Essays on the Demand for Catastrophe Insurance

Evidence from California's Residential Earthquake Insurance Market

by

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A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Business)

at the

UNIVERSITY OF WISCONSIN–MADISON

2014

Date of final oral examination: 06/03/2014

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Acknowledgments

This thesis is the last step of my five-year doctoral study at the University of Wisconsin-Madison. I could not get this project done without the help and guidance of many others. I thank my professors, colleagues, friends and family, and anyone who has supported me at various stages of my dissertation process.

I would like to express my very great appreciation to my advisor, Dr. Justin Sydnor, for his valuable and constructive suggestions throughout this project. He always has so many intuitions and brilliant ideas. He inspires me to think like an economist, and sets an example for me on how to be passionate about research and teaching. He is also a well-rounded advisor. Being a young scholar himself, he shared with me the most relavant experience and valuable insights on career in general. I owe a big part of my research and success to him.

I am also grateful to my other committee members for their input. I might have written on a completely different subject if it were not for Professor Mark Browne. Mark gave me an opportunity to go to California and have a closer look at the earthquake insurance market there. He is the person who opened up a door and lit up the first parts of the road for me. Professor Edward (Jed) Frees has been patiently answering any of my statistical questions for five years. His never-ending energy in pursuing high-quality research sets a standard for me. Professor Margie Rosenberg paid great attention to every word I wrote. She also pointed me to the most current census data needed for part of my research. Within the limited amount of time that I've known Dr. Jennifer Alix-Garcia, she has given me advise on various topics, from general economic intuitions, to econometric methods, and map generating techniques. She is alwasy quick to respond to my emails and obviously cares a lot about students. I feel very lucky to have all these wonderful professors on my committee. This thesis would not be nearly as good without them.

A crucial part of this thesis is getting to know the institutional background in California and getting my hands on the earthquake insurance data. I thank the people whom I worked with for three months at the California Earthquake Authority. I also thank the people at the Statistical Analysis Division of the California Department of Insurance, in particular, Luciano Gobbo and Debra Buenconsejo. They sent me the data that I asked for at no charge. Without the insurance data, this project would have been impossible.

I certainly have had ups and downs during the long dissertation process. I value the accompany of fellow graduate students in my office. Especially, Xiaoli Jin and Marc Ragin. I also thank my friends at the University of Wisconsin-Madison for sharing laughters and joyful experiences with me. To name just a few, Wolfgang Schopf, Chris Moss, and Vedant Bhatnagar.

Last but not least, I want to thank my parents, Guanghua Lin and Suzhi Zhang. They supported me unconditionally. Although being far away from them most of the time, I know I'm not alone.

Completing this thesis marks the end of one journey but the start of another. Thank you for helping me achieve what I've achieved by now, and preparing me for the journey ahead.

Abstract

The demand for catastrophe insurance worldwide has remained low despite growing losses due to natural disaster. This study investigates catastrophe insurance demand issues in the context of California's residential earthquake insurance market, where risk classification by the dominant public insurer is limited, and where earthquake insurance coverage is voluntary, even the earthquake hazard is high.

I first show that the California Earthquake Authority (CEA) charges the same rate for areas with substantial variation in underlying seismic risk. I find clear evidence that this limited geographic risk classification leads to adverse selection: people living in higher-risk areas are more likely to take up CEA earthquake policies, all else equal. I then compare the patterns of take-up from private earthquake insurers, who use finer geographic risk classification schemes. My results are on average consistent with the prediction that finer pricing mitigates the positive correlation between risk and demand. However, the effects of finer pricing show heterogeneity across regions. Overall, it appears that people have other considerations besides the comparison of expected loss (risk) and insurance price. Lastly, I exploit geographic heterogeneity in the experience of earthquakes using a database that records the areas where earthquake shaking was reported. I find only a slight increase in demand in the year following an earthquake, with the increased demand fully dissipating after one year. This suggests that personal experiences with shaking events do not strongly alter homeowners' insurance purchase decisions. Instead, as classic theory would predict, the demand for earthquake insurance is affected more by levels of (relatively constant) probabilistic seismic risk, rather than recent experience with random earthquake events.

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Chapter 1

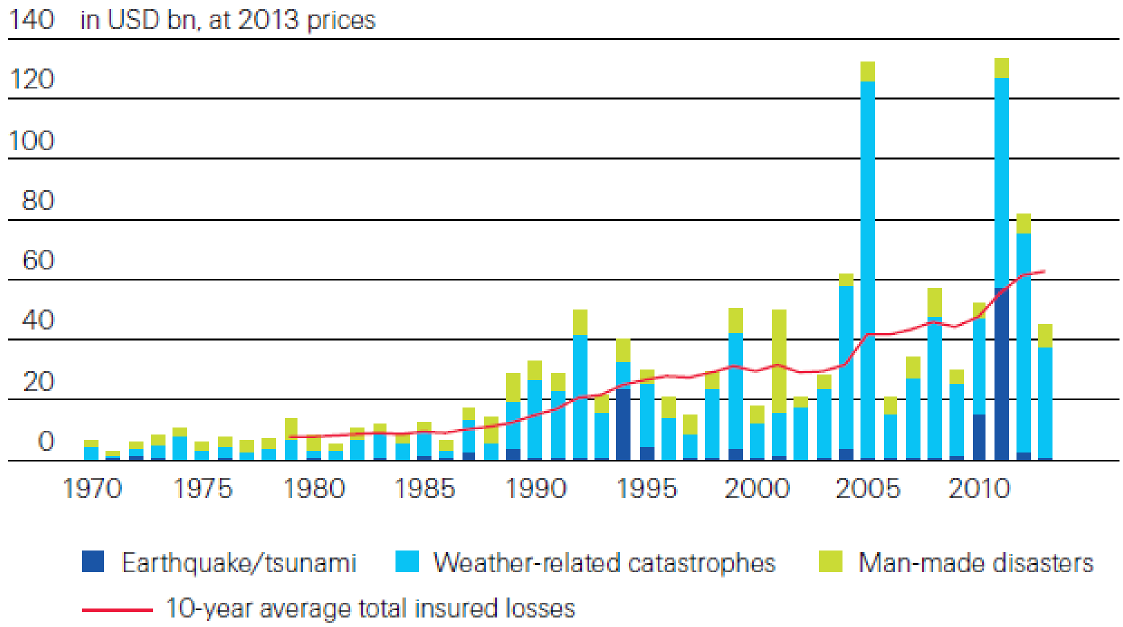
Introduction

Catastrophe losses worldwide have been increasing faster than ever in recent decades, largely due to growing population and increased economic activity in hazard-prone areas. The inflation-adjusted average annual insured catastrophe loss for the last ten years has been growing exponentially, but is still only a small part of the total economic losses. In 2011, natural and man-made catastrophes cost society over $370 billion (in 2011 USD) in economic losses, the highest amount ever recorded, of which $116billion (in 2011 USD) were insured losses.[1] Figure 1.1 shows the trend of insured catastrophe losses for earthquake/tsunami, weather-related catastrophes, and man-made disasters from 1970 to 2013. Some notable catastrophes that cost billions of dollars of insured losses in recent decades include: Super Storm Sandy (2012), the 2011 Japan and New Zealand earthquakes, the 2010 Chile and New Zealand earthquakes, Hurricane Ike (2008), Hurricane Katrina (2005), 9/11 attacks (2001), the Northridge earthquake (1994), and Hurricane Andrew (1992). Despite the risk of substantial destruction from catastrophe events, only a small portion of losses from natural disasters are covered by insurance. There are certainly some institutional limitations on catastrophe insurance markets. But individual demand for catastrophe insurance remains low in general, even

[1]Sources: Swiss Re: sigma No.2/2012.

when insurance is available. Earlier surveys by Kunreuther et al. (1978) and Palm (1995) suggest that individuals underestimate the probability of a disaster and, when probability falls below a certain threshold, even ignore it.

Figure 1.1: Insured Losses Worldwide



Source: Swiss Re Economic Research & Consulting

In an effort to better understand the drivers of the demand for catastrophe insurance, this study investigates the demand for residential earthquake insurance policies. The overall goal is to understand market participant behavior, especially the nature of homeowners' demand for insuring infrequent catastrophic events. I address four major empirical questions: First, how do insurers classify and price catastrophe risks geographically? Second, does limited risk classification lead to adverse selection by insurance buyers? Third, if it does, then does finer pricing mitigate possible adverse selection inefficiencies and attract more demand, especially from those relatively low-risks? Finally, what are some other determinants of demand for catastrophe insurance besides price and expected costs, and in particular, is recent disaster experience a contributing factor?

I focus my attention on the market for residential earthquake insurance in California. Despite the high earthquake exposure, there is no mandate on insurance coverage by homeowners. On the supply side, a dominant semi-public organization called the California Earthquake Authority (CEA) provides the majority of the residential earthquake coverage. Meanwhile, a private fringe also remains outside of the CEA.

In the next four sub-sections, I introduce each of the four empirical questions in greater details, and highlight their specific motivations and contributions. The rest of the dissertation proceeds as follows. Chapter 2 presents historical background on the development of California's residential earthquake insurance market. Chapter 3 conducts the literature review. Chapter 4 describes the data used in this study. Chapter 5 answers the first empirical questions on geographic risk classification. Chapters 6 and 7 answer the next two empirical questions about the specifics of homeowners' adverse selection against different types of insurers. Chapter 8 provides an alternative framework and econometric models to answer and interpret those questions. Chapter 9 answers the last empirical question about the effects of disaster experiences on demand for insurance. Chapter 10 concludes and discusses a few areas for research in the future.

1.1 Geographic Risk Classification for Earthquake Risk in California

First, this study provides an explicit comparison of pricing strategies employed by the public and the private insurers in a particular catastrophe insurance market. A number of prior studies have examined the degree of risk classification in catastrophe insurance markets. But most of these studies have focused on one type of government-provided or regulated disaster insurance policy (for example, see Kriesel and Landry (2004), Czajkowski et al. (2012)), and only speculate that private insurers might price at a more granular level.

The dominant residential earthquake insurer in California is a semi-public organization called California Earthquake Authority (CEA). The CEA uses a rather coarse geographic risk classification, drawing only 19 rating territories across California. Jaffee and Russell (2000) argue that CEA rates are tempered by political pressures and marketing concerns. In fact, the law requires CEA rates to be actuarially-sound, but discourages too much rate discrimination.[2] By studying the CEA's rate manuals, I quantitatively analyze to what extent its prices are cross-subsidized. I find that its territorial prices are risk-based and high correlation exists between CEA rates and territory-average seismic risks. However, I also find that there is substantial risk variation within individual territories where the CEA charges a constant rate.

The private insurers who, by policy count, represent about 25% of California's residential earthquake insurance market generally use finer risk classification schemes. For example, GeoVera and Chartis, the 2^{nd} and 3^{rd} players[3] in this market, both have varied their rates at a more granular level than the CEA.

This evidence of cross-subsidization in price by the CEA and finer pricing by the private insurers leads to the question of whether the CEA will face adverse selection in demand from homeowners, and whether or not the private market is able to attract lower-risk homeowners and get a better risk pool.

[2] California Insurance Code (2005) Section 10089.40 (b): Scientific information from geologists, seismologists, or similar experts shall not be conclusive to support the establishment of different rates...unless...it is not the intent of the legislature in adopting this subdivision to mandate a uniform statewide flat rate for California Earthquake Authority policies. (c): The classification system established by the board shall not be adjusted or tempered in any way to provide rates lower than are justified for classifications that present a high risk of loss or higher than are justified for classifications that present a low risk of loss.

[3] Source: California Department of Insurance P&C Market Share Reports.

1.2 Adverse Selection Against CEA Earthquake Insurance

In order to test for evidence of adverse selection, I focus on the take-up rates of CEA policies[4] by homeowners with different risk faced with the same insurance price. In my demand function, I control for a host of socioeconomic and demographic factors, such as median home value and educational level. For the main independent variable of interest, the seismic risk measured by Peak Ground Acceleration (PGA), a strong positive correlation is found between the zip-code level PGA and the zip-code level take-up rate of CEA policies within a CEA territory. The magnitude of the coefficient signifies strong evidence of adverse selection against the CEA: an increase in risk level roughly equivalent to a doubling in expected loss is associated with a 7 percentage point increase in the CEA take-up rate, which represents an approximately 70% increase from the current statewide take-up rate of about 10%.

Methodology-wise, in my test for adverse selection, I use "objective risk" to measure risk levels which is different from the standard coverage-risk correlation test. The standard test uses ex-post claims as proxies for risk types (e.g., Chiappori and Salanie (2000)).[5] By using exogenous objective risk, I avoid the ambiguities of deductibles (or "pseudo-deductibles") and moral hazard issues, which results in a cleaner test. In my case, the information setting is also unique; the insurer should have more information on seismic risk than the buyers, but the insurer does not use all of its information in pricing. The situation described in the paper is similar in spirit to the Finkelstein and Poterba (2004) paper on adverse selection evidence from the U.K. annuity market, where insurers collect extensive information related to an annuitant's survival probability but use only age and

[4] Defined as the number of CEA earthquake policies divided by the number of CEA participating insurers' homeowners' policies. The denominator is the homeowners eligible to purchase CEA earthquake policies.

[5] There are a few studies that have used other proxies for risk type. For example: Browne (1992) uses predicted claims instead of realized ex-post claims; some health insurance literature uses subjective measurement such as self-evaluated health condition.

gender in determining the price.

Also, using "objective risk" extends catastrophe-insurance-demand literature in two ways. First, relatively few studies use "objective risk" in their demand analysis.[6] Second, even when they do, they generally do not have much variation in risk measures, and cannot isolate risk variation from insurance price variation. My study contributes to the existing literature both by having enough risk variation, as my dataset encompasses all areas in California and has the risk measure at the zip-code level, and by further isolating objective risk from all other factors, price in particular.

The strong evidence of adverse selection found in this study suggests the possibility of efficiency loss relative to a scenario where price segmentation is perfect and people with different risks purchase policies with different prices. Acknowledging that people act on information that is correlated with risk level and that is not priced by the CEA, further disentangling the sources of that information is important because it has different implications for how the market would change if insurers were to price at a finer level. Ideally, we would run an experiment on how people react to finer pricing, but that type of experiment is difficult and unlikely to be observed in reality. However, the coexistence of private insurers and the CEA allows us to partly answer these questions.

1.3 Comparison of Demand for CEA and Private Earthquake Insurance

The opportunity for the private market to "cherry-pick" lower-risk homeowners from the CEA was brought up a long time ago by an official at the California Department of Insurance (CDI), who wrote,[7] "The CEA territories are very crude. They start out with rates based on expected costs in

[6] Most of them rely on loss experience or survey questions to measure risk levels.

[7] Quote from the email correspondence between the CDI and GeoVera documented in the rate filings by GeoVera in 1998.

a particular zip-code, then lump together contiguous zip-codes in a sometimes arbitrary process. The highest loss cost territories are then lumped together with lower cost territories to bring the highest indicated rates down. This provides a tremendous opportunity for GeoVera and the other private companies to *select the lower cost risks*..."

To test the speculation that private insurers are getting a better risk pool than the CEA, I compare the demand patterns for these two types of insurers. I test whether the CEA captures the same proportion of the market everywhere within its pricing territory or if it has relatively larger market shares in higher-risk areas. I find that the CEA's earthquake market shares are on average positively correlated with risk levels. As such, the evidence is consistent with the prediction based on finer risk classification by the private market. However, heterogeneity exists between different areas: risk-share correlation slopes vary between territories, and not all of the territories have positive slopes. The fact that the CEA's earthquake market share is not uniformly positively related to risk could suggest other important drivers of demand beyond price and expected loss. One possible explanation is that insurers may have employed marketing tactics that are unrelated to risk. For example, the private insurers may focus more on higher-end homeowners because of a higher profit margin. In fact, this possibility seems to be suggested by summary statistics showing that the coverage amount for house structure is on average higher for a private policy than for a CEA policy. Other explanations could be that homeowners only engage in very limited comparison shopping when buying earthquake policies, or that homeowners' exogenous risk levels are positively correlated with risk preferences or perceptions that are not yet captured.

This chapter informs debates about the government's role in risk classification in catastrophe insurance markets. Catastrophe insurance markets are characterized by strong government intervention.[8] These markets often involve cross-subsidized rates (Kunreuther and Michel-Kerjan (2009), Nyce and Maroney (2011)). In both the flood insurance market in the U.S. and the earthquake insurance market in Japan, cross-subsidizations are found to be associated with adverse selections (Czajkowski et al. (2012), Naoi et al. (2007), Naoi et al. (2010), and Dumm et al. (2013)). Czajkowski et al. (2012) propose that hypothetical private insurers could do better at pricing, alleviating the adverse selection inefficiency. But none of the previous studies have looked at a real-world market where both public and private sectors exist. My study bridges this gap. I confirm that the limited classification used by the public insurer causes adverse selection in the sense of a positive risk-demand correlation. The private market seems to be getting a better risk pool, but the patterns are not uniform and not very strong, suggesting potentially limited efficiency gains from finer risk classification.

1.4 Effects of Shaking Experiences on Demand for Earthquake Insurance

Personal disaster experience stands out as a possible determinant of earthquake insurance demand. After the destructive 1989 Loma Prieta Earthquake, demand for earthquake insurance in California did surge (Palm (1995)). Given that strong earthquakes are very infrequent events, what scientists or seismologists define to be "high risk" may be ignored by homeowners, especially when homeowners in those "high risk" areas have not experienced a significant number of shaking events for an extended period of time.

To complement my previous definition of a constant objective seismic risk (PGA), I look for a

[8] Paudel (2012) conducts a comparative study of catastrophe insurance systems in ten countries, where many have public or semi-public insurance systems; In the United States, Kousky (2011) summarizes 10 state insurance programs; Klein (2008) and Klein (2009) discuss the politics and regulations in Florida's homeowners' market.

time-varying measure of actual shaking experiences. Gathering information on experience with earthquakes can be a little challenging. It is not possible to use insured losses because there are very few damaging earthquakes. It is also inappropriate to use seismic data directly, because the seismic data reports many earthquakes, but most are never felt. So I take a novel approach that uses data on reported shaking experience. I collect annual data on "significant earthquake events" as defined by the U.S. Geological Survey (USGS) and reported by internet users. I label a zip-code as either affected or not affected by at least one such event in a particular year. Then I draw on an 8-year bi-annual panel of insurance policy count data to conduct this analysis. I find that the impact of previous year's earthquakes on demand is somewhat positive, but the effects entirely disappear after one year. It seems that homeowners are not too responsive to those (mostly) non-destructive earthquakes, and the variations in experience with earthquakes do not seem to explain much of the changes in demand.

A string of literature has considered how catastrophe insurance demand is more closely related to perceived risk, as often measured by disaster events or incurred losses. But most of them have focused on flood risks and flood losses. In comparison, earthquake experiences have rarely been discussed in catastrophe insurance research papers, probably due to the rarity of earthquake events and the difficulty of defining what constitutes a significant shaking event. This study contributes to the current literature by examining the effects of recent earthquake experiences on insurance take-up, by using a unique dataset to measure earthquake experiences.

Chapter 2

Background

2.1 Earthquakes and Earthquake Insurance in California

California is highly vulnerable to earthquakes, as it sits on multiple fault lines, including the most famous and active, the San Andreas fault.[1] Based on estimated current exposures, eight out of ten of the most costly earthquakes in the United States happened in California.[2] Not surprisingly, California has the largest earthquake insurance market in the United States, with $1.6billion of direct premiums written in 2010, topping the second and third ranked states by a large margin.The state of Washington ranks second, and has $142 million direct premiums written in 2010. Missouri is the third, with $87 million direct premiums written in 2010. [3]

The evolution of California's earthquake insurance market cannot be separated from its history of earthquakes, or from the legislative changes that often come after major earthquake events. In order to provide a clear and complete background on California's earthquake insurance market,

[1]The San Andreas Fault runs through the northern and southern parts of California. Other notable faults include the Newport-Inglewood fault in Southern California and the Hayward fault in Northern California.

