake Aid." *New York Times* Sectoin A:13.

Noll, Roger G. 1996. "Reforming Risk Regulation." In *Challenges in Risk Assessment and Risk Management*, eds. Howard Kunreuther and Paul Slovic, Thousand Oaks: Sage.

Noll, Roger G. and James E. Krier. 1990. "Some Implications of Cognitive Psychology for Risk Regulation." *Journal of Legal Studies* 19:747–779.

Odean, Terrance T. 1997. *Essays on Investor Behavior.* Ph.d., University of California, Berkeley California.

Ogul, Morris. 1976. *Congress Oversees the Bureaucracy.* Pittsburgh: University of Pittsburgh Press.

Palm, Risa. 1990. *Natural Hazards: an Integrative Framework for Research and Planning.* Baltimore and London: Johns Hopkins University Press.

—. 1998. "Demand for Disaster Insurance: Residential Coverage." In *Paying the Price: The Status and Role of Insurance Against Natural Disasters in the United States*, eds. Howard Kunreuther and Richard J. Roth Sr., Washington D.C.: Joseph Henry Press.

Parks, Richard. 1967. "Efficient Estimation of a System of Regression Equations When Disturbances are Both Serially and Contemporaneously Correlated." *Journal of the American Statistical Association* 62:500–509.

Peltzman, Sam. 1985. "An Economic Interpretation of the History of Congress in the Twentiety Century." *American Economic Review* 75:656–675.

Platt, Rutherford H. 1999. *Disasters and Democracy: The Politics of Extreme Natural Events.* Washington, D.C.: Island Press.

Pollack, Robert A. 1996. "Government Risk Regulation." In *Challenges in Risk Assessment and Risk Management*, eds. Howard Kunreuther and Paul Slovic, Thousand Oaks: Sage Periodicals Press.

Popkin, Roy S. 1990. "The History and Politics of Disaster Management in the United States." In *Nothing to Fear: Risks and Hazards in American Society*, ed. Andrew Kirby, Tucson: The University of Arizona Press.

Pratt, John W. and Richard J. Zeckhauser. 1982. "Inferences from Alarming Events." *Journal of Policy Analysis and Management* 1(3):371–385.

Priest, George. 1996. "The Government, the Market, and the Problem of Catastrophic Risk." *Journal of Risk and Uncertainty* 12(2/3):219–238.

Quattrone, George and Amos Tversky. 1988. "Contrasting Rational and Psychological Analysis of Political Choice." *Amerian Political Science Review* 82(3):719–736.

Rauch, Jonathan. 1992. "Pennies From Heaven." *The National Journal* 24(41):2299.

Rogers, George O. 1997. "The Dynamics of Risk Perception: How Does Perceived Risk Respond to Risk Events?" *Risk Analysis* 17(6):745–757.

Rossi, Peter H., James D. Wright, and Eleanor Weber-Burdin. 1982. *Natural Hazards and Public Choice.* New York: Academic Press.

Schelling, Thomas. 1978. *Micromotives and Macrobehavior.* New York: W.W. Norton & Co.

Siddiq, Ali and Paul Slovic. 1994. "A Psychological Study of the Inverse Relationship Between Perceived Risk and Perceived Benefit." *Risk Analysis* 14(6):1085–1100.

Slovic, Paul, Baruch Fischoff, and Sarah Lichtenstein. 1985. "Regulation of Risk: A Psychological Perspective." In *Regulatory Policy and the Social Sciences*, ed. Roger G. Noll, Berkeley, CA: University of California Press.

Smith, Kerry, William H. Desvousges, and John W. Payne. 1995. "Do Risk Information Programs Promote Mitigating Behavior." *Journal of Risk and Uncertainty* 10:203–221.

Spence, David B. 2001. "The shadow of the Rational Polluter: Rethinking the Role of Rational Actor Models in Environmental Law." *California Law Review* (Forthcoming).

Spiegelhalter, D.J., A. Thomas, N.G. Best, and W.R. Gilks. 2000. "WinBUGS: Bayesian Inference Using Gibbs Sampling, Version 1.3."

Starobin, Paul. 1992. "Those Quaking Insurers." *The National Journal* 24(23):1360.

Sunstein, Cass R., ed. 2000. *Behavioral Law and Economics.* Cambridge: Cambridge University Press.

Sunstein, Cass R. and Timur Kuran. 1999. "Availability Cascades and Risk Regulation." *Stanford University Law Review* .

Thaler, Richard H. 2000. "Illusions and Mirages in Public Policy." In *Judgment and Decision Making: An Interdisciplinary Reader*, eds. Terry Connolly, Hal R. Arkes, and Kenneth R. Hammond, Cambridge: Cambridge University Press.

Tsebelis. 1989. "The Abuse of Probabiliy in Political Analysis: The Robinson Crusoe Fallacy." *American Political Science Review* 83(1):77–91.

Tversky, Amos and Daniel Kahneman. 1973. "Availability: A heuristic for judging frequency and probability." *Cognitive Psychology* 5(2):207–232.

Viscusi, W. Kip. 1993. "The Risk Business of Insurance Pricing." *Journal of Risk and Uncertainty* 7:117–139.

—. 1995. *Fatal Tradeoffs: Public & Private Responsibilities for Risk.* New York: Oxford University Press.

—. 1996. "Alternative Institutional Responses to Asbestos." *Journal of Risk and Uncertainty* 12(2/3):147–170.

—. 1999. "Does Consumer Choice Need to be Managed: Using Warnings to Extend the Boundaries of Consumer Sovereignty." *Harvard Journal of Law & Public Policy* 23:211–230.

Viscusi, W. Kip and Harrell Chesson. 1999. "Hopes and Fears: The Conflicting Effects of Risk Ambiguity." *Theory and Decision* 47:153–178.

Viscusi, W. Kip and Wesley A. Magat. 1992. "Bayesian decisions with ambiguous belief aversion." *Journal of Risk and Uncertainty* 5(4):371–387.

Weinstein, N. 1980. "Unrealistic Optimism about Future Life Events." *Journal of Personality and Social Psychology* 39:806–820.

Wildavsky, Aaron and Karl Dake. 1990. "Theories of Risk Perception: Who fears what and why?" *Daedalus* 119(4):41–60.

Wilson, James. 1974. "The Politics of Regulation." In *Social Responsibility and the Business Predicament*, ed. J. McKie, Washington, D.C.: Brookings Institution.

Yates, Y.F. 1990. *Judgement and Decision making.* Englewood Cliffs, NJ: Prentice Hall.

Zeckhauser, Richard. 1996. "The Economics of Catastrophes." *Journal of Risk and Uncertainty* 12(2/3):113–140.

Zhang, Jianbo. 1997. "Strategic Delay and the Onset of Investment Cascades." *Rand Journal of Economics* 28(1):188–205.