[2]Sources: U.S. Geological Survey and California Geological Survey.

[3]Sources: Swiss Re and Insurance Information Institute.

the following discussion is organized chronologically and is punctuated by California's three most influential earthquakes.

2.1.1 The 1906 San Francisco Earthquake

The 1906 San Francisco earthquake and subsequent fires are ranked as the worst natural disaster in history of United States in terms of property damage and losses (*Best's Review*). It was caused by a huge rupture of the San Andreas fault, and it almost destroyed the entire city of San Francisco.[4] It was also the worst single incident for the insurance industry before the September 11, 2001 attacks:[5] insurance companies were faced with claims of $250 million (about $6.4 billion in today's dollars).[6]

Separate earthquake insurance policies first became available in 1916 (Steinbrugge, 1982) and were purchased as an addendum to fire insurance policies. However, the demand for such policies was low, probably due to impressions formed after the 1906 San Francisco earthquake, where over 80% of losses were caused by fires resulting from the earthquake, and were therefore covered by standard fire insurance policies. Even after the 1971 San Fernando earthquake,[7] the demand for earthquake insurance remained low.[8] The first systematic survey of earthquake insurance purchases, conducted in 1974, showed that only five percent of homeowners were insured against this risk (Kunreuther et al., 1978).

To raise public awareness of earthquake risk, a hazard disclosure legislation act (the Alquist-Priolo Act) was passed in 1972, then later amended to require real estate agents or sellers to disclose

[4]It is estimated that the 7.8 Magnitude earthquake and subsequent fires claimed over 3,000 lives and destroyed over 80% of San Francisco, though there is some disagreement on the exact magnitude and death toll from the official numbers (Sources: Berkeley Seismological Laboratory, USGS, and the Virtual Museum of the city of San Francisco).

[5]History Channel International Series *Mega Disasters*, "San Francisco Earthquake", 2006

[6]The *New York Herald* of April 21, 1906

[7]This earthquake caused substantial damages to homes, businesses, and public buildings, and different from the 1906 San Francisco earthquake, the losses were not caused by fire and the incident caught a lot of people uninsured.

[8]Nevertheless, this earthquake did result in an increase in earthquake insurance demand, mostly for commercial policies. SeeRoth (1998).

that a property was in a special earthquake studies zone (SSZ) (California Public Resources Code, sec. 2621-2630). However, responses from home buyers, real estate agents and lenders were minimal, nor did homeowners engage more in earthquake mitigation measures or buy more insurance. Palm (1981) undertook a survey of residents of Special Study Zones (SSZ) in Berkeley and Contra Costa County in 1979, and found that people are more likely to purchase earthquake insurance, but are not more likely to engage in certain mitigation measures, when they received the disclosure that their property is within a SSZ. The legislation also mandates the mapping of seismic hazard zones, including areas susceptible to "strong ground shaking, liquefaction, landslides, and other ground failure" (California Public Resources Code, sec. 2690-2699.6).

Another form of disclosure legislation was aimed at property owners who carry homeowners insurance. The statute went into effect in 1984 and requires insurers writing homeowners insurance to offer earthquake coverage on these structures (California Insurance Code, sec. 10081), commonly known as the "mandatory offering law." The law, however, was not instigated by consumers. Rather, it was passed to overcome a lower court decision which was to enable homeowners to collect for earthquake damage even if they had not purchased earthquake insurance. The lower court decision was eventually overturned by the Supreme Court. However, insurers stuck themselves with the mandatory offering law, being forced to insure structures that are so old or in such poor condition that they should not be provided with coverage (Roth (1998)).

By the late 1980s, an earthquake insurance policy in California had a largely uniform premium and typically carried a 10% deductible.[9] Though this premium was not formidably high for such catastrophic coverage, surveys show that few people purchased insurance, nor did most people

[9]Premiums and deductibles are determined by the insurance rate zone and the type of home construction. In the 1980s, California includes three rate zones, with most of urban California in the zone of the greatest risk. So the earthquake insurance premium looks largely uniform. Typically, coverage for wood-frame residential dwellings (the most common type of construction) costs about $2 to $2.50 per $1,000 coverage with a 10% deductible (Palm and Hodgson, 1992).

undertake any other disaster mitigation measures. In a survey in 1989, fewer than 10 percent of the respondents affirmatively claimed that they have performed some mitigation measures (Palm et al. 1990). Mileti et al. (1990) conducted a survey in Coalinga, Paso Robles, and Taft, California, where a Parkfield earthquake was predicted to happen in the next 30 years. Still, fewer people than expected undertook earthquake mitigation measures.

2.1.2 The 1989 Loma Prieta Earthquake

The Loma Prieta earthquake occurred on October 17, 1989. The earthquake's epicenter was 16 km northeast of Santa Cruz on the San Andreas fault, and its magnitude was 7.1. The earthquake resulted in 63 deaths and more than $6.0 billion (about $11.5 billion in today's dollars) of damage (Palm and Hodgson (1992)). This earthquake also dramatically changed the public's attitude towards earthquake hazards and the legislative environment in California.

After the Loma Prieta earthquake, consumers protested to the insurers about the 10% deductible levels. In the fall of 1991, the California legislature established the California Residential Earthquake Recovery Fund (CRERF) to cover the 10 percent deductible by providing mandatory insurance of up to $15,000. However, the CRERF was only in existence for a year before it was repealed.[10]

Despite the short existence and limited impact of the CRERF, consumer demand for earthquake insurance increased during the early 1990s. Three consecutive surveys of homeowners in four California Counties (Contra Costa, Santa Clara, Los Angeles, and San Bernardino counties) in 1989, 1990, and 1993 showed a dramatic increase in earthquake insurance purchase: over 40 percent of the homes in many areas along the coast were insured against earthquake damage (Palm (1995)).

[10]The CRERF program was repealed at the request of insurance commissioner for three reasons: 1) the management and cost of the program became a financial burden; 2) claims adjustment was costly and inefficient; and 3) the insurance commissioner was afraid that the CRERF could not pay the claims in full in the case of a damaging earthquake event, therefore creating political problems (Roth (1998)).

The above surveys also tried to answer a more general question about the impacts of an earthquake experience on attitudes and behavior. Palm (1995) found that the largest increase of insurance purchase was in the county that was most impacted by the Loma Prieta earthquake. In counties less impacted, however, there was little increase in catastrophic insurance subscription.

The survey findings also suggest that general attitude toward earthquake vulnerability is the primary factor inducing insurance purchase and that direct experience with an earthquake provides an impetus to insurance purchase.[11]

2.1.3 The 1994 Northridge Earthquake

The magnitude 6.7 Northridge earthquake struck a neighborhood in the Los Angeles area on January 17, 1994. The earthquake killed 60 people, injured more than 7,000, and damaged more than 40,000 buildings (Source: USGS). The 1994 Northridge earthquake was also one of the costliest natural disaster events in modern history. With insured losses of more than $21 billion (indexed to 2011 USD), it is ranked only after Hurricane Katrina in 2005, Japan's 2011 earthquake and tsunami, and Hurricane Andrew in 1992 (Source: Swiss Re, 2012).

The Northridge earthquake caused large losses for the insurance industry. There was a surge in demand for earthquake policies from homeowners right after the earthquake. The insurance companies had just sustained big losses, and after reevaluating their earthquake exposures, they decided that they could not risk selling earthquake policies any more.

In view of the mandatory offer law, insurers cannot simply stop offering earthquake insurance without exiting the homeowners market entirely. Insurers lobbied to repeal the mandatory offer

[11] Surveys also show that there has been a shift in primary factors influencing insurance purchase decisions: the Kunreuther survey of 1973-1974 suggests the insurance purchase decision is mostly influenced by friends and neighbors, while the Palm surveys from 1989-1993 suggest more economic motivations such as worry that an earthquake will destroy the house and family wealth tied up in home equity.

law, but failed. Subsequently, 90 percent of the insurance companies either stopped offering new homeowners' policies or placed restrictions on selling them (Roth Jr., 1998). The homeowners insurance market in California suddenly became almost nonexistent.

After discussions among regulators, lawmakers, and the industry, the California Insurance Department finally proposed the formation of a state-run earthquake insurance company - the California Earthquake Authority (CEA). Individual insurers would have the opportunity to cede their earthquake exposures to the CEA, and remain in California's homeowners insurance market.

2.2 The California Earthquake Authority (CEA)

A legacy of the 1994 Northridge earthquake, the California Earthquake Authority (CEA) became operational at the end of 1996. The CEA is a publicly managed but, largely privately funded organization. As a publicly managed organization, its board members consist of the Governor, the State treasurer, and the State insurance commissioner or their named designees. On the other hand, its funding comes almost entirely from private sources, including start-up capital contributions from participating insurers (exempt from federal and state income taxes and the state premium tax), additional assessment on the industry, a layer of reinsurance, some revenue bond, and a further contingent policyholder assessment.[12] The CEA's claim-paying capacity is claimed to be over $10 billion.[13]

The CEA represents a public-private partnership. Private insurers participate in the CEA program on a voluntary basis. The combined holdings of the insurers who have joined the CEA

[12]The CEA is not permitted to file bankruptcy. If an earthquake causes insured damage greater than the CEA's claims-paying capacity, policyholders who are victims of that quake may be paid a prorated portion of their covered losses.

[13]http://www.earthquakeauthority.com/. There has been some recent issuance of catastrophe bonds, as well as legislative efforts by the CEA to get federally guaranteed funding (Catastrophe Obligation Guarantee Act of 2009, H.R. 4014).

equal roughly 70% of the California homeowners market (Jaffee and Russel, (2000)). To date, there are 20 participating insurers.[14] A participating insurer agrees to offer CEA earthquake coverage to its home insurance policyholders, with the effect that earthquake risk becomes the responsibility of the CEA. Policies are serviced and claims are adjusted by the participating insurance companies in conjunction with their basic homeowners' policies. The CEA reimburses the participating companies for distributing and servicing the policies.

CEA policies are only available to customers of participating insurers. The CEA's "basic" policy of 1996 featured coverage corresponding to the statutory minimums. The policy limit on structural coverage (coverage A) is the same as that of companion homeowner's policy, and a deductible of 15% is applied to the coverage A. The limit on content coverage (coverage C) is $5,000, and the coverage limit on loss of use is $1,500. The CEA started offering supplemental coverage in 1999. The supplemental policy increased the maximum contents coverage limit to $100,000 and the maximum loss of use limit to $15,000; it also offered the option of a lower deductible of 10% on structural coverage.

The CEA divides California into 19 rating territories based on different levels of seismic risk. Rates are further based on the year built, type of construction (wood-frame or not), story (one- or multi-story), and use of property (homeowners, renters, condominiums, or mobile homes).[15]

Although the majority of residential earthquake risk was effectively transferred to the CEA within a year of its inception, a significant and growing private fringe remained outside the CEA. An insurer that sells homeowners' policies in California can choose to stay independent from the CEA as long as it fulfills the mandatory offering law and manages the earthquake exposure that comes with

[14] Insurers participate on a group basis. In 2009, when the main dataset in this study was collected, there were 19 participating insurers. A complete list of CEA participating insurers can be found at http://www.earthquakeauthority.com.

[15] Information from public filings of rate manuals, available at the California Department of Insurance website: http://www.insurance.ca.gov/.

its homeowners business. Alternatively, an insurer can be a specialist in the earthquake business, in which case, it underwrites and manages only its own earthquake exposures. To summarize, the earthquake insurance market in California consists of the CEA, non-CEA homeowners insurers, and earthquake specialists. The latter two types of insurers form the private market. The coexistence of the public and private underwriting persists today.

Despite the formation of the CEA and continuing efforts by insurers, regulators, and policy makers, earthquake insurance take-up rates have fallen to their lowest point since the 1994 Northridge earthquake. Statewide, the take-up rate was about 10 percent in 2009, compared to 36 percent in the year after the Northridge earthquake (Marshall (2009)). LaTourrette et al. (2010) suggest that the high prices, uncertain risk, and long recurrence interval between events are likely to be contributing factors to the low demand. But there have been very few systematic analyses on the nature of demand and the earthquake insurance market in California aside from the earlier surveys performed decades ago.

Chapter 3

Literature Review

This section consists of reviews of the relevant literature. I begin by broadly reviewing the theories on and empirics of adverse selection and risk classification in insurance markets. I then focus on catastrophe insurance markets, especially how restricted risk segmentation plays out in this market. Last, I review the literature on catastrophe insurance demand, emphasizing the role of different definitions of risk levels and risk perceptions.

3.1 Adverse Selection and Risk Classification

The theory of adverse selection was established in the 1970s by Akerlof (1970) and Rothschild and Stiglitz (1976). In Akerlof's model, there is an adverse selection death spiral resulting from asymmetric information. Rothschild and Stiglitz (1976) develop Nash equilibria where the insurer offers various contracts and consumers self-select to purchase various policies. Depending on the assumptions about a firm's behavior, either separating or pooling equilibrium with cross-subsidization across risk class can be achieved (see Wilson (1977) and Miyazaki (1977) as examples).

To alleviate the problems of adverse selection, insurers can also actively employ risk classification techniques. For example, in the auto insurance industry, insurers typically price based on driver age, car type, and zip-code. Risk classification however, introduces equity concerns when individuals face the risk of being classified unfavorably, thereby having to pay higher premiums, or be uninsured. For example, in the case of genetic testing in health insurance, some consumers may be better off not making their information available, or choosing to not be classified (Doherty and Thistle (1996)). In reality, governments often ban the use of certain information in underwriting out of fairness concerns (one of the most debated examples is the pre-existing condition exclusions in health insurance in the U.S).[1] For theoretical work on the welfare implications of risk classification, Crocker and Snow (1986) and Crocker and Snow (2000) argue that risk classification improves welfare, especially when information or categorization is costless. They also state conditions under which classification increases or decreases social welfare. Rothschild (2011) makes a stronger argument that, even when categorization is costly, alleviating categorical pricing bans will lead to a Pareto improvement in the well-being of insurance buyers, as long as the government can simultaneously provide partial social insurance. For empirical work, Harrington and Doerpinghaus (1993) find inefficiencies resulting from rate classification restrictions in the auto insurance industry. Buchmueller and DiNardo (2002) examine the effects of health insurance reforms, especially the consequences of community rating. Although they do not find a death spiral, they do observe individuals shifting away from the more comprehensive indemnity insurance toward more restricted plans such as HMOs, resembling the Rothschild-Stiglitz models with separating equilibrium where the low risks get partial insurance (HMO penetration increases in small group and individual markets). Peter et al. (2011) summarize the welfare implications of risk classification, and the government's restrictions on risk classification.

[1] Insurers use pre-existing condition exclusions to deal with adverse selection concerns that only the sickest individuals buy health insurance. But the majority of Americans (eight in ten) favor a requirement that insurance companies insure people even if they suffer from pre-existing conditions (Source: Kaiser health tracking poll, September 2009. Washington, D.C.: Kaiser Family Foundation).

They also empirically show why people demand risk classification insurance. Overall, the welfare implications of risk classification are ambiguous.

The amount of risk classification needed also hinges on whether or not adverse selection inefficiency exists. Empirical studies sometimes fail to find evidence of adverse selection in some insurance markets (for example, see Cohen and Siegelman (2010), and Einav and Finkelstein (2011) for a review of theories and empirical findings). Finkelstein and McGarry (2006) find evidence of advantageous selection in the long-term care market, where consumers' behavior may be explained by their risk preferences. Aside from heterogeneity in risk preference, private information in other dimensions, such as income, education, financial literacy, and cognitive ability has also been suggested to be correlated with expected loss.

Empirically, the typical test for adverse selection is a "positive correlation test" between risk type and insurance coverage, controlling for information observed and priced by the insurers. Based on the features of various insurance markets, scholars have chosen different proxies for risk type and insurance coverage. Proxies for risk type are usually observed ex-post claims amount (for example, see Chiappori and Salanie (2000)) or predicted claims (for example, Browne (1992) uses estimates from the group health insurance market to predict claims in the individual health insurance market). These proxies can also be subjective measures, such as self-evaluated health condition, or objective ones, such as buyer age, as used by Buchmueller and DiNardo (2002). These tests are carried out to control as completely as possible the variables observed by insurers. There are times, however, when insurers collect more information than that what is actually used in pricing, such as the case in the U.K.'s annuity market (Finkelstein and Poterba (2004)). The U.K.'s annuity insurers only used age and gender for pricing even though they had more information on the annuitants. The U.K.'s annuity market setting is quite similar to the one in my study. The implication of adverse selection in those insurance markets may not be that insurers do not know enough about the buyers, but that other institutional factors prevent insurers from using more information in risk classification.

3.2 Catastrophe Insurance Markets and Catastrophe Risk Classification

The catastrophe insurance market has many unique features that distinguish it from other insurance markets, one of which is the presence of strong government influence. Earlier literature focuses on the question of the insurability of catastrophe risks. Kunreuther et al. (1995) suggest that private insurers are reluctant to underwrite catastrophe risk due to "ambiguity aversion." Scholars have also investigated whether and how the insurance industry can increase its capacity to pay for the "big one" (Cummins et al. (2002)), and allocate risk more efficiently (Niehaus (2002)). Due to the highly correlated loss and potentially disastrous consequences for the industry, many point to the role of government in addressing such market failure (see for example, Jaffee and Russell. (1997)). Within the last several decades, catastrophe insurance markets have been widely established, with, unsurprisingly, various forms of government intervention. Around the globe, governments' roles range from being regulators, to providing guarantees or reinsurance, to being partners with private firms; they are sometimes even the direct insurers (see OECD (2005), Paudel (2012)). In the United States, since the inception of the National Flood Insurance Program in 1968, federal and state insurance programs have become popular (see a summary of 10 state insurance programs by Kousky (2011)). With reference to the three major kinds of natural disasters faced by the U.S., Klein (2008) and Klein (2009) examine government regulation and the residual market for property insurance with windstorm/hurricane coverage, Michel-Kerjan (2010) provides an overview of the NFIP's 40 years of operation in managing flood risks; and Zanjani (2008) discusses the operation and challenges faced by the largest underwriter for earthquake risks in the U.S., the CEA. These researchers largely agree that the government can cover part of the extreme losses in order to keep the insurance system viable, while letting private insurers sell and manage policies and claims. Some literature also suggests that the government should step back when the private sector regains its capacity. As Kousky (2011) summarizes, "all these programs should strike a balance between affordability, cross-subsidies, and claims-paying ability".

Recent literature has begun to examine publicly involved catastrophe insurance programs more closely, particularly their restrictive methods of risk classification, as reflected by their rate structures. Picard (2008) shows that, theoretically, for insurance against natural disasters, risk-based pricing with an adequate transfer schedule through tax Pareto-dominates uniform insurance pricing from government-imposed restrictions (in the extreme case), because only risk-based prices convey the right incentive for mitigation or other risk management plans. However, government-related programs' ability to charge fully risk-based price is often compromised by political pressures (for example, see discussions by Jaffee and Russell (2000), Kleindorfer and Klein (2003)). Empirical evidence of cross-subsidized rates is found in the property insurance and flood insurance market in the U.S. Kunreuther and Michel-Kerjan (2009) examine homeowners' insurance premiums in four states (Florida, South Carolina, Texas, and New York). They divide their policy data into quartiles based on wind risks, and calculate the real price as a percentage price-cost spread. They find that the real price is much higher in lower wind-risk quartiles than in higher wind-risk quartiles, suggesting that policies in the low-risk areas are subsidizing those in the high-risk areas. The cross subsidization is most obvious in Florida, where the regulation is most stringent and the residual market is the largest. In a similar fashion, Nyce and Maroney (2011) call into question the accuracy of rating territories in Florida, in that the current rates represent a significant cross-subsidization of windstorm risks. They suggest using distance to coast (DtC) as a rating factor to allow more granular pricing of windstorm peril. Czajkowski et al. (2012) provide case studies on the NFIP rates, focusing on two counties (Travis and Galveston) in Texas. Based on their calculations, current NFIP pricing does not always reflect local conditions; consequently, some properties are being undercharged while others are overcharged.

On the consequences of the limited risk classification, most studies find evidence of adverse selection. Naoi et al. (2007) construct a Quality of Life Index (QOLI) based on hedonic regressions on housing price and wages, and estimate the social cost of earthquake hazards. They illustrate an "adverse selection" picture that, within the same rating zone, people living in areas with a higher social cost of earthquake hazard are more likely to purchase earthquake insurance, which is effectively a result of the cross-subsidization of policyholders from the less risky areas to the riskier areas. In a following paper, Naoi et al. (2010) use simulation to demonstrate that by replacing the current community rating system with a finer rate scheme, demand for earthquake insurance in Japan could increase substantially. It is interesting to note that their "role-model" is the earthquake insurance market in California, where the biggest insurer, CEA, uses 19 rating territories, as compared to the 4 rating zones in Japan. Jaffee and Russell (2000) however, do not agree that the price segmentation in California is enough. They point out that the CEA tempers its rate (it both lowers the overall premiums and lowers the differences in premiums between high-risk and low-risk areas) due to political pressures, and that the CEA only offers partial insurance due to the importance of maintaining their claim-paying capacity. These particular issues related to the CEA give private insurers a chance to "cherry-pick" the CEA customers: private insurers can lower rates in low-risk areas, or offer more attractive contracts to homeowners. On a similar note, Zanjani (2008) also speculates about a migration by potential CEA policyholders to stand-alone policies offered by private insurers, and Czajkowski et al. (2012) point out the potential for private flood insurance to complement the current NFIP.

3.3 Demand for Catastrophe Insurance

Since my study emphasizes the demand side of catastrophe insurance markets, particularly whether limited risk classification causes adverse selection by insurance buyers and whether insurance purchase decisions are determined by factors such as risk perception or personal disaster experiences, this section provides an extensive review of the literature on catastrophe insurance demand in this section.

3.3.1 Determinants of Catastrophe Insurance Demand

According to earlier surveys, many homeowners do not purchase disaster insurance, even if the price is subsidized, because they generally underestimate the probability of a natural disaster or their perceived probability of such a low-frequency catastrophe event falls below a certain threshold, causing them to ignore the event entirely. See Kunreuther et al. (1978), Kunreuther (1996), and a review of literature on the decision process of low-probability events by Camerer and Kunreuther (1989) for examples. A series of surveys on Californian homeowners' attitudes towards earthquake insurance show that the decision to purchase earthquake insurance is an example of "decision making under ignorance" (Palm (1981), Palm and Hodgson (1992), and Palm (1995)), since both costs and benefits are unknown to the decision makers. These surveys find that the factor that consistently and most significantly affects purchase decision is people's perceived vulnerability towards natural hazards, formed largely by their personal experience with natural disasters.

Efforts to explain the demand for catastrophe insurance continue. There has been a growing literature that conducts an empirical search for demand determinants using observational data and a larger set of covariates. Browne and Hoyt (2000) provide one of the first demand analyses on flood insurance using observational data on the state level. They find that price is a significant determinant, though price elasticity is low. They also find that the purchase of flood insurance is highly correlated with flood losses in the past, suggesting the important role of risk perception. Michel-Kerjan and Kousky (2010) offer a more detailed analysis using policy-level data in Florida (7.5 million flood policies-in-force, representing about 40% of the NFIP portfolio). They find that while the majority of policies are on the 100-year flood plain (the highest risk area), people may have acquired the insurance not due to risk concerns, but rather due to mortgage loan requirements. In fact, these people are also more likely to choose higher deductibles, probably because they were only getting coverage because they were forced to buy it. To summarize, empirical research has found that the demand for catastrophe insurance is generally price-inelastic (Athavale and Avila (2011), LaTourrette et al. (2010), Kunreuther and Michel-Kerjan (2009)),[2] that it is significantly affected by income (Browne and Hoyt (2000)), and that it can be affected by mandatory requirements (Kriesel and Landry (2004)) and subsidized rates or guarantee fund provisions (Grace et al. (2004)), but is not affected by information disclosure (Palm (1981) and Palm and Hodgson (1992)).

3.3.2 The Role of Risk and Risk Perception

There are at least two definitions of "risk" variables: One is based on science, relatively objective and constant, such as flood zones with certain return period, or earthquake ground acceleration under certain probability of exceedance. The other is based on people's changing perceptions through

[2]Except in a study by Grace et al. (2004), where they investigate bundle homeowners' policies with both catastrophe and non-catastrophe coverage, and find that the price elasticity for catastrophe coverage is higher than that for the non-catastrophe coverage. One of their major conclusions is that the rate suppression in high windstorm risk area greatly increases demand for homeowners' insurance.

experience. Commonly-used risk measures of disaster experience include, for example, the dollar amount of flood losses incurred, or whether a region is hit by Presidential Disaster Declaration floods during a period of time (usually a year).

On the probabilistic measure of risk, most studies only have crude risk class or a small geographic region with limited risk variations. Earlier surveys on earthquake insurance adoption by Kunreuther et al. (1978) and Palm (1995) show that "objective risk" is an insignificant predictor of demand in their survey responses. This may be due to limited risk variation in their survey design and interviewed population. Athavale and Avila (2011) use only 5 categories of "objective risk", as based on earthquake science, in the entire State of Missouri. They find that insurers have taken that risk variation into account for pricing. Therefore, the authors do not find any residual effects of risk or price. On measuring flood risks, a more refined measure than either 100- or 50-year flood plain may be a distance measure, such as "distance-to-coast". Nyce and Maroney (2011) suggest that the current territorial rating models should incorporate distance-to-coast as a rating factor, as they do find that people living further away from the coast are less likely to insure, holding all other factors constant.

For risk measure based on experiences, most literature has focused on flood insurance and flood risks. Browne and Hoyt (2000) use loss experience from flood in the previous year as a proxy for risk perception and find that risk perception is positively related to demand for flood insurance. Gallagher (2011) uses a 17-year panel of national flood insurance policy data and claims data on Presidential Disaster Declaration floods to investigate how people learn and update their expectation of a flooding event based on experience. He finds that flood insurance take-up in flooded communities increases by 9% after a flood and then steadily declines, with the effects fully disappearing after 9 years. He also develops an augmented Bayesian learning model to explain this phenomenon. Most recently, a working paper by Dumm et al. (2013) uses a representative heuristics model to explain the diminishing effects of flood losses on flood insurance take-up. As for earthquakes, history shows that destructive and deadly earthquakes have induced people to seek protective measures including buying insurance. In an earthquake state like California, where deadly events are rare (once in several decades) but significantly felt shaking events happen more than a couple times a year, no study has yet examined how homeowners react to these not-so-deadly but still significant earthquakes.

Chapter 4

Data

This study utilizes data from several different sources, including the California Department of Insurance (CDI), the Census Bureau, and the U.S. Geological Survey (USGS). Because the insurance policy data from the CDI are at the zip-code level, all other data are aggregated to this level as well, which will be the unit of observation of this study.

4.1 Insurance Policy Count and Coverage Data

Zip-code level policy count and coverage data serve as our source of dependent variables representing insurance demand. Every two years, the California Department of Insurance (CDI) tallies the number of policies written by every insurer that sells homeowners policies in California.[1] Individual insurers' data are aggregated for all companies at the zip-code level, and also specifically for CEA participating insurers. At the zip-code level, the information on policies written by the two groups includes: a count of homeowners' policies, the total value of coverage A (the coverage limit for home structures) of homeowners' policies, a count of earthquake insurance policies, and

[1] Insurers with written premiums of at least $5 million in 2009

the total value of coverage A of earthquake policies. Such data are available for the years 2005, 2007, 2009, and 2011. Please note that only homeowners' policies[2] are included in this study, any renters, condominium, mobile home, or dwelling fire policies are excluded.

Table 4.1 provides basic summary statistics on counts of homeowner and earthquake policies in California for the years 2005, 2007, and 2009. Statistics are further broken down by CEA and non-CEA insurers (their market shares are in the parentheses). Table 4.1 also displays three sets of take-up rates. The CEA take-up rate is defined as the number of CEA earthquake policies divided by the number of CEA homeowners' policies;[3] the non-CEA take-up rate is the number of non-CEA earthquake policies divided by the number of non-CEA homeowners' policies; and the overall take-up rate is the total number of earthquake policies (both CEA and non-CEA) divided by the total number of homeowners' policies (both CEA and non-CEA).

Table 4.1: Total Policy Counts by Year

	2005		2007		2009	
Overall Homeowners Policies	5,817,236		5,821,557		5,879,965	
CEA Homeowners Policies	4,431,046	(76.2%)	4,418,387	(75.9%)	4,380,782	(74.5%)
nonCEA Homeowners Policies	1,386,190	(23.8%)	1,403,170	(24.1%)	1,499,183	(25.5%)
Overall Earthquake Policies	807,660		805,083		803,797	
CEA Earthquake Policies	590,357	(73.1%)	593,228	(73.7%)	582,075	(72.4%)
nonCEA Earthquake Policies	217,303	(26.9%)	211,855	(26.3%)	221,722	(27.6%)
Overall Earthquake Policy Take-up Rate*	13.88%		13.83%		13.67%	
CEA Earthquake Policy Take-up Rate**	13.32%		13.43%		13.29%	
nonCEA Earthquake Policy Take-up Rate***	15.68%		15.10%		14.79%	

Note: These are counts of policies written in California during a particular year (not policies in-force).
The percentage values in parenthesis are corresponding market shares for the CEA insurers and the non-CEA insurers.
*The overall earthquake policy take-up rate is the total number of earthquake policies (both CEA and non-CEA) divided by the total number of homeowners' policies (both CEA and non-CEA) in California.
**The CEA earthquake policy take-up rate is the number of CEA earthquake policies divided by the number of CEA homeowners' policies in California.
***The non-CEA earthquake policy take-up rate is the number of non-CEA earthquake policies divided by the number of non-CEA homeowners' policies in California.

[2] Including ISO standardized forms HO1, HO2, HO3, HO5, and HO8

[3] To be accurate, the CEA does not sell homeowners' insurance, but CEA participating insurers do. So the CEA's homeowners' policy count refers to the homeowners' policies sold by its participating insurers. In the rest of the paper, including tables and graphs, "CEA homeowners' policy" is short for CEA's participating insurers' homeowners' policy.

In 2009, there were about 5.88 million homeowners' policies written in California, of which 74.5% were written through CEA participating insurers. In the same year, there were 803,797 earthquake policies written in the entire state, of which 72.4% were CEA earthquake policies. From 2005-2009, the number of earthquake insurance policies written and the take-up rate of earthquake policies among homeowners in general declined, except for the CEA over the years 2005-2007.

Table 4.2: Average Coverage A($) by Year

	2005	2007	2009
Overall Homeowners Coverage A	273,450	322,085	355,283
CEA Homeowners Coverage A	263,872	307,888	337,683
nonCEA Homeowners Coverage A	304,070	366,786	406,712
Overall Earthquake Coverage A	335,297	403,750	462,270
CEA Earthquake Coverage A	303,817	350,320	391,078
nonCEA Earthquake Coverage A	420,819	553,362	649,164

Note: These are average coverage limit for home structure (coverage A) among all policies written in California during a particular year

Table 4.2 provides summary statistics on the dollar amount of coverage limits for home structures (coverage A). The data are again divided into CEA and non-CEA insurers. The table reveals several interesting facts: first, the average coverage limit for home structures is always higher for earthquake policies than for homeowners' policies, implying that homeowners with higher-valued homes are more likely to take up earthquake policies. Second, homeowners' policies' home structure coverage limits are on average lower for CEA participating insurers than for non-CEA insurers. Third, the same pattern is true as regards to the home structure coverage limits to earthquake policies: the limits are lower for CEA policies than for non-CEA policies, and the gap in coverage limit values is even bigger between CEA and non-CEA earthquake policies.

Table 4.3 provides summary statistics by zip-codes for the 2009 cross-sectional data. Policy counts for both homeowners and earthquake policies, as well as take-up rates, are calculated for the overall market, the CEA, and the non-CEA insurers. Different from Table 4.1, the take-up rates in Table 4.3 are averages of zip-code level take-up rates. The distributions of take-up rates among zip-codes are generally right-skewed, shown by higher means than medians and a few extreme values. Comparing the take-up rates of different insurers, the non-CEA insurers' take-up rates are on average higher than the CEA insurers'.

Table 4.3: Summary Statistics of Policy Counts and Take-up Rates by Zip-code

	Mean	Standard Deviation	Min*	Median	Max
Overall Homeowners Policies	3,594	3,474	11	2,576	16,674
CEA Homeowners Policies	2,678	2,594	4	1,926	13,015
nonCEA Homeowners Policies	916	1,037	0	593	7,111
Overall Earthquake Policies	491	658	0	202	4,947
CEA Earthquake Policies	356	465	0	147	3,729
nonCEA Earthquake Policies	136	244	0	47	2,268
Overall Earthquake Policy Take-up Rate	12.84%	10.97%	0.00%	9.86%	69.29%
CEA Earthquake Policy Take-up Rate	12.38%	10.25%	0.00%	9.50%	54.55%
nonCEA Earthquake Policy Take-up Rate	15.56%	21.70%	0.00%	9.09%	450%**

Note: The observations are 1636 zip-code areas. Only the cross-sectional data in 2009 is used.
*Zip-codes that have fewer than 10 total homeowners policies are deleted from the final dataset.
**There are 21 zip-codes with a take-up rate for non-CEA policies larger than 1. The reasons for this is that some of the households may have their homeowners' policies with one of the CEA participating insurers, but purchase non-CEA earthquake policies

4.2 Geological Data

Constructing seismic risk measures and shaking experience measures at a relatively fine geographic level is essential to this study of homeowner' demand for earthquake insurance. I obtained geological data from the U.S. Geological Survey (USGS). Their website (http://earthquake.usgs.gov) contains extensive public information about earthquakes.

4.2.1 Peak Ground Acceleration (PGA)

A set of seismic hazard maps are developed under the USGS National Seismic Hazard Mapping Project (NSHMP). The maps incorporate information on potential earthquakes and associated ground shaking and are derived from science and engineering workshops involving hundreds of participants. These national seismic maps represent the current assessment of the "best available science" in earthquake hazards estimation for the United States (Petersen et al. (2008)).

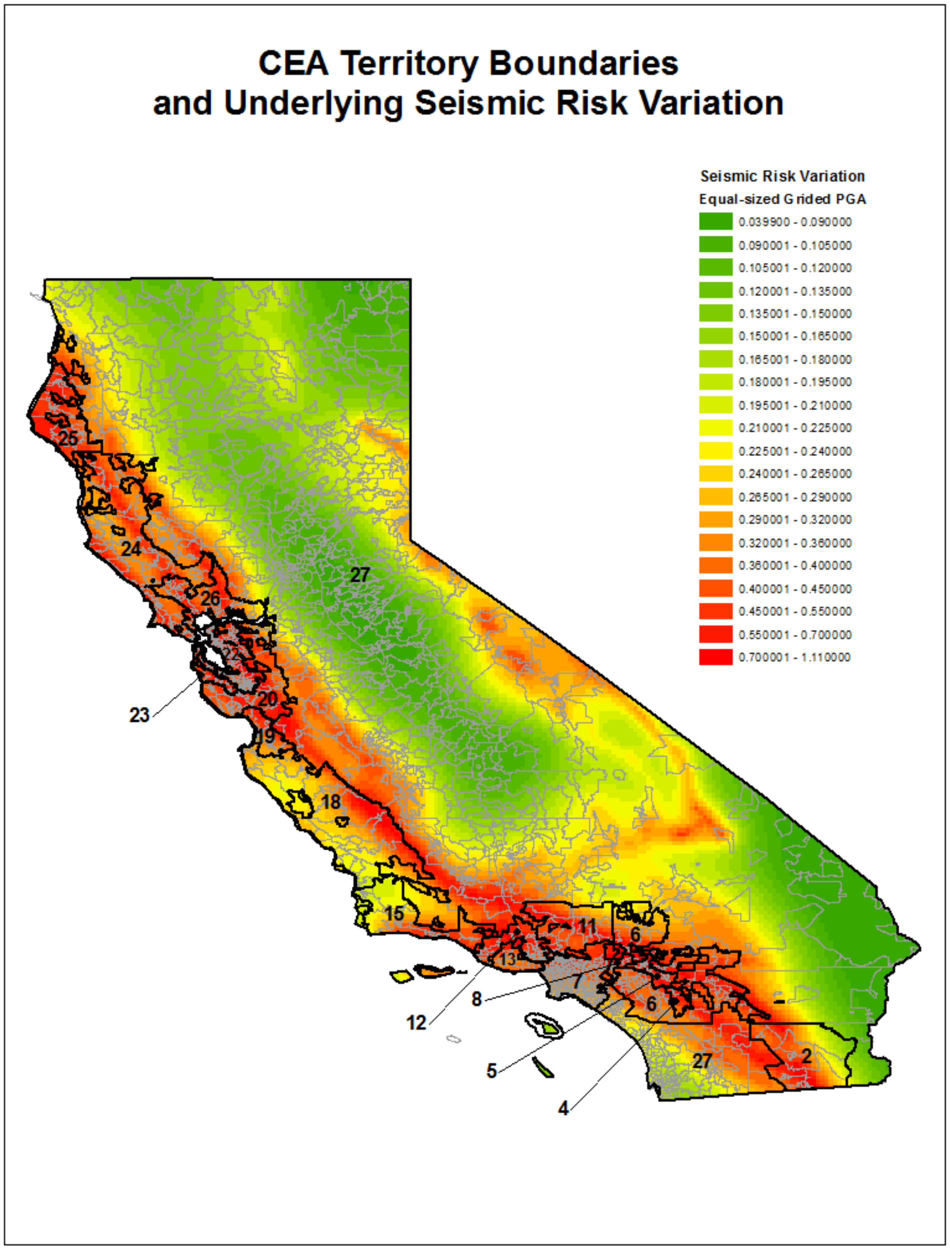
The underlying data files for the NSHMP maps contain rectangular gridded data in 0.05-degree increments in longitude and latitude, starting from a northwest point at $50°N\ 125°W$ and ending at a southeast point at $24.6°N\ 65°W$ (over the conterminous 48 States). For every gridded geographic point with longitude and latitude values as described above, a Peak Ground Acceleration (PGA) value[4] is assigned, which is a measure of earthquake acceleration on the ground[5] to be experienced in a region along with a probability of exceedance (such as 10% in 50 years). In an earthquake, damages to buildings and infrastructure are related more closely to ground motion, than the magnitude of the earthquake. For moderate earthquakes, PGA is the best determinant of damage; in severe earthquakes, damage is more often correlated with peak ground velocity.[6] Figure 4.1 shows the underlying seismic risk variation defined by those PGA values across California. In order to get a set of ground motion values at the zip-code level to match with the rest of data set for this study, I calculate the geographically weighted average PGA for each zip-code.

[4]During an earthquake, ground acceleration is measured in three directions: vertically (V or UD, for up-down) and two perpendicular horizontal directions (H1 and H2), often north-south (NS) and east-west (EW). The peak acceleration in each of these directions is recorded, with the highest individual value often reported (PGA).

[5]The ground motion units are in g where $1g = 980.5cm/s^2$, which is the acceleration due to Earth's gravity.

[6]"ShakeMap Scientific Background. Rapid Instrumental Intensity Maps". *Earthquake Hazards Program.* U.S. Geological Survey.

Figure 4.1: PGA and CEA Territories.



PGA values are classified into 20 levels, represented by 20 colors produced on a graduant. The categories do not necessarily have equal intervals. The larger the PGA value (from red to green), the riskier an area is. 19 CEA territories boundaries are drawn and numbered (note that the numbers do not range from 1 to 19).

4.2.2 Did You Feel It? (DYFI?) and Significant Earthquake Events

"Did you feel it?" (DYFI?) is a web-based program developed by the USGS. Internet users use the website (http://earthquake.usgs.gov/dyfi/) to report their experiences of any earthquakes that they have or have not felt.[7] The data comes in by events. For each event, the event time, location, magnitude, and depth of epicenter are known, as well as the affected zip-codes, the average intensity (MMI) by zip-code, the number of responses by zip-code, and the zip-codes' distances from the epicenter.

Although the dataset has records dated back to the 1970s (the earliest event on file is the Sylmar earthquake in February 1971 with a highest reported intensity of IX and 1089 responses), the "DYFI?" program became popular only in the last few years. The USGS seismic mobile app was launched in October 2006. The latest version, *Quake Feed*, was developed in Nov 2010, with functionality linking it to the USGS website, including the DYFI? web page.

One of the problems of the DYFI? dataset is that there is a surge in the number of relatively insignificant events, as well as total responses, after 2007. Rather than being due to more seismic activity, it is likely this is due to more internet users.[8] To get around this problem, we ideally would want to select a set of earthquakes that were substantial enough to be recorded and reported, even before the USGS website and the DYFI? program were broadly popularized.

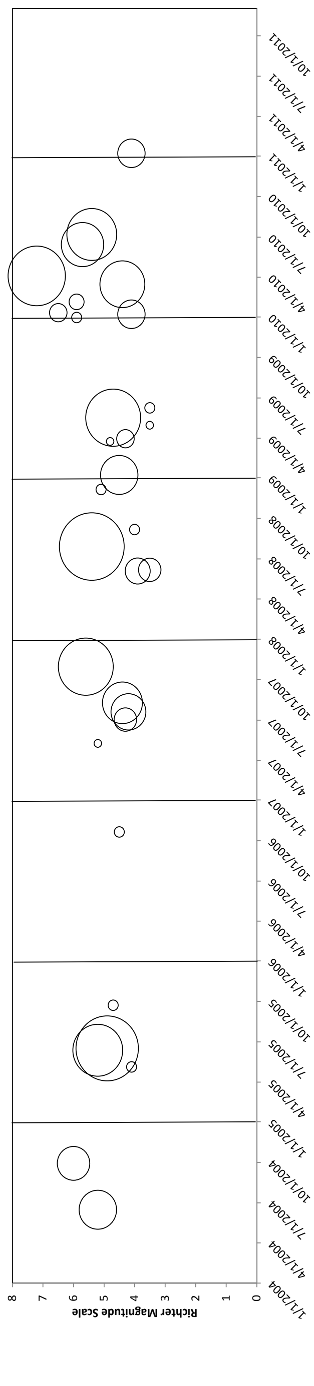
USGS kept another catalog called the "Significant Earthquakes Archive". The recorded number of events in California in this dataset seems stable for at least the last 10 years, ranging from 1-10 events per year. See Figure 4.2.

There is no exact description to the classification of the USGS significant earthquakes, but

[7] Individuals are also encouraged to report "not felt" experiences: in areas of lighter shaking, the "not-felt" responses are needed to prevent the average ZIP-code intensities from being too high.

[8] There are many evidences pointing to this conclusion, besides the timing of the development of mobile apps. Statistics show that the total number of people who reported they felt an earthquake with intensity of at least IV increased by more than 300 times from 2006 to 2007, and then stabilized.

Figure 4.2: Timing of Significant Earthquakes from 2004 to 2011



Y-axis is the Richter scale of an earthquake, measuring the overall energy released in an event. The center of each bubble corresponds to an event date (X-axis) and an event magnitude (Y-axis). The size of the bubble represents approximately the total population in affected zip-code areas. Each block represents one year, and there are 8 years of earthquake observations in this study.

the general idea is that, the events should have a relatively high magnitude and, maybe more importantly, have a relatively high intensity as measured by MMI,[9] or have received some media attention.[10]

I then link these significant events to the "DYFI?" reporting web page, obtaining detailed zip-code level information. Each year, at least one significant earthquake event hit certain areas in California. In the shake maps in Figure 4.3, I geographically show the location of the areas hit from Year 2004 to Year 2011. A zip-code is either affected or not affected in a particular year, and multiple events that affected the same zip-codes during the same calendar year are not counted more than once (it is quite rare that zip-codes were affected more than once in a particular year, except for Year 2005 and Year 2010[11]). Across these 8 years, there are obvious geographic variations in the shakings of zip-codes.

4.3 Census Data

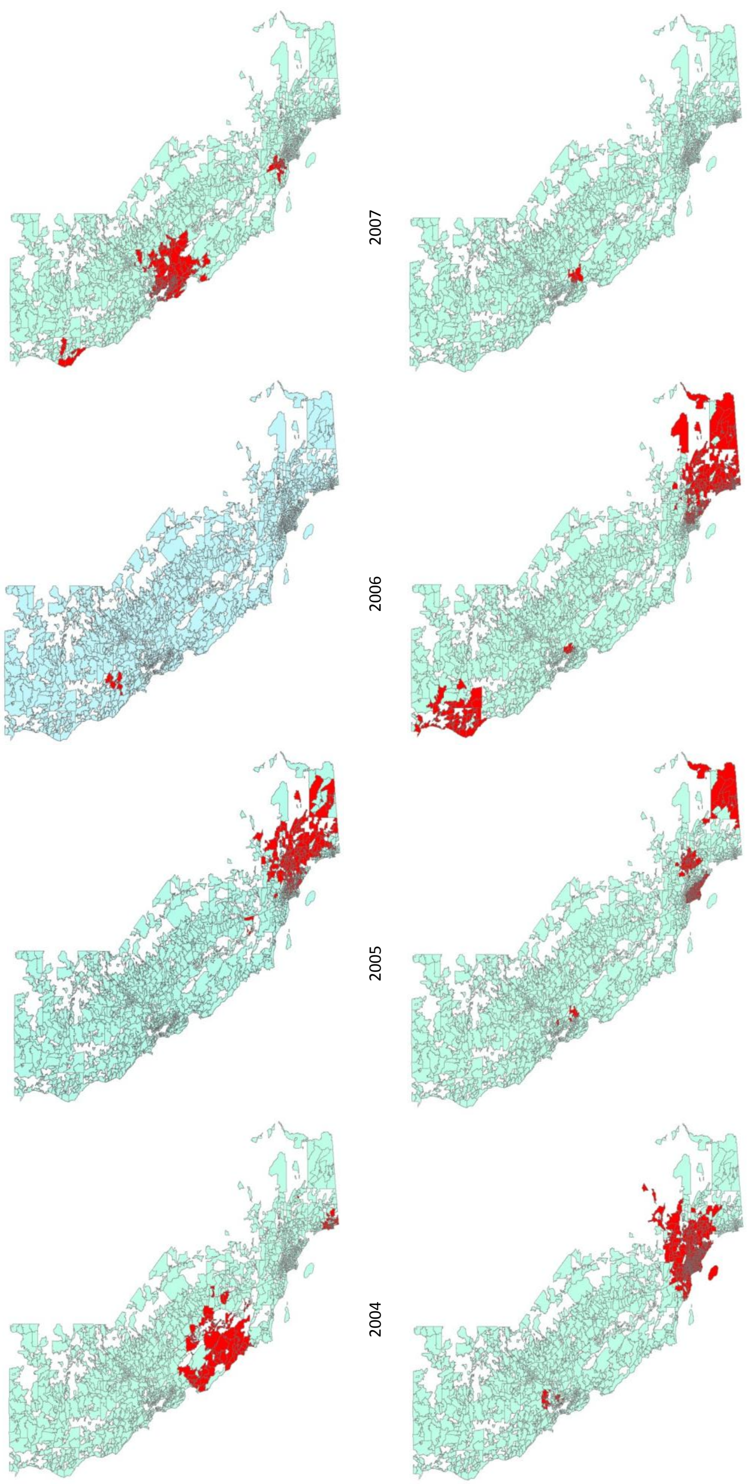
I extract zip-code level variables from the U.S. Census Bureau and link them to the zip-code level insurance and geological data. These census variables describe the population's demographic and socioeconomic profiles. It is useful to include them in my regression models for two reasons. First, they are important control variables, because they might be correlated with both insurance purchase and objective risk (my main independent variable), in which case the estimate of the objective risk

[9]Because while the Magnitude measures the total amount of energy released, the Modified Mercalli Intensity (MMI) refers to the effects actually experienced in that location. These two measures are different; an earthquake can have a large magnitude but not felt at all if it is very deep and under the ocean. On the other hand, an earthquake with a small magnitude can be significantly felt if it is very shallow and right in the city center. As such, MMI is a better measure than the Magnitude for the purpose of this study.

[10]For example, the series of earthquakes that happened in La Habra California at the end of March 2014 were much talked about, despite not having very high magnitudes (3.5). These two La Habra earthquake events (which happened on two consecutive days) have made it to the list of 2014 significant earthquakes.

[11]In 2005, 297 unique zip-codes were affected by at least one significant earthquake event, among which 72 zip-codes were affected twice. In 2010, 469 unique zip-codes were affected by at least one significant earthquake event, among which 267 zip-codes were affected twice, and 79 zip-codes were affected 3 times.

Figure 4.3: Shake Maps from 2004 to 2011



Each year, zip-codes that were affected by at least one significant earthquake event (defined by the USGS) are colored in red. Both Year 2006 and Year 2011 had only one significant event that affected only a handful of zip-codes.

coefficient will be biased. Second, they have economic interpretations on their own. For example, it is interesting to find out whether and how much education level affects homeowner' purchase decisions for earthquake insurance.

Table 4.4 provides summary statistics of demographic and socioeconomic characteristics by zip-code. The list of census variables includes population, population density, median age, median household size, gender proportion, racial composition, percentage of household with children (under 18 years old), percentage of adult population (over 25 years old) with a bachelor's degree or higher, median household income, and median owner-occupied home values. There are wide ranges of variations for most of these variables. For example, the 25^{th} percentile and 75^{th} percentile for a zip-code's median household income are, respectively, about \$43,000 and \$77,000, and the 25^{th} percentile to 75^{th} percentile for a zip code's median home value ranges from about \$246,400 to \$574,000. Such variations in explanatory variables are essential to the estimates of the regression models described later.

4.4 Insurer Rating Schemes and Menus

The insurance premium data are obtained from insurers' rate manuals, which are public information in California, and can be downloaded directly from the CDI website.[12] Table 4.5 lists the CEA's historical rates from 1999 to 2007.[13] For basic earthquake coverage, there are in total 19 different rates based on the 19 CEA territories controlling for housing characteristics. The rates for most territories have decreased quite dramatically, especially from 1999 to 2005. A geographic representation of the CEA territories is also shown in Figure 4.1. Even with just casual observation, there are obvious

[12] http://interactive.web.insurance.ca.gov/warff/index.jsp

[13] In this period, there are 3 complete rate filings, with 3 major across-the-board rate changes. In the meantime, the CEA has filed other changes to either part of their products, policy forms, or minor revisions.

Table 4.4: Summary Statistics of Demographic and Socio-economic Characteristics by Zip-code

Variable	Mean	Min	10%	25%	Median	75%	90%	Max
Total Population	22,709	33	594	2,555	18,948	36,684	52,911	105,549
Median Age	39.6	19.7	29.1	33.1	38.9	45.3	50.5	76.8
Median Household Size	2.8	1.3	2.1	2.3	2.7	3.1	3.7	5.2
Percentage of Female (%)	49.7	21.0	46.8	48.9	50.2	51.3	52.1	79.7
Population Per Square Mile	3,397	0	10	62	833	5,076	9,639	50,983
Percentage of White People (%)	67.0	5.5	39.1	52.2	70.7	84.5	89.9	97.9
Percentage of Black or African American (%)	4.2	0.0	0.3	0.7	1.7	4.6	10.8	83.7
Percentage of Asian (%)	9.0	0.0	0.6	1.2	4.0	11.1	24.7	71.6
Percentage of Household with Children under 18 Years Old (%)	43.5	0.3	29.1	37.1	44.2	50.8	56.7	76.7
Percentage of Population over 25 Years Old with At Least College Degree (%)	28.7	0.0	7.5	14.1	24.4	40.1	57.4	100
Median Household Income ($)	62,579	2,500	32,533	42,817	57,744	77,048	98,932	240,833
Median Value of Owner-Occupied Homes ($)	432,911	10,000	172,450	246,375	372,200	574,025	814,900	1,000,000

Note: the observations are 1636 zip-code areas. House values are top-coded
Source: U.S. Census Bureau, 2007-2011 American Community Survey

cases where different levels of risk are lumped together into one single territory. For example, Territory 27 encompasses the majority of California's land (aside from the coastal areas).

Table 4.5: CEA Policy Base Rates (Per $1,000)

	CEA Rates			Zip-code Counts	Population
	2007	2005	1999		
Territory 5	2.97	2.64	3.95	15	589,670
Territory 4	2.97	2.64	3.95	4	124,174
Territory 8	2.60	2.54	2.95	12	561,002
Territory 22	2.31	2.19	3.30	145	4,573,183
Territory 2	1.96	2.12	3.95	15	265,982
Territory 11	1.88	1.88	2.00	24	706,251
Territory 6	1.85	1.91	1.55	98	2,729,267
Territory 12	1.83	1.81	3.75	45	1,655,539
Territory 23	1.77	1.67	2.80	19	604,702
Territory 25	1.74	1.72	1.50	25	126,989
Territory 26	1.42	1.39	2.00	33	906,002
Territory 20	1.34	1.27	1.95	40	780,120
Territory 24	1.31	1.23	1.43	69	335,807
Territory 7	1.27	1.25	2.10	276	10,072,615
Territory 13	1.18	1.12	2.10	14	434,666
Territory 15	0.98	0.99	1.50	24	480,299
Territory 19	0.90	0.90	2.80	16	381,936
Territory 27	0.41	0.41	0.80	726	11,374,384
Territory 18	0.36	0.38	0.85	36	449,012
				Total Zip = 1636	Total Population = 589,670

Note: These rates are for a 1-level, wood-frame house, built after 1990
Base rates apply to policies with the base coverage limit and 15% deductible
Territories are sorted by order of rates

After the public insurer CEA, the 2^{nd} and 3^{rd} largest earthquake insurance underwriters are, respectively, GeoVera and Chartis. I summarize their rating procedures in Table 4.6. Besides differences in rating schemes, insurers also provide different policy forms and different coverage menus. Table 4.6 also lists the policy forms, coverage, and deductibles of these three insurers. In contrast to the CEA's 19 rating territories, both GeoVera and Chartis base their rates on more finely divided geographic units. Especially GeoVera, who has pricing variations even within a single zip-code. It is almost impossible to provide an exhaustive list of the earthquake policy rates for GeoVera, but I illustrate its finer price-risk correlation in the next chapter.

Table 4.6: Comparison of Insurance Terms Among CEA, GeoVera, and Chartis

	CEA		GeoVera		Chartis	
Program Types	**B**ase Limit	**I**ncreased Limit	**S**tandard	**C**omprehensive	**B**asic	**B**road
Coverages	Coverage A plus B must be identical to the Coverage A limit of the companion homeowners' insurance	Coverage A plus B must be identical to the Coverage A limit of the companion homeowners' insurance	A Combined Singel Limit (CSL) applies to all coverages. The minimum CSL is the full replacement cost of the dweling structure. No Coverage B	Provide coverage to other permanent home structure (Coverage B)	Coverage A for dwelling structure. No Coverage B Limited sub-limit for other coverages such as Building code and debris removal	Provides Coverage B Higher sub-limit for other coverages such as building code and deris removal
	Coverage C limit: $5,000	Coverage C limits can be increased to $25,000, $50,000, $75,000, or $100,000	The sub-limit for Coverage C is $5,000	No sub limit as long as it is within the CSL	Coverage C limit cannot exceed the contents limit of homeowners' insurance	Coverage C limit is 70% of the amount of the dwelling limit
	Coverage D limit: $1,500	Coverage D limits can be increased to $10,000 or $15,000	The sub-limit for Coverage D is $1,500	No sub limit as long as it is within the CSL	Coverage D limit: $1,500	Coverage D limit is 30% of the amount of the dwelling limit
Deductibles	15% deductible applies to Coverage A, Coverage C will be paid only when Coverage A deductible amount has been exceeded	Deductible can be lowered to 10%	15% deductible applies to CSL	10%, 15%, 20%, or 25% deductible options	15% deductible applies to Coverage A, Coverage C will be paid only when Coverage A deductible amount has been exceeded	Same rule as the Basic program
Rating Procedure	Determine a territory (19 territories)		Determine base rates based on MMI band (7 bands) and year built (7 categories), multiplied by territory multiplier (7 territories, based on MMI band and zip code)		One base rate multiplied by a size factor (the higher limit, the cheaper), a territory factor (10 territories), a soil grade factor (7 soil grades), and a distance-to-fault factor (9 levels)	
	For a base-limit policy, apply separate rates for one-story vs. greater than one-story, woodframe vs. other construction, and year built (5 levels)		Apply construction debits and credits (based on year built, levels, grade under house, and foundation type)		multiply by a contruction type/year built factor, and a number-of-stories factor	
	retrofitting discount		retrofitting discount		retrofitting discount	
	For increased limits, add additional premiums		Adjusted to deductible levels (Comprehensive product has 4 levels)		Coverage C and coverage D charge additional premiums (even for the basic levels)	

Chapter 5

Geographic Risk Classification for Earthquake Risk in California

In this chapter I show specifically how the CEA, and one of its major private competitors, GeoVera, classify risks geographically. I construct zip-code level PGA values by geographically weighting the original PGA data that are in grids of 0.05-degree increments in longitude and latitude. I then use the zip-code level PGA value as my unit of measure of objective risk, and investigate its relationship with the CEA rate and GeoVera rate respectively.

5.1 The Case of CEA

Although PGA could be a close proxy for objective risk, it is unlikely to be the only input in any catastrophe models. In reality, earthquake insurers have been using much more sophisticated catastrophe risk models provided by providers such as RMS and EQECAT.[1] These models take into

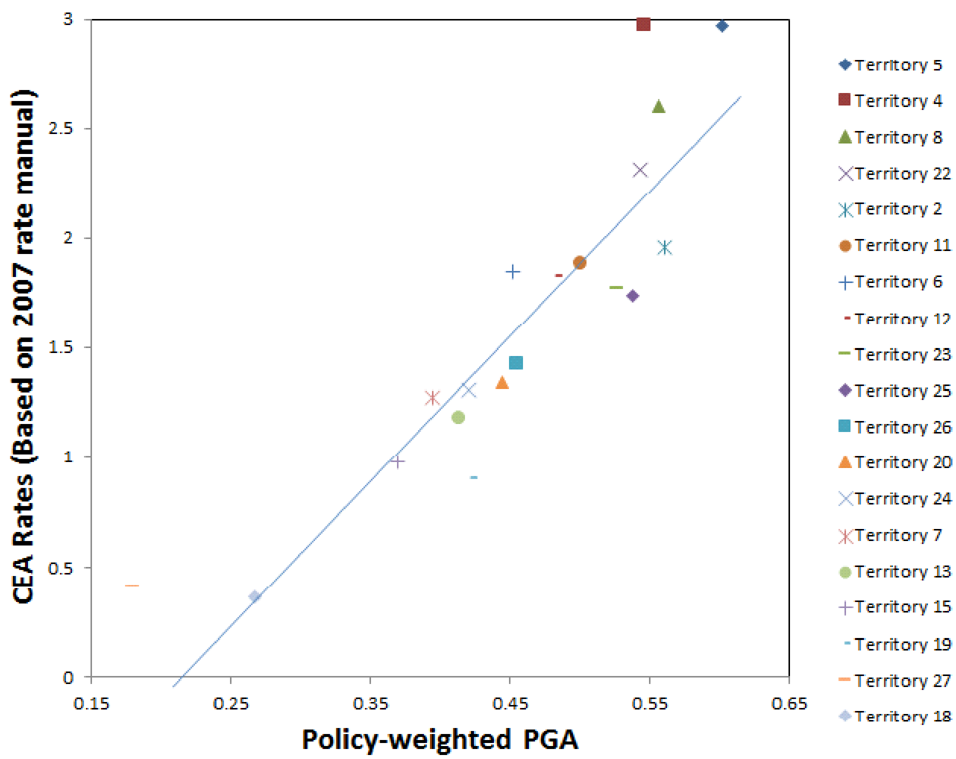
[1] According to the rate manuals of several earthquake insurers in California. Sometimes insurers may also blend the outputs from different catastrophe models to get final estimates on expected loss.

account other factors that also correlate with expected losses, such as, house structure, soil type, distance to fault line, and liquefaction potential. I use PGA as the single seismic risk measure for simplicity and practical reasons. To see whether the CEA rates are risk-based at the territory level, I plot the CEA base rates (based on 2007 rate manual) versus PGA. There are 19 territories, and within each territory, I weight the zip-code level PGA values by the number of CEA policies in that zip-code to get the policy-weighted PGA for that territory. The scatter plot in Figure 5.1 displays a very strong positive correlation between CEA's rates and a given territory's policy-weighted average PGA. The relationship is almost linear with an R-square of 80%, meaning that the CEA is probably basing rates on a model closely tied to the PGA values.[2] This is significant because I have proved that CEA sees PGA alone as a close proxy to risk.

The proceeding demonstrated that the CEA's territory rates are very related to average PGA, next, I explore whether the territory is a fine enough unit to price the geographic risk variation. Ideally, if the CEA does a good job classifying risks by drawing territories, then homogenous PGA values would be grouped into one territory. To see how the CEA's existing territories divide risks, I generate a set of boxplots of PGA distributions for those 19 territories, as shown in Figure 5.2. Figure 5.2 shows that the risk levels still vary widely within a territory. A single territory can have wide PGA distribution, and different territories often have overlapping PGA ranges. This adds to the evidence that the CEA may not have enough pricing variations, and that there is cross-subsidization of risks within territory.

[2]According to the CEA's rate manuals, the relationship between its base rates and expected loss estimated from catastrophe models is linear, multiplying the latter by a constant "loss cost multiplier". The multiplier is a gross representative of risk financing cost (mainly the cost of reinsurance), commission, tax, and operating expenses, but without underwriting profit, since the CEA is required by law to be a nonprofit organization.

Figure 5.1: CEA Rates vs. PGA by Territory.



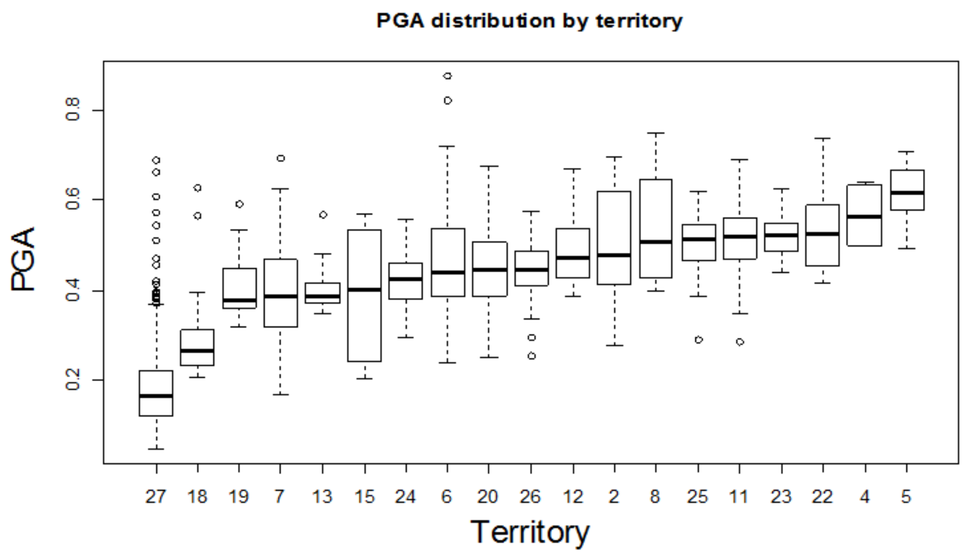
The territory-level PGAs are calculated as a weighted average of zip-code-level PGAs. The weights are the number of CEA policies in each zip-code. The CEA rates are for those policies with base limit, the same as those in Table 4.5. The territories in the legend are ranked by rates from high to low.

5.2 The Case of a Private Insurer

In this section, I look within the CEA territory, and investigate whether GeoVera prices differently where the CEA charges a flat rate. And if so, whether GeoVera's rates are risk-based, that is, further correlate with PGA at least at the zip-code level. I choose GeoVera for a case study because it is the 2^{nd} biggest player in California's earthquake insurance market, and it has relatively detailed rating information available to the public. Based on GeoVera's rating manual, theoretically, there are 49 possible combinations[3] of base rates for houses with the same characteristics and located within

[3]Each zip-code can fall into any one of the seven MMI bands, and any one of the seven GeoVera territories, resulting in 49 (7 by 7) combinations of rates.

Figure 5.2: PGA Distributions by the CEA Territory.



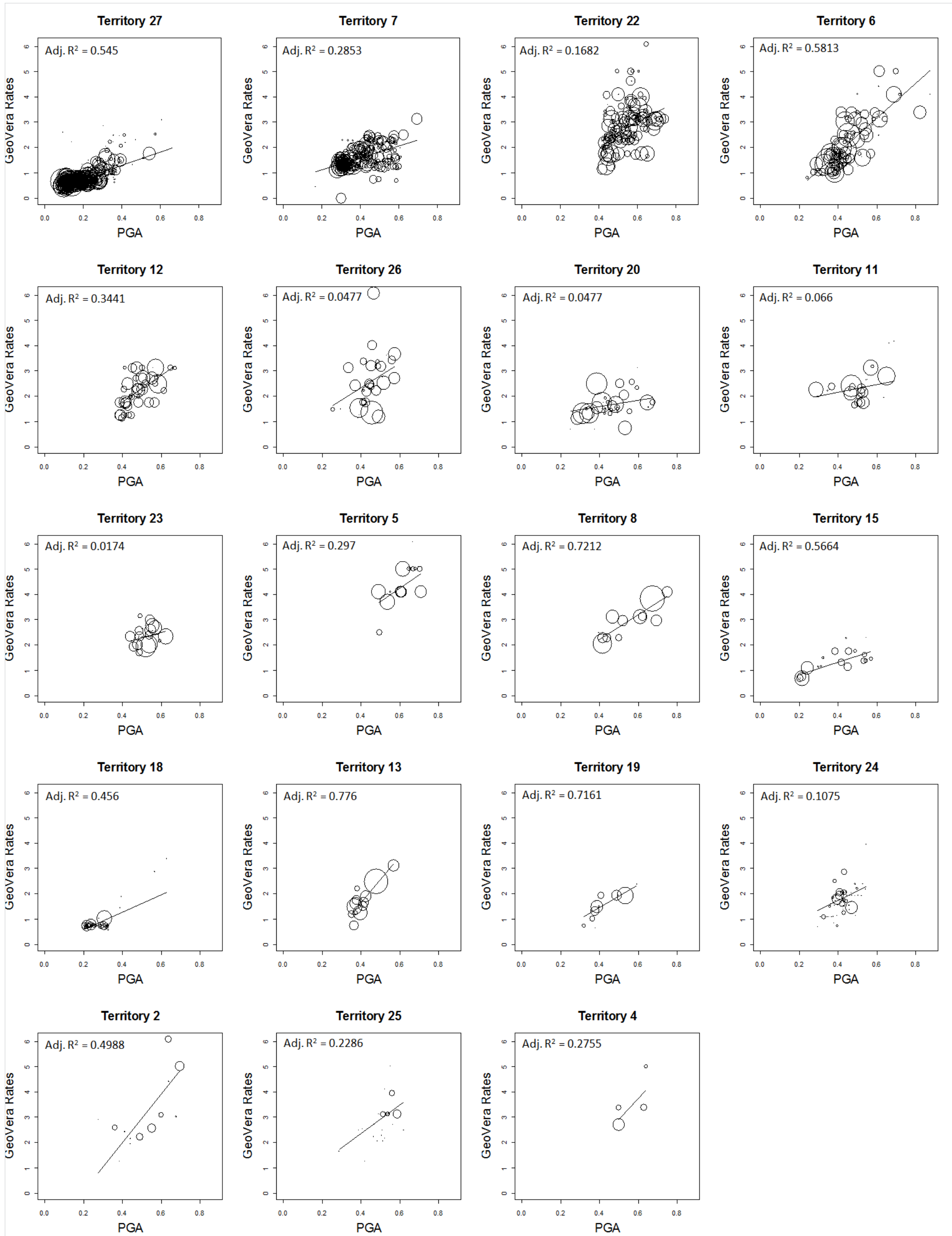
Each boxplot represents PGA distributions in one CEA territory, so that there are in total 19 boxplots. Territories are ranged by their median PGA values.

the same zip-code. I calculate the average of all possible rates for each zip-code. Figure 5.3 shows a set of scatterplots of the zip-code level GeoVera rates vs. PGA values by CEA territory. Within all of the CEA territories, there are obvious positive correlations between GeoVera's rates and PGA values at the zip-code level. This is significant because I just proved that the private insurers are using finer geographic-risk-classification. So the next steps would be to see that if finer pricing leads to a better risk pool.

5.3 Conclusion

To summarize, the CEA rates are risk-based on average at the territory level, but there is large risk variation within a CEA pricing territory, which raises possibilities of adverse selection by the CEA policyholders. In comparison, GeoVera uses finer geographic-risk-classification schemes, and its prices further correlate with risk levels within a territory where the CEA charges the same rate.

Figure 5.3: GeoVera Rates vs. PGA by the CEA Territory.



Territories are ranged by total population. Each dot represents a zip-code.The size of a zip-code is proportional to the total number of homeowners' policies in that zip-code. The fitted line is weighted by the size of each zip-code (weights also based on the number of total homeowners' policies)

This builds a foundation to test the speculation that private insurers may cherry-pick the better risks from the CEA.

Chapter 6

Demand for CEA Earthquake Insurance

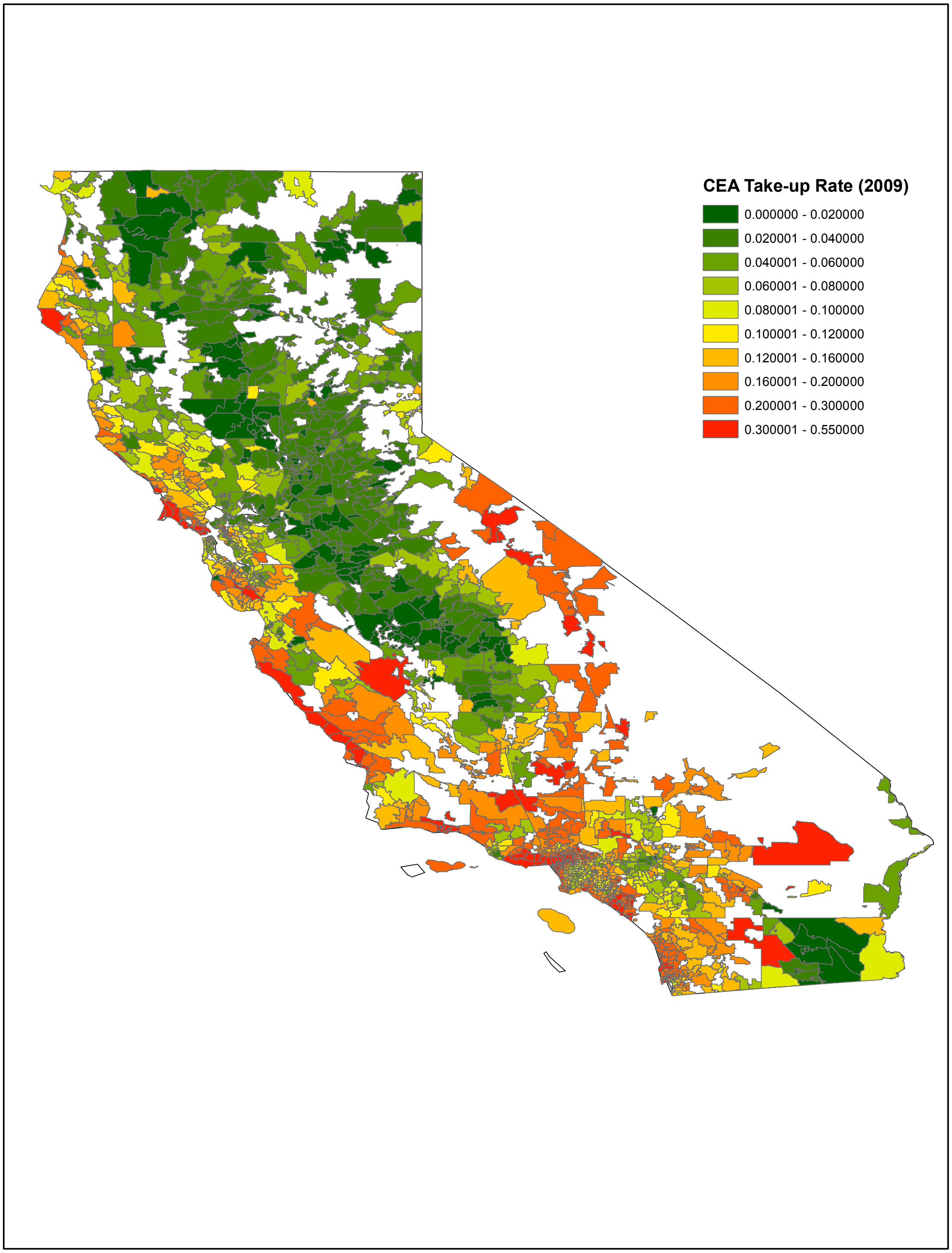
6.1 Geographic Variation in Earthquake Insurance Demand

Before proceeding to regression analysis on the determinants of demand for earthquake insurance and the issues of adverse selection, I first present some results in graphics.

Figure 6.1 shows geographically how the CEA take-up rates vary across California. Each unit on the map represents a zip-code. Zip-codes are most concentrated in the Greater Los Angeles Area (Figure 11.1 in Appendix) and the San Francisco Bay Area (Figure 11.2 in Appendix), the two most densely populated areas in California. As we can see, across the State, areas along the coast tend to have higher take-up rates of CEA earthquake policies. In addition, a few inland zip-codes in the more sparsely populated desert area also have relatively high take-up rates.

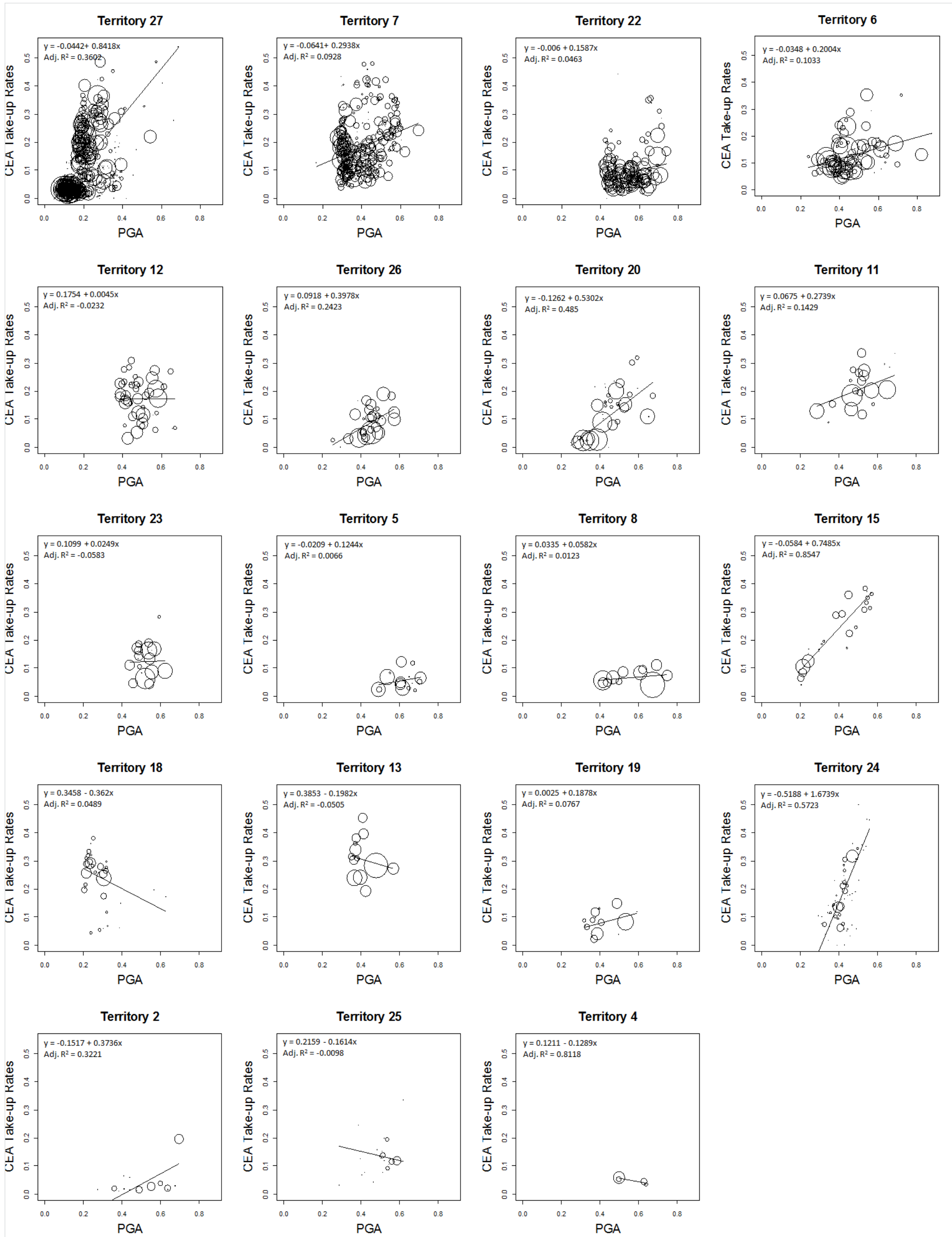
To explore whether the demand for CEA policies correlates with underlying risk, holding price fixed, I plot the CEA take-up rates against the PGA by territory. Figure 6.2 shows a set of 19 scatter plots of the CEA take-up rate vs. PGA by CEA territory, where each scatter plot consists of zip-codes within one territory, and each zip-code has a size proportional to the total number of homeowners'

Figure 6.1: CEA Take-up Rates in California.



Zip-code level CEA take-up rates range from 0 to 55%. These take-up rates are classified into 10 categories, represented by 10 colors produced by a graduant from green to red.

Figure 6.2: CEA Take-up Rate vs. PGA by Territory.



Each plot represents one territory. Y-axis is CEA take-up rate, x-axis is PGA. The scales for all the plots are the same. The fitted line is weighted by the size of each zip-code (weights are based on the number of total homeowners' policies.)

policies in that zip-code. Zip-codes in the same scatter plot are faced with the same CEA rate, despite the variation in their individual risk level. For a lot of territories, there appears to be some patterns of positive correlation between risk and demand, as shown by the upward sloping fitted lines (the fitted lines are based on weighted least square equations). Though for a few others, no obvious patterns exist, maybe because some territories (e.g., Territory 4) have too few observations.

Figure 11.3 shows the risk-demand relationship on a map. PGA values are represented by a color ramp consists of a range of colors from green (low-risk) to red (high-risk). Hatched areas represent above median CEA take-up rates within a particular territory. The above-median CEA take-up rates are often associated with colors representing higher risks, especially for Territory 27 (the largest territory), further pointing to a positive risk-demand correlation.

6.2 Regression Framework

The previous section has explored the relationship between risk and demand through graphics. This section provides a regression analysis. The main purpose in this chapter is to determine whether the correlation between risk and demand still stands after controlling for other covariates that affect demand.

To answer the empirical question on the demand for earthquake insurance, the following form of regression model is considered:

$$\begin{aligned} &\textit{Demand for CEA Earthquake Policies}_i = \beta_0 + \beta_1\textit{(Objective Risk)}_i + \beta_2\textit{Ln (Home value)}_i \\ &+ \beta_3\textit{Ln (Income)}_i + \beta_4\textit{(Demographic characteristics)}_i + \beta_5\textit{(Territory)}_{it} + \epsilon_t \end{aligned}$$

The main model is estimated using the take-up rate of CEA policies as the dependent variable. Observations are at the zip-code level, and only the cross-sectional data from 2009 is used. Regression models are estimated based on a weighted least square method, with the number of total homeowners' policies being the weight for each zip-code.

The main independent variable of interest is *Objective Risk (PGA)*, which is a set of probabilistic estimates of seismic activities based on scientific models. This is a direct measure of risk type. If the coefficient β_1 turns out significantly positive, then it is consistent with the prediction from adverse selection. This however, does not imply asymmetric information: it is unlikely that the insurer (the CEA) does not have the information on buyers' risk types; instead, it simply does not use this information in pricing, due to marketing concern, political pressure, or regulatory requirement. On the other hand, although homeowners are unlikely to outwit insurers or catastrophe modeling firms in turns of earthquake science, they are probably to some degree knowledgeable of their home location's underlying seismic risks, through mass media, neighbors, insurers, real estate agents (especially when the information disclosure law applies), or other experiences that make them aware of their vulnerability to earthquake hazards. This knowledge could become homeowners' "private information" when insurers are restricted in their ability to use information to classify risks.

Among other explanatory variables, *Ln (Home value)* is the logarithm of median owner-occupied home value in a zip-code. *Ln (Income)* is the logarithm of median household income in a zip-code. *Demographic characteristics* refer to zip-code characteristics such as measures of education level, average household size, racial composition. *Territory* is a set of dummy variables indicating which territory a zip-code lies in according to CEA's rating manuals. Since territory is the only location factor that the CEA uses for pricing, this variable will capture price effect and other variations across territories.[1] Because different territories use different prices, the standard errors are clustered at the territory level.

[1]The advantages of using dummy variables instead of numerical price values are: it relaxes the assumption of a linear relationship between price and demand; it also accounts for differences in housing structures across territories that affect the average price in that territory.

Table 6.1: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate in 2009 as Dependent Variable and Territory Fixed Effects as Controls)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.4233	0.1357	**	0.3368	0.1140	**	0.3453	0.1059	**
Log (Median Home Value)				0.0910	0.0136	***	0.0736	0.0147	***
Log (Median Household Income)				-0.0750	0.0223	***	-0.0288	0.0186	
Pop% with At Least College Degree				0.2666	0.0685	***	0.2231	0.0361	***
Median Household Size							-0.0362	0.0069	***
Gender (female%)							-0.3741	0.0704	***
Median Age							0.0003	0.0010	
Pop% of Black or African American							0.0032	0.0130	
Pop% of Asian							-0.0180	0.0170	
Pop% of other races							0.1215	0.0393	**
Household with Children							-0.0127	0.0397	
Log (Population Per Square Mile)							0.0074	0.0009	***
Territory Fixed Effects	X			X			X		
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.3581			0.7025			0.7226		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight. Standard errors are clustered at the territory level. Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

In alternative versions of the main regression model, I use log of territory-level premium rates (per $1,000 coverage) instead of Territory dummies to directly measure the price elastisity. I also interact these Territory dummies (or premiums rate) with PGA values, to allow for different slopes of risk-demand correlation in different territories.

6.3 Regression Results

Table 6.1 reports the weighted least square estimates for demand for earthquake insurance measured by the CEA take-up rate. Table 6.2 uses premium rate instead of territory fixed effects to measure price effects directly.

Objective Risk: The coefficients of PGA are highly significant and consistent in signs and magnitudes (around 0.35) across different models. Every territory has a PGA range of at least 0.2, and a coefficient of 0.35 equates the 0.2 change in PGA with a 7 percentage point change in take-up rate.

Table 6.2: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate in 2009 as Dependent Variable and Log of Premium Rate as Control)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.3873	0.1435	**	0.2817	0.1247	*	0.3135	0.1188	**
Log (Premium Rate)	-0.0718	0.0226	**	-0.0687	0.0283	*	-0.0695	0.0274	*
Log (Median Home Value)				0.0810	0.0353	*	0.0654	0.0290	*
Log (Median Household Income)				-0.0661	0.0297	*	-0.0618	0.0341	.
Pop% with At Least College Degree				0.2103	0.0705	**	0.2485	0.0408	***
Median Household Size							0.0238	0.0230	***
Gender (female%)							-0.2761	0.1455	.
Median Age							-0.0008	0.0011	
Pop% of Black or African American							-0.0283	0.0370	
Pop% of Asian							-0.1964	0.0631	**
Pop% of other races							-0.1385	0.1134	
Household with Children							-0.1371	0.0594	*
Log (Population Per Square Mile)							0.0094	0.0029	**
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.1235			0.4476			0.4972		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight. Standard errors are clustered at the territory level. Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Considering that the current median CEA take-up rate in California is about 10%, a 7 percentage point increase represents a 70% increase in the current take-up rate, therefore is quite substantial. Based on the scatter plot in Figure 5.1 and assuming a linear relationship between PGA and CEA rate, an increase of 0.2 in PGA roughly corresponds to an increase in the CEA base rate of $1.25 per $1,000 coverage. The current average CEA base rate is about $1.23 per $1,000 coverage,[2] so an increase of 0.2 in PGA is roughly equivalant to doubling the CEA base rate, or doubling the expected loss.[3] To summarize, a coefficient of 0.35 means that the take-up rate could increase by 70% with an increase in PGA of 0.2 (which is a common range of risk variation within a CEA territory), which is equivalant to doubling the current expected loss.

Home Value: The results show that a zip-code's median home value has a positive effect on earthquake insurance demand in that area. A coefficient of 0.09 means that, all else equal, for a

[2]A CEA policy charges a base rate from as low as $0.36 in the lowest-risk territory to as high as almost $3 in the highest-risk territory per $1,000 coverage. The author calculated that the policy-weighted state-wide average rate of a basic CEA policy is about $1.23 per $1,000 coverage.

[3]the CEA rate is proportional to expected loss, illustrated in its rate-making data sheet in the rate manual.

1% increase in median home value, the take-up rate of earthquake policies will increase by 0.09 percentage points. Or, for a typical zip code with a median home value of $200,000, if the value would be higher by 20% to $240,000, then the take-up rate of earthquake insurance would increase by 1.8 percentage points.

Income: The effect of an area's median household income is negative after controlling for other variables such as median home value, which is a little counterintuitive. One possible interpretation would be that holding home value constant, higher income households have higher sense of security, resulting in lower demand for insurance. On the other hand, income and median house value are highly correlated (with a Pearson's correlation coefficient of about 0.7), the presence of collinearity may be another reason that causes the income variable to be negative. According to the regression estimate, a coefficient of -0.06 means that, all else equal, for a 1% increase in median household income, the take-up rate of earthquake policies will fall by 0.06 percentage point. Or, for a typical zip code with a median household income of $50,000, if the income would be higher by 20% to $60,000, then the take-up rate of earthquake insurance would drop by 1.2 percentage points.

Education (Percentage of Population over 25 Years Old with At Least a College Degree): The education variable is significant and consistent across different models. A coefficient of 0.2 means that, for every 1 percentage point increase in the ratio of population (Age25 or older) with at least a college degree, the take-up rate increases by 0.2 percentage points. For a typical zip-code where 20% of its population (Age 25 or older) has at least a college degree, if that ratio would increase to 25%, then the take-up rate of earthquake insurance would increase by 1 percentage point. We observe that this education ratio ranges from 0% to 100% among all the zip-codes in California; thus, the take-up rate can differ by many as 20 percentage points, holding other factors constant.

Other Demographics: The racial composition variables are not significant, and neither is the

Age variable. An area's population density is significant, displaying a positive effect on insurance demand. The Gender variable's magnitude matters moderately here - with the majority of zip-codes' female proportion fall into the range of 47% to 52%, the take-up rate varies by 1.5 percentage points, all else equal. Household size seems to be negatively related to take-up rate. A coefficient of -0.03 means that, if the median household size of a zip code would increase from 2 members to 3 members, then the take-up rate of earthquake policies would drop by 3 percentage points. Since most household sizes range from 2 to 4 people, the variation in take-up rate is about 6 percentage points, all else equal.

Territory: These variables capture territory fixed effects including price effects. Most of them are highly significant, and the signs generally point in the direction that price has a negative effect on demand. Some of the magnitudes appear to be very large (a 20 percentage point difference in take-up rates for some territories), reflecting the vast heterogeneity among territories.

Premium Rate: As expected, price is negatively correlated with demand. The coefficient of the log of CEA's premium rate is about -0.07, which is the change in take-up rate for every 1% increase in premium. If the premium rate increase by 20%, then the take-up rate of earthquake policies would drop by 1.4 percentage point on average, or 14% from the current level of a 10% median take-up rate. In terms of price elasticity, the estimated elasticity is roughly 0.7. This is consistent with most prior studies about the relatively price inelasticity of demand for catastrophe insurance.

Table 11.1 is estimated including interaction terms of Territory dummies and PGA. Table 11.2 includes interaction terms of CEA premium rate and PGA. Interaction terms allow for different effects of PGA on demand among territories that charge different prices. The differences seem quite substantial: the effects of PGA on take-up rate in Territory 27 is particularly large: a coefficient of 0.75 translates into a 15 percentage point increase in CEA take-up rate for every 0.2 increase in PGA value. On the other hand, not all territories have significantly positive signs for the PGA variable, such as the case for Territory 12 and 13.

I also try alternative models for robustness check. First, I use the CEA coverage A take-up as dependent variable (see results in Table 11.3 and Table 11.4). Second, I use the number of CEA homeowners' policies rather than total homeowners' insurance policies as weights. Results change very little, and that the effects of PGA on demand measured by coverage dollar amount is on average slightly larger. Similar heterogeneity exists when estimated including interaction terms.

6.4 Conclusion

This chapter investigates the consequences of limited risk classification by the semi-public insurer CEA in California's earthquake insurance market, having shown that the CEA offers highly cross-subsidized rates, concerns about adverse selection and consequent inefficiency issues arise.

I do find evidence of adverse selection against the CEA: people who live in riskier areas are more likely to buy CEA policies, all else equal. The earthquake insurance take-up rate could increase by as many as 7 percentage points, if the risk level increases by 0.2 PGA (which is roughly equivalent to a doubling in the current average expected loss). This indicates that people use information that is not priced by the CEA to inform their purchase decisions, resulting in the higher-risks buying more insurance than the lower-risks. However, whether this clear positive risk-demand correlation indicates significant efficiency loss is not obvious. If such observed demand pattern is due to other factors that correlate with both risk levels and insurance purchase decisions (e.g. risk preference: if people who live in higher-risk areas tend to be more risk-averse), then homeowners may not be responsive to finer pricing schemes, and demand may not change at all.

Chapter 7

Comparison of Demand for CEA and Private Earthquake Insurance

7.1 Geographic Variation in the Demand for CEA vs. for Private Earthquake Insurance

If the major public insurer CEA is selected against because of its coarse classification and cross-subsidized rates, then can a finer pricing structure mitigate the positive risk-demand correlation observed in the case of the CEA? Although we cannot suddenly change the way the CEA classifies risks, we can compare the demand for CEA and private earthquake insurance to see that whether the private sector achieves a better risk pool through finer risk classification. Figure 12.1 includes two sets of risk-demand correlation plots for each territory. The solid lines are the best fitted lines for the risk-demand correlation of the CEA; the dashed lines are the best fitted lines for that of the non-CEA insurers.

Next, I compose one variable to reflect the comparison of demand. I define CEA's earthquake market share as the CEA policy counts divided by all earthquake policies sold $\left(= \frac{\text{\# of CEA earthquake policies}}{\text{\# of total earthquake policies}}\right)$. I then calculate CEA's earthquake market share at the zip-code level and the average of those for each of the 19 territories. Finally, the variable I create is called *CEA EQ share* $\left(= \frac{\text{CEA's earthquake market share}}{\text{territory average of the CEA's earthquake market share}}\right)$.[1] How this variable changes within territory implies how the demand in private sector varies compared with that for the CEA. Figure 7.1 plots the *CEA EQ share* variable against the PGA by territory, and shows the risk-share correlations. For a few territories, the slopes tend to be positive, telling a seemingly consistent adverse selection inefficiency story: given that the private insurers price lower for the below-average risks, and higher for the above-average risks within a CEA territory, they seem to get relatively larger share of the below-average risks, and relatively smaller share of the above-average risks.[2] On the other hand, the pattern is not uniform for all territories. Questions remain if such relationship holds after controling for other factors, and if the heterogeneous correlation patterns point to a different story.

7.2 Regression Framework

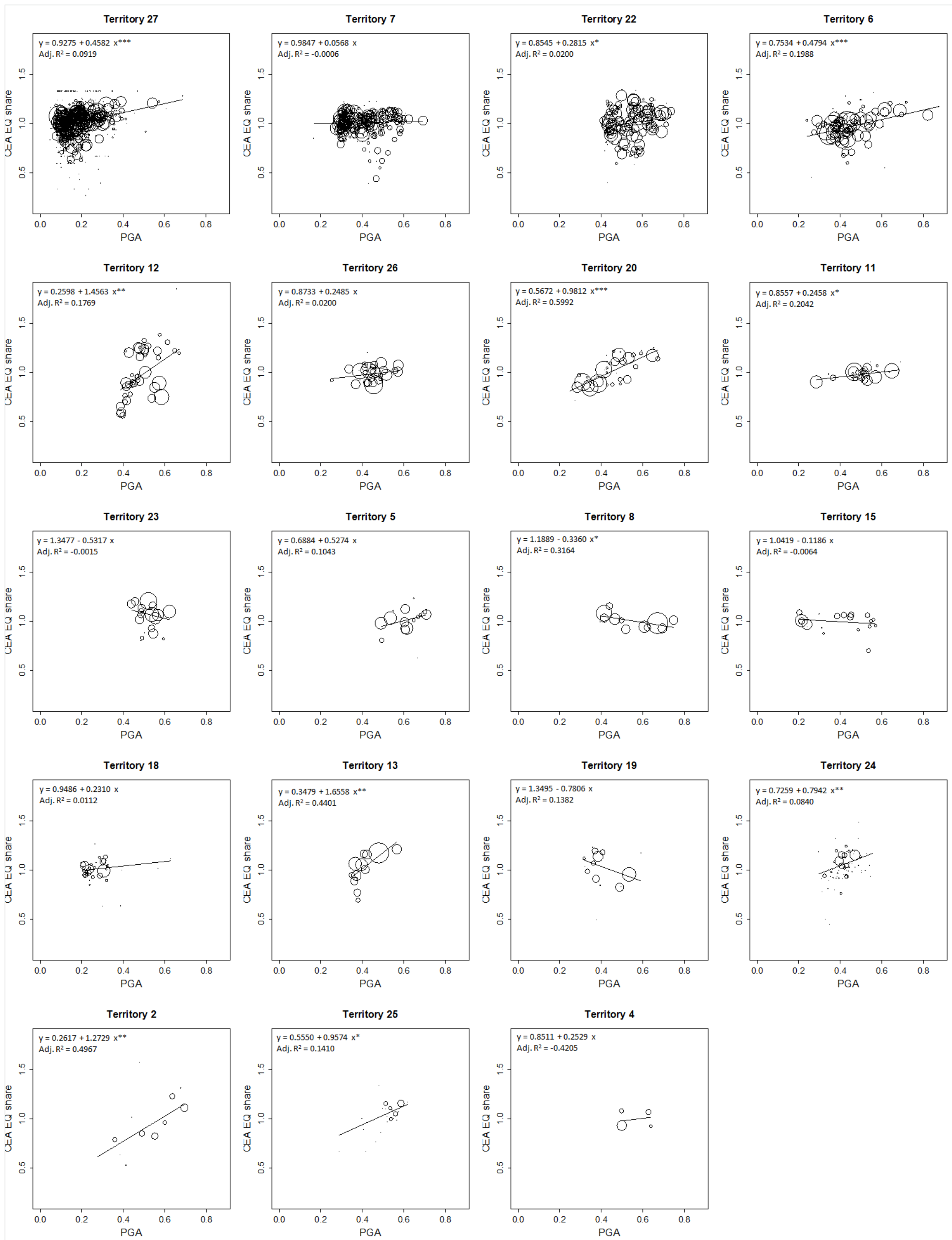
To provide a more rigorous analysis, the following form of regression model is considered:

$$\begin{aligned}
&\textit{Relative Demand for CEA Earthquake Policies}_i = \beta_0 + \beta_1\textit{(Objective Risk)}_i \\
&+ \beta_2\textit{(CEA HO market share)}_i + \beta_3\textit{Ln (Home value)}_i + \beta_4\textit{Ln (Income)}_i + \beta_5\textit{(Demographic characteristics)}_i \\
&+ \beta_6\textit{(Territory)}_{it} + \epsilon_t
\end{aligned}$$

[1]Another potential variable to measure the relative demand for CEA earthquake insurance is called *CEA share* $\left(= \frac{\text{\# of CEA earthquake policies/\# of total earthquake policies}}{\text{\# of CEA homeowners' policies/\# of total homeowners' policies}}\right)$, which is the ratio of the CEA's earthquake insurance market share to the CEA participating insurers' homeowners market share, which is also the ratio of the CEA take-up rate to the overall market (including both the CEA and the private sector) take-up rate. A ratio of 1 means that the CEA captures the same proportion of homeowners as other private earthquake insurers do. A higher ratio signifies a relative shift in demand towards the CEA policies among homeowners. The *CEA share* variable takes into account the additional variation in CEA participating insurers' homeowners market share compared with the *CEA EQ share* variable. But the *CEA EQ share* variable has more straight forward interpretation, while the variation in CEA participating insurers' homeowners market share can be accounted for in regression models later.

[2]The author also tried plotting the *CEA share* variable against the PGA by territory to show the risk-share correlations. The figures look quite similar to those in figure 7.1.

Figure 7.1: CEA EQ Share vs. PGA by Territory.



Each plot represents one territory. Y-axis is CEA EQ share, x-axis is PGA. The scales for all the plots are the same. The fitted line is weighted by the size of each zip-code (weights also based on the number of total homeowners' policies.)

The main model is estimated using the *CEA EQ share* as the dependent variable (an alternative dependent variable is the *CEA share*). The same sets of model specifications are estimated as in the *Demand for CEA earthquake Insurance* section, and the same set of independent variables and observations are used, only adding one more independent variable *CEA HO market share*. This variable is to account for the possibility that the CEA's earthquake market share is partly driven by its participating insurers' homeowners market share. Again, standard errors are clustered at the territory level.

7.3 Regression Results

Table 7.1 reports the weighted least square estimates of coefficients using territory fixed effects as controls. Table 7.2 is estimated using CEA's premium rate as control. The only consistently significant coefficients are the Objective Risk Measure (PGA) and the CEA participating insurers' HO market share.

Objective Risk: The coefficient of PGA is significantly positive, with a magnitude around 0.28. This is saying that for a 0.2 difference in PGA, CEA earthquake market share relative to territory average will change on average 0.056. Since the lowest territory average is 54.10% (Territory 12) and the highest is 81.64% (Territory 11), the CEA earthquake market share will vary by about 7 to 10 percentage points.

CEA participating insurers' HO market share: This variable is significantly positive, meaning that in areas where the CEA participating insurers capture more homeowners' insurance market, the CEA will have larger earthquake insurance market share as well. Homeowners typically shop their home insurance first, and then weigh the options for an additional earthquake coverage. On the other hand, the variation in CEA participating insurers' homeowners' insurance market cannot

Table 7.1: Relative Demand for CEA Earthquake Insurance (Use CEA EQ Share as Dependent Variable and Territory Fixed Effects as Controls)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.2712	0.1006	**	0.2809	0.0884	**	0.2822	0.0803	***
CEA PIs' HO market share	0.8641	0.1449	***	0.8743	0.1363	***	0.9499	0.1383	***
Log (Median Home Value)				0.0105	0.0363		0.0284	0.0350	
Log (Median Household Income)				0.0435	0.0341		0.0444	0.0257	.
Pop% with At Least College Degree				-0.1808	0.0501	***	-0.2018	0.0704	**
Median Household Size							-0.0076	0.0127	
Gender (female%)							-0.2116	0.1440	
Median Age							-0.0034	0.0010	***
Pop% of Black or African American							0.1480	0.0591	*
Pop% of Asian							0.0837	0.0846	
Pop% of other races							-0.0969	0.1450	
Household with Children							0.0636	0.0690	
Log (Population Per Square Mile)							0.0050	0.0031	
Territory Fixed Effects	X			X			X		
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.2793			0.3003			0.3467		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight. Standard errors are clustered at the territory level
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 7.2: Relative Demand for CEA Earthquake Insurance (Use CEA EQ Share as Dependent Variable and Log of Premium Rate as Control)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.2887	0.0766	***	0.3189	0.0676	***	0.3375	0.0677	***
Log (Premium Rate)	-0.0897	0.0198	***	-0.0945	0.0173	***	-0.0975	0.0182	***
CEA PI's HO Market Share	0.5042	0.0769	***	0.6121	0.0792	***	0.6244	0.0861	***
Log (Median Home Value)				-0.0387	0.0458		-0.0196	0.0425	
Log (Median Household Income)				0.0517	0.0309	.	0.0318	0.0289	
Pop% with At Least College Degree				-0.1012	0.0433	*	-0.1537	0.0669	*
Median Household Size							0.0001	0.0197	
Gender (female%)							-0.2378	0.1500	
Median Age							-0.0031	0.0015	*
Pop% of Black or African American							0.0152	0.0415	
Pop% of Asian							0.0159	0.0917	
Pop% of other races							-0.2445	0.1471	.
Household with Children							0.1059	0.1450	
Log (Population Per Square Mile)							0.0004	0.0059	
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.1995			0.2035			0.2503		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight. Standard errors are clustered at the territory level.
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

explain all of the variation in CEA's earthquake insurance market share, and the coefficient of PGA stays significant even after we control for this HO market share variable.

Table 12.1 estimates models with interaction terms between Territory dummies and PGA to allow for different slopes. Not all territories have significantly positive slopes, meaning that while the claim of the private market getting a better risk pool than the CEA is confirmed on average, there is heterogeneity across different areas.[3] This futher implies that a finer pricing does not necessarilty result in efficiency improvement everywhere, probably because homeowners' purchase decisions are affected by other factors besides a comparison of expected loss and price. While what are those factors is a question beyond the scope of this paper, possible answers could be people's risk preference, their awareness of earthquake risk, and influences by the marketing efforts of some insurers.

For further robustness check, first, I estimate models using CEA coverage A market share as the dependent variable, see Table 12.2 and Table 12.3. Second, models with *CEA share* as dependent variable are also estimated (in such models, CEA participating insurers' HO market share is no longer an independent variable, since it has been accounted for as the denominator of the dependent variable), see Table 12.4 and Table 12.5. The results all tell a very similar story, and models with interaction terms show similar heterogeneity.

7.4 Conclusion

In order to understand the nature of the private information in this setting, and how people would react to finer price segmentation, in this chapter, I compare the demand for the CEA policies vs.

[3]Models with *CEA share* as dependent variable are also estimated (in such models, CEA participating insurers' HO market share is no longer an independent variable, since it has been accounted for as the denominator of the dependent variable). The results on average tell a very similar story, models with interaction terms also show similar heterogeneity.

private policies. The hypothesis of the private insurers getting a better risk pool than the CEA by using finer geographic-risk-classification schemes is confirmed on average. However, heterogeneity exists such that some areas do not have the expected demand pattern at all. The heterogeneity seems to suggest potentially limited efficiency gains through a finer pricing. Possible explanations include limited comparison shopping by homeowners, heterogeneity in underlying risk preferences, and different marketing tactics employed by the insurers.

The policy implications from this study can be extended to other types of markets where risk classification is limited. The function of a competitive private sector depends on the nature of demand, and the intervention of government programs should find a balance between equity gains and efficiency loss.

Chapter 8

Discrete Choice Modeling

8.1 Introduction

The proceeding two chapters use zip-code level insurance take-up rate as the dependent variable, and use OLS or WLS as estimation methods. In Chapter 6 testing for adverse selection, I focus on eligible homeowners who have insured their homes with the CEA participating insurers. In Chapter 7 comparing the demand for CEA and private earthquake policies, I again leave out the discussion of home insurance choices. Homeowners' entire choice sets are not fully identified in my data. For example, for a homeowner who purchases a private earthquake policy, we do not know if he has purchased a home insurance from one of the CEA participating insurers or from a non-CEA participating insurer. It is thereby important to supplement the previous chapters with additional analysis on home insurance purchase decisions. Choice modeling provides a good framework for this analysis.

I define my population as homeowners with home insurance. A homeowner has two choices when purchasing a home insurance policy: to get it from one of the CEA participating insurers, or from a non-participating insurer. Next, if a homeowner purchases a CEA participating insurer's home insurance policy, he will have three choices in terms of earthquake coverage: purchase a CEA policy, purchase a private earthquake policy, or go without earthquake coverage. If a homeowner purchases a non-CEA participating insurer's home insurance policy instead, then he will only have two choices for earthquake coverage: purchase a private earthquake policy, or uninsured, because he is not eligible for a CEA policy. In really, I do not observe counts of all of the five choices homeonwers make, but have to make assumptions of some unobserved variables. This chapter dicusses homeowners' choices in detailed steps.

Methodology wise, insurance purchase decisions can be treated as categorical dependent variables. Discrete choices and event counts can be modeled using a range of models accommodating discrete outcomes, such as multinomial logit and Poisson models (see Frees (2004), Greene (2010), and Rodriguez (2007) for example).

Specifically, for a homeowner i, denote the probability of choosing the jth category as $\pi_{ij} = Prob(y_i = j)$, so that $\sum_j \pi_{ij} = 1$ for each i. Because we don't observe individual homeowner's choices, and instead observe the grouped choices within each zip-code (group), we introduce random variables representing counts of choices in various categories. Let n_i denote the total number of homeowners in the zip-code i, and let Y_{ij} denote the number of homeowners from zip-code i that choose the j_{th} category, with observed value y_{ij}. Note that $\sum_j y_{ij} = n_{ij}$, i.e. the counts in the various choice categories adds up to the total number of homeowners in each zip-code.

The probability distribution of the counts Y_{ij} given the total number of homeowners in each zip-code n_i follows the multinomial distribution:

$$Prob\,(Y_{i1} = y_{i1}, \ldots, Y_{iJ} = y_{iJ}) = \binom{n_i}{y_{i1}, \ldots, y_{iJ}} \pi_{i1}^{y_{i1}} \ldots \pi_{iJ}^{y_{iJ}} \qquad (1)$$

The special case, where J=2 (when we have only two choice categories) follows a binomial distribution.

Now we consider models for the probabilities π_{ij}. We pick one category J as a baseline and calculate the odds that a member of group i falls in category j as opposed to the baseline as $\frac{\pi_{ij}}{\pi_{iJ}}$, and assume that the log-odds of each response follow a linear model:

$$\eta_{ij} = ln\frac{\pi_{ij}}{\pi_{iJ}} = \alpha_j + x_i^{'}\beta_j \qquad (2)$$

Where $j = 1, 2, \ldots, J-1$, and β_j is a vector of regression coefficients. Note that this model is analogous to a logistic regression model, except that now we have $J-1$ equations instead of one. The $J-1$ logit equations contrast each of categories $1, 2, \ldots, J-1$ with the baseline category J. Estimates of regression coefficients can be obtained by maximizing the multinomial likelihood (Equation (1)) with the probabilities π_{ij} being viewed as functions of the parameters in Equation (2). Specifically, the sum of log likelihood is:

$$Log(L) = \sum_i ln\binom{n_i}{y_{i1},\ldots,y_{iJ}}\sum_{j=1}^{J} y_{ij} ln\pi_{ij} \qquad (3)$$

Where π_{ij} can be written as $\pi_{ij} = \frac{exp(\eta_{ij})}{\sum_{j=1}^{J} exp(\eta_{ij})} = \frac{exp(\alpha_j + x_i^{'}\beta_j)}{\sum_{j=1}^{J} exp(\alpha_j + x_i^{'}\beta_j)}$.

Applying this framework to the specific setting of California's residential earthquake insurance market, the first strategy is to assume that homeowners make their decisions in a sequential fashion: First, choose a homeowner insurance and second, choose an earthquake insurance. We thereby define a hierarchy of nested logit models for these two subsets of choices. The second strategy is to assume that homeowners make their purchase decision of earthquake insurance directly, and that the choices are independent with each other.

Section 8.2 describes a nested logit model assuming homeowners make their choices in a sequential fashion: In the first step, they choose a homeowners insurance either from one of the CEA participating insurers or from a non-CEA participating insurer. In the second step, conditional on having chosen a CEA participating insurer's homeowners insurance policy (thus making them eligible for a CEA earthquake insurance policy), those homeowners then choose whether or not to take up the CEA earthquake policy. Section 8.3 describes a multinomial logit model assuming homeowners have three final independent choices when it comes to earthquake coverage: choosing a CEA earthquake insurance policy, choosing a private earthquake policy, or choosing no earthquake coverage.

8.2 Sequential Choices of Homeowners Insurance and Earthquake Insurance

It is of great interest to not only understand homeowners' earthquake insurance purchase decisions, but to also have an idea about their home insurance purchase decisions, since most homeowners should have purchased a homeowner policy prior to buying an earthquake policy. In fact, we can conveniently model homeowners' sequential choices separately because an important practical feature of the hierarchical logit model is that the multinomial likelihood factors out to a product of binomial likelihoods, which may then be maximized separately.

Assume that homeowners are divided into three categories: (1) Those who did not purchase CEA participating insurer homeowners insurance and thus are not eligible for a CEA earthquake policy. (2) Those who purchased a CEA earthquake policy. (3) Those who did not purchase a CEA earthquake policy even though they are eligible for one.

The multinomial likelihood for group (zip-code) i has the form:

$$L_i = \pi_{i1}^{y_{i1}} \pi_{i2}^{y_{i2}} \pi_{i3}^{y_{i3}} \qquad (4)$$

Multiply and divide equation (4) by $(\pi_{i2} + \pi_{i3})^{y_{i2}+y_{i3}}$, which is the probability of buying CEA participating insurer homeowners insurance raised to the total number of homeowners who have bought such homeowners insurance, and we obtain:

$$L_i = \pi_{i1}^{y_{i1}} (\pi_{i2} + \pi_{i3})^{y_{i2}+y_{i3}} \left(\frac{\pi_{i2}}{\pi_{i2}+\pi_{i3}}\right)^{y_{i2}} \left(\frac{\pi_{i3}}{\pi_{i2}+\pi_{i3}}\right)^{y_{i3}} \qquad (5)$$

Let $\rho_{iH} = \pi_{i2} + \pi_{i3}$ denote the probability of buying homeowners insurance from a CEA participating insurer in zip-code i, and let $\rho_{iE} = \frac{\pi_{i2}}{\pi_{i2}+\pi_{i3}}$ denote the conditional probability of buying a CEA earthquake insurance given that the homeowner has already had a CEA homeowners insurance. Using this notation we can rewrite equation (5) as:

$$L_i = \rho_{iH}^{y_{i2}+y_{i3}} (1 - \rho_{iH})^{y_{i1}} \rho_{iE}^{y_{i2}} (1 - \rho_{iE})^{y_{i3}} \qquad (6)$$

The two right-most terms involve the first-step choice of a homeowners' insurance policy, and the two left-most terms involve the second-step choice - the conditional choice of a CEA earthquake insurance policy given that the homeowner is eligible for it. We can maximize these two likelihoods separately.

Table 8.1: Odds Ratio of Choosing CEA HO vs. nonCEA HO

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Objective Risk Measure (PGA)	1.593	1.558	1.630	1.355	1.325	1.387	1.485	1.451	1.521
Log (Median Home Value)				1.470	1.456	1.485	1.375	1.360	1.389
Log (Median Household Income)				0.840	0.832	0.848	0.824	0.813	0.835
Pop% with At Least College Degree				0.671	0.655	0.687	0.412	0.400	0.426
Median Household Size							0.970	0.961	0.980
Gender (female%)							0.845	0.766	0.931
Median Age							1.006	1.005	1.007
Pop% of Black or African American							0.453	0.440	0.467
Pop% of Asian							1.489	1.455	1.523
Pop% of other races							0.551	0.524	0.579
Household with Children							0.816	0.776	0.858
Log (Population Per Square Mile)							1.008	1.006	1.010

8.2.1 CEA Homeowners Insurance vs. nonCEA Homeowners Insurance

In the first step, I contrast ρ_{iH} to $(1 - \rho_{iH})$, and use equation (2) to estimate regression coefficients by maximizing the likelihood function in equation (3). Results are shown in Table 13.1. To facilitate interpretation, Table 8.1 presents the odds ratio estimates of choosing a CEA participating insurer's homeowners policy. For robustness check, Table 13.5 presents the odds ratio estimates from a model allowing heterogeneity of slope of the risk coefficient.

Objective Risk: The odds ratio estimates and confidence intervals for the coefficient of PGA are all significant and fall into ranges consistently above 1. This means that homeowners in higher risk areas are more likely to choose homeowners insurance from CEA participating insurers. To see how large the magnitude is, we consider a change of 0.2 in PGA value (a typical range, and consistent with illustrations in previous chapters), which then results in an average effects on odds ratio of 1.078. So, for a zip-code that is riskier than another zip-code by 0.2 PGA value, homeowners are on average 1.078 times more likely to buy their homeowners insurance from one of the CEA participating insurers relative to from a non-CEA participating insurer, all else equal.

Other Socioeconomic and Demographic Factors: The median value of owner-occupied homes in a zip-code is positively related to the odds of buying homeowners insurance from CEA participating

Table 8.2: Conditional Odds Ratio of Choosing CEA EQ vs. Otherwise

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Objective Risk Measure (PGA)	27.716	26.876	28.583	15.416	14.932	15.922	18.312	17.722	18.930
Log (Median Home Value)	1.943	1.931	1.955	2.669	2.628	2.710	2.256	2.219	2.294
Log (Median Household Income)				0.590	0.582	0.599	0.932	0.913	0.951
Pop% with At Least College Degree				5.685	5.492	5.885	2.868	2.734	3.007
Median Household Size							0.654	0.645	0.664
Gender (female%)							0.050	0.043	0.059
Median Age							1.006	1.005	1.007
Pop% of Black or African American							1.061	1.013	1.110
Pop% of Asian							0.992	0.961	1.023
Pop% of other races							2.465	2.279	2.665
Household with Children							1.539	1.435	1.651
Log (Population Per Square Mile)							1.073	1.070	1.076

insurers, while the median household income, education level, and median household size show negative relationships with buying that type of homeowners insurance.

8.2.2 CEA Earthquake Insurance vs. Otherwise

In the second step, I contrast the conditional probability of buying a CEA earthquake insurance policy ρ_{iE} with the conditional probability of choosing otherwise $(1 - \rho_{iE})$. The regression coefficients and odds ratio estimates are presented in Table 13.2 and Table 8.2. For robustness check, Table 13.6 presents the odds ratio estimates from a model allowing heterogeneity of slope of the risk coefficient.

Objective Risk: The odds ratio estimates and confidence intervals for the coefficient of PGA are all significant and fall into ranges well above 1. The magnitudes seem quite large compared to those in the first step estimates. For example, consider again a change of 0.2 in PGA value, which increases the odds ratio by anywhere from 1.710 to 1.955. So for a zip-code that is 0.2 PGA value risker, eligible homeowners are on average about 1.8 times more likely to take up CEA earthquake policy than to not do so, all else equal.

Other Socioeconomic and Demographic Factors: The median value of owner-occupied homes in a zip-code is positively related to the odds of buying CEA earthquake insurance policies, as is the educational level in the zip-code. On the other hand, the median household income and median household size are negatively related to the decision of taking up CEA earthquake insurance.

To summarize these two steps: the results from the second step-the choice of whether or not to take up CEA earthquake insurance among eligible homeowners-are quite consistent with the estimates from the previous chapters, showing adverse selection against the CEA in the form of a positive risk-demand correlation. Step one provides insights that supplement previous chapters, where we ignore the choices of homeowners insurance but simply look at the final choices of earthquake insurance. The results here show a slight positive correlation between risk and demand for CEA participating insurer's homeowners policies. This suggests the possibility that higher-risk homeowners may be more likely to buy CEA participating insurer's homeowners policy because of the additional option of getting a CEA earthquake policy later. But other possibilities also exist, such that homeowners' insurance decisions are affected by other unobserved factors not completely orthogonal to their underlying risk levels, or that certain type of home insurers are more present in areas that systematically correlate with risk levels.

8.3 Choices Among CEA Earthquake Insurance, Private Earthquake Insurance, and No Earthquake Coverage

This section independently looks at homeowners' final choices of earthquake coverage. There are in total three possibilities: purchase a CEA earthquake insurance, purchase a private earthquake insurance, or do not purchase any earthquake insurance. I choose purchasing a private policy as the base category, and contrast the other two choices to the baseline.

Table 8.3: Odds Ratio of Choosing CEA EQ vs. Private EQ

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Objective Risk Measure (PGA)	4.816	4.551	5.096	4.159	3.923	4.409	4.180	3.938	4.436
Log (Median Home Value)				1.019	0.991	1.047	1.092	1.060	1.125
Log (Median Household Income)				1.210	1.181	1.239	1.304	1.257	1.352
Pop% with At Least College Degree				0.326	0.307	0.346	0.224	0.206	0.243
Median Household Size							0.867	0.844	0.890
Gender (female%)							2.015	1.525	2.663
Median Age							0.991	0.989	0.992
Pop% of Black or African American							1.029	0.941	1.125
Pop% of Asian							2.031	1.918	2.151
Pop% of other races							0.947	0.823	1.090
Household with Children							1.718	1.522	1.940
Log (Population Per Square Mile)							1.032	1.026	1.037

8.3.1 CEA Earthquake Insurance vs. Private Earthquake Insurance

Table 13.3 and Table 8.3 present the results from the contrast of buying a CEA policy vs. buying a private earthquake policy. Table 13.3 first reports straightforward coefficient estimates from the models, and Table 8.3 calculates corresponding odds ratio estimates for ease of interpretation. To investigate the heterogeneous effects of the risk variable, Table 13.7 estimates the odds ratio based on a model including interaction terms of risk and territory.

Objective Risk: the odds ratio estimates and confidence intervals for the coefficient of PGA are all significant and fall into ranges consistently above 1. It means that people who live in the higher risk areas are more likely to choose a CEA earthquake insurance policy than a private earthquake insurance policy. To see the size of the magnitude, we again consider a change of 0.2 in PGA value. It results in effects on the odds ratio ranging from 1.351 to 1.385. So if a zip-code is riskier than another zip-code by 0.2 PGA value, homeowners are on average about 1.36 times more likely to buy CEA policies than private policies, all else equal. This is consistent with the previous results that, on average, CEA picks up worse risk than its private counterparts, which is again consistent with the notion that private insurers may cherry pick the better risk using finer pricing schemes.

Other Socioeconomic and Demographic Factors: neither the median value of homes nor the median

Table 8.4: Odds Ratio of Choosing No EQ vs. Private EQ

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Objective Risk Measure (PGA)	0.159	0.152	0.168	0.263	0.250	0.278	0.223	0.212	0.236
Log (Median Home Value)				0.359	0.350	0.368	0.458	0.446	0.471
Log (Median Household Income)				2.143	2.098	2.189	1.484	1.437	1.532
Pop% with At Least College Degree				0.057	0.054	0.061	0.089	0.083	0.096
Median Household Size							1.333	1.302	1.365
Gender (female%)							37.244	29.083	47.695
Median Age							0.982	0.980	0.983
Pop% of Black or African American							1.150	1.062	1.246
Pop% of Asian							1.901	1.807	2.001
Pop% of other races							0.462	0.408	0.524
Household with Children							1.051	0.944	1.171
Log (Population Per Square Mile)							0.960	0.955	0.965

income in a zip-code tells a consistent story about people who are more likely to choose CEA earthquake policies, but education seems to be significantly negatively related to the likelihood of buying a CEA policy versus a private one. Other variables that are significant and are positively correlated with choosing a CEA earthquake insurance policy rather than taking up a private policy are gender percentage and percentage of households with children under 18 year old.

8.3.2 No Earthquake Insurance vs. Private Earthquake Insurance

Table 13.4 and Table 8.4 present the results from the contrast of buying a private earthquake policy vs. remaining uncovered. Interpretations for Table 8.4 are below. To allow for different slopes of the risk variable, Table 13.8 estimates the odds ratio based on a model including interaction terms of risk and territory.

Objective Risk: The odds ratio estimates and confidence intervals for the coefficient of PGA are all significant and fall in ranges consistently below 1. This means that people who live in the higher risk areas are less likely to remain uninsured. If a zip-code is riskier than another zip-code by 0.2 PGA value, then homeowners are on average about 0.75 times as likely to not purchase private earthquake insurance, all else equal. Considering that risk also has a positive effect on choosing

CEA over private earthquake policy, this result suggests that risk has an even larger positive effect on purchasing CEA earthquake policies than not purchasing any earthquake coverage. These are also consistent with the previous results that, on average, the extent to which the private insurers are able to mitigate the risk-demand positive correlation is economically small, especially compared to the overall adverse selection effects (the overall positive correlation between risk and demand for earthquake insurance).

Other Socioeconomic and Demographic Factors: Higher median home value and higher educational level are associated with less likelihood of being uninsured for earthquake risks. However, higher median income is associated with higher likelihood of stay uncovered, particularly in contrast to buying a private earthquake insurance policy.

To summarize, people living in higher risk areas are more likely to purchase earthquake insurance, especially the CEA earthquake policies. Areas with higher home value and higher education are also more likely to purchase either kind of earthquake insurance. Higher education is associated with higher likelihood of choosing a private policy than a CEA policy. However, median home value and median income has less predictive power for determining which kind of policy is more likely to be chosen.

8.4 Conclusion

This chapter supplements the results in chapter 6 and 7 in two ways. First, it provides a micro-level analysis framework using discrete choice modeling. This also facilitates interpretation of demand comparison in terms of likelihood of choices. Second, chapter 8.2 provides additional analysis on the first stage decisions: purchase a CEA home insurance or a non-CEA home insurance. Although not directly related to the demand for earthquake insurance, most homeowners do consider buying home insurance prior to getting earthquake coverage.

The significance and magnitude of coefficients estimated in this chapter are quite consistent with those in the previous two chapters. The fundamental interpretations do not change; among eligible homeowners, those living in higher-risk areas are more likely to take-up CEA earthquake insurance. When comparing the demand for CEA and private earthquake insurance, those living in higher-risk areas are more likely to choose a CEA earthquake policy over a private earthquake policy.

The additional first-stage analysis provides new information on homeowners' first-step choice of home insurance. The sequential choice modeling does suggest that a slightly non-random first-stage choice might exist. But the magnitude is small enough that it does not cause concerns about the overall conclusions.

Chapter 9

Effects of Shaking Experience on Demand for Earthquake Insurance

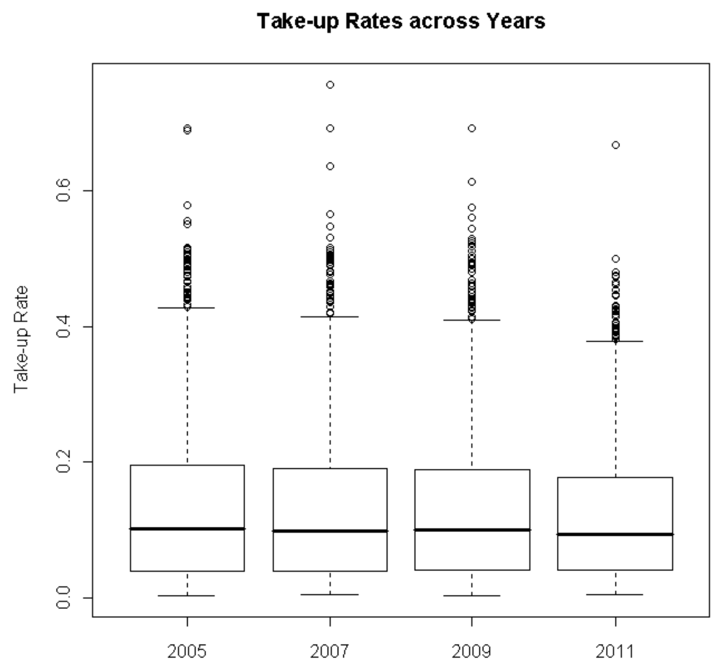
9.1 Panel Data Exploration

In this section, I explore how the take-up rate of earthquake insurance in California varies over time, its correlation with explanatory variables, and the correlation among explanatory variables.

I create a bi-annual balanced dataset of four time periods with 1585 zip-codes for each period (zip-codes with fewer than 25 home insurance policies in any of the years are dropped). The distributions of zip-code level take-up rates across the four sampled years are shown in Figure 9.1. Overall the take-up rates are quite stable, with a slight decrease in the Year 2011. Regarding shaking experiences, in addition to the geographic representation of shook regions in Figure 4.3, Table 9.1 summarizes the percentage of zip-codes that shook with at least an intensity of IV in each year from 2004 to 2011, and the percentage of homeowners' insurance policies in affected zip-codes.

I then create four time-varying shaking indicator variables: S_{i0} indicates if zip-code i shook in

Figure 9.1: Earthquake Insurance Take-Up Rates Across Years



Take-up rates are calculated at the zip-code level, as the number of total earthquake insurance policies divided by the number of total homeowners' insurance policies in a zip-code. There are 1585 observations in each year. Zip-codes with fewer than 25 home insurance policies in any of the years are dropped.

Table 9.1: Percentage of Zip-codes and Homeowners Affected by Earthquakes from 2004-2011

Year	Zip	Homeowners
2004	6.19%	6.49%
2005	18.19%	24.87%
2006	0.32%	0.13%
2007	16.74%	22.05%
2008	30.64%	40.35%
2009	16.55%	18.96%
2010	22.80%	27.75%
2011	0.76%	1.16%

Note: the total number of zip-codes in this sample is 1585, and there was an average of 5,862,715-total homeowners' insurance policies in the 4 observation years

Table 9.2: Averages of Take-Up Rate by Level of Shaking Indicator Variables

Shake indicator	Present	1 year ago	2 years ago	3 years ago
0 (Did not shake)	8.46% (87%)	8.21% (85%)	8.37% (84%)	8.46% (90%)
1 (Shook)	12.12% (13%)	13.27% (15%)	11.42% (16%)	13.53% (10%)

The sample is the pooled panel dataset which includes (1585 zips x 4 years=) 6340 observations.
The numbers in the parenthesis are the percentage of zip-codes in that category.

Table 9.3: Averages of PGA by Level of Shaking Indicator Variables

Shake indicator	Present	1 year ago	2 years ago	3 years ago
0 (Did not shake)	0.32 (87%)	0.33 (85%)	0.32 (84%)	0.33 (90%)
1 (Shook)	0.44 (13%)	0.39 (15%)	0.43 (16%)	0.40 (10%)

The sample is the pooled panel dataset which includes (1585 zips x 4 years=) 6340 observations.
The numbers in the parenthesis are the percentage of zip-codes in that category.

the current year ($S_{i0} = 1$ for "shook" and $S_{i0} = 0$ for "did not shake"). Similarly, S_{i1} indicates if zip-code i shook in the previous year, S_{i2} indicates if zip-code i shook 2 years ago, and S_{i3} indicates if it shook 3 years ago. Table 9.2 examines the variations in take-up rates by the level of each of these four time-varying shaking indicator variables. It seems that the average take-up rates are higher in places that experienced shaking in recent years, and that the differences in take-up rates do not vary too much if the earthquake happened in the present year, 1 year ago, 2 years ago, or 3 years ago. Table 9.3 tells us that, at the same time, places that shook more often also tended to be inherently higher-risk areas, as shown by higher average PGA values (an objective measure of probabilistic seismic risk). It is already known that PGA and take-up rate are positively correlated. The next section will explore whether recent shaking itself has an impact once we control for PGA.

9.2 Regression Framework and Main Results

I use the following specifications for my regression models. When using log of take-up rate as the dependent variable, for the several zip-codes with zero take-up rates, I use imputed values[1] which give take-up rates very close to zeros as inputs.

$$Ln(takeup_{i,t\neq 2005}) = \alpha_0 + \alpha Ln(takeup_{i,2005}) + \textstyle\sum_{\tau=0}^{3}\beta_\tau S_{i\tau} + X_i + T_{tj} + \epsilon_{it} \tag{1}$$

$$Ln(takeup_{i,t\neq 2005}) = \alpha_0 + \alpha Ln(takeup_{i,t-2}) + \textstyle\sum_{\tau=0}^{2}\beta_\tau S_{i\tau} + X_i + T_{tj} + \epsilon_{it} \tag{2}$$

$$Takeup_{i,t\neq 2005} = \alpha_0 + \alpha Takeup_{i,2005} + \textstyle\sum_{\tau=0}^{3}\beta_\tau S_{i\tau} + X_i + T_{tj} + \epsilon_{it} \tag{3}$$

$$Takeup_{i,t\neq 2005} = \alpha_0 + \alpha Takeup_{i,t-2} + \textstyle\sum_{\tau=0}^{2}\beta_\tau S_{i\tau} + X_i + T_{tj} + \epsilon_{it} \tag{4}$$

Based on summary statistics and observations from the panel data, a homeowner's home insurance and earthquake insurance status displays strong consistency over time. Therefore, in models (1) and (3), I use the earliest observation of insurance take-up rate which is in 2005 to control for prior insurance conditions. In models (2) and (4), I use the insurance take-up rate 2 years ago (this is a biannual dataset) as a control. I also try both log models (models (1) and (2)) and non-log models (models (3) and (4)).

The main variables of interest, $S_{i\tau}$, are the zip-code level shaking indicator variables. $S_{i0} = 1$ if zip-code i shook in the same calendar year, and $S_{i\tau,\tau=1,2,3} = 1$ if zip-code i shook in the calendar year that was τ year ago. For example, if zip-code i shook in 2005, then $S_{i0} = 1$ for the year 2005 and $S_{i0} = 0$ for all other years, and $S_{i2} = 1$ for the year 2007 and $S_{i2} = 0$ for all the other years, since 2007 was 2 years after the earthquake shaking in 2005.

[1] 1/10 of the minimum non-zero take-up rate

Table 9.4: Effects of Earthquakes on Take-Up Rate: Model Specification (1)

	(I)			(II)			(III)		
	Pooled OLS			Pooled WLS			Zip-code RE		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
log(TUR in Year 2005)	0.8944	0.0124	***	0.9072	0.0046	***	0.8974	0.0123	***
Shaking in the Current Year(S_0)	-0.0139	0.0094		-0.0173	0.0113		-0.0038	0.0081	
Shaking in Year t-1(S_1)	0.0555	0.0119	***	0.0466	0.0101	***	0.0132	0.0094	
Shaking in Year t-2(S_2)	-0.0059	0.0095		-0.0094	0.0091		-0.0162	0.0071	*
Shaking in Year t-3 (S_3)	0.0294	0.0142	*	0.0228	0.0140		0.0050	0.0102	
PGA	0.2730	0.0547	***	0.1918	0.0320	***	0.2781	0.0554	***
log(Median Home Value)	0.0064	0.0064		0.0343	0.0087	***	0.0075	0.0049	
Pop% with At Least College Degree	0.1981	0.0491	***	0.1213	0.0247	***	0.1951	0.0491	***
Territory by Year FE	X			X			X		
Zip-code RE							X		

Observations are 1585*3=4755 zip-years. Robust standard errors are reported here.
(III) vs. (I) BP Lagrange Multiplier test: Chisq=1556***. Reject (I)

X_i represents zip-code characteristics, such as objective risk level (PGA), median home value, and educational level. Alternatively, X_i can also be modeled as zip-code random effects or fixed effects.[2]

T_{tj} is a set of territory by year dummy variables. They control for territory fixed effects (or price effects), year effects, and the interaction effects between territory and year.[3] Specifically, the changes in territory-based prices over time could vary among territories, with some experiencing price increase while others experience price decrease.[4]

Table 9.4 shows the set of results for model (1), Table 9.5 shows the set of results for model (2), and Table 9.6 and Table 9.7 respectively present the results for models (3) and (4).

The coefficient of S_1 (shaking in year t-1) is generally positive, though the magnitude is economically small and the statistical significance is not very strong for all model specifications. The positive coefficient is consistent with the story that homeowners are slightly more likely to take

[2]Since in the model there are only 3 time periods, while there are 1583 cross-sectional zip-code observations, fixed-effects do not fit the data well.

[3]According to CEA's rating manuals, the boundaries of CEA territories underwent some changes in 2005, then have stayed almost unchanged till now. From 2005-2011, CEA updated its rates a couple times, with major changes to some territories.

[4]Alternative, I also try using a separate set of territory dummies and year dummies without interaction terms, or a more limited set of interaction terms based on the assumptions that only a couple territories experience different price changes from all the others. But statistical tests prefer the full set of interaction dummies to other models.

Table 9.5: Effects of Earthquakes on Take-Up Rate: Model Specification (2)

	(I)			(II)			(III)		
	Pooled OLS			Pooled WLS			Zip-code RE		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
log(TUR in Year t-2)	0.9409	0.0060	***	0.9485	0.0036	***	0.9329	0.0064	***
Shaking in the Current Year(S_0)	-0.0181	0.0080	*	-0.0198	0.0088	*	-0.0170	0.0081	*
Shaking in Year t-1(S_1)	0.0167	0.0082	*	0.0161	0.0078	*	0.0134	0.0083	
Shaking in Year t-2(S_2)	0.0003	0.0076		-0.0014	0.0070		-0.0009	0.0075	
PGA	0.1272	0.0270	***	0.0829	0.0249	***	0.1534	0.0282	***
Log(Median Home Value)	0.0054	0.0036		0.0166	0.0068	*	0.0058	0.0036	
Pop% with At Least College Degree	0.1063	0.0217	***	0.0663	0.0191	***	0.1261	0.0225	***
Territory by Year FE	X			X			X		
Zip-code RE							X		

Observations are 1585*3=4755 zip-years. Robust standard errors are reported here.
(III) vs. (I) BP Lagrange Multiplier test: Chisq=27.96***. Reject (1)

Table 9.6: Effects of Earthquakes on Take-Up Rate: Model Specification (3)

	(I)			(II)			(III)		
	Pooled OLS			Pooled WLS			Zip-code RE		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
TUR in Year 2005	0.8904	0.0149	***	0.927141	0.003057	***	0.8910	0.0148	***
Shaking in the Current Year(S_0)	-0.0024	0.0013	.	-0.00338	0.000736	***	-0.0010	0.0014	
Shaking in Year t-1(S_1)	0.0115	0.0016	***	0.007066	0.000663	***	0.0071	0.0013	***
Shaking in Year t-2(S_2)	-0.0025	0.0013	*	-0.00354	0.000608	***	-0.0035	0.0013	**
Shaking in Year t-3(S_3)	0.0064	0.0020	**	0.001446	0.000929		0.0036	0.0017	*
PGA	0.0210	0.0069	**	-0.00126	0.002317		0.0223	0.0070	**
Log(Median Home Value)	0.0000	0.0006		0.005609	0.000894	***	0.0005	0.0005	
Pop% with At Least College Degree	0.0124	0.0054	*	-0.00233	0.002252		0.0126	0.0054	*
Territory by Year FE	X			X			X		
Zip-code RE							X		

Observations are 1585*3=4755 zip-years. Robust standard errors are reported here.
(III) vs. (I) BP Lagrange Multiplier test: Chisq=965.971***. Reject (I)

Table 9.7: Effects of Earthquakes on Take-Up Rate: Model Specification (4)

	(I)			(II)		
	Pooled OLS			Pooled WLS		
	Estimate	Std. Error		Estimate	Std. Error	
TUR in Year t-2	0.9233	0.0100	***	0.9468	0.0024	***
Shaking in the Current Year(S_0)	-0.0037	0.0011	**	-0.0034	0.0006	***
Shaking in Year t-1(S_1)	0.0050	0.0010	***	0.0035	0.0005	***
Shaking in Year t-2(S_2)	-0.0001	0.0011		-0.0011	0.0005	***
PGA	0.0128	0.0041	**	-0.0001	0.0018	
Log(Median Home Value)	0.0000	0.0003		0.0040	0.0007	***
Pop% with At Least College Degree	0.0100	0.0032	**	-0.0021	0.0018	
Territory by Year FE	X			X		
Zip-code RE				X		

Observations are 4755 zip-years. Robust std err are reported.
***Random effects cannot be estimated due to negative variance

up earthquake insurance in the year following an earthquake. However, this positive effect is very short-lived: the coefficient of S_2 (shaking in year t-2) immediately becomes insignificant, and even the signs are inconsistent across different models. All of the coefficients for S_3 (shaking in year t-3) show inconsistency in signs as well. In equations (2) and (4), I only include two lags for the earthquake event indicators, and at the same time include the insurance take-up rate 2 years earlier to control for any prior insurance conditions. The results do not change much, with S_1 being the only consistent and slightly significant coefficients among all of the earthquake event indicators.

The same-calendar-year effects of an earthquake has no significant magnitudes. One possible explanation for not finding any significant positive effect here is that homeowners may not immediately update their earthquake insurance coverage. Earthquake insurance is typically bought as a rider to existing homeowner insurance. Technically, earthquake coverage can be obtained at any time, not just at the homeowner insurance policy's annual renewal. However, homeowners may still treat it as related to home insurance, and may not set out to update their earthquake coverage separately from home insurance, causing delays in take-up changes.

Based on the log equations (1) and (2), the coefficients of S_i (shaing in year $t-i$) are interpreted as percent change in the take-up rate. Take the magnitude of the S_1 coefficient as 0.02 for an example: it means that the earthquake insurance take-up rate increases by 2% on average in the year following a significant earthquake. Based on a prior median take-up rate of 10%, the take-up rate will only increase to a level of 10.2%. This is a very small magnitude compared to the change in demand with respect to the change in PGA (see discussions in Chapter 5: a 0.2 change in PGA results in a 70% increase in take-up rate, or, a change from 10% to 17%).

Based on the non-log equations (3) and (4), the coefficients of S_i (shaing in year $t-i$) are interpreted as additive changes in the take-up rate. A coefficient of 0.005, though statistically

Table 9.8: Effects of Earthquakes of Different Intensities on Take-Up Rate: Model Specification (1)

	(I) Pooled OLS			(II) Pooled WLS		
	Estimate	Std. Error		Estimate	Std. Error	
log(TUR in Year t-2)	0.8434	0.0228	***	0.8757	0.0062	***
Shaking (IV) in the current year (S0)	-0.0130	0.0084		-0.0098	0.0128	
Shaking (V) in the current year (S0)	0.0507	0.0183	**	0.0458	0.0245	*
Shaking (IV) in Year t-1 (S1)	-0.0007	0.0181		-0.0092	0.0263	
Shaking (V) in Year t-1 (S1)	0.0276	0.0195		0.0194	0.0119	
Shaking (IV) in Year t-2 (S2)	0.0111	0.0085		0.0073	0.0138	
Shaking (V) in Year t-2 (S2)	-0.0084	0.0145		-0.0091	0.0256	
PGA	0.4294	0.0733	***	0.3008	0.0472	***
log(Median Home Value)	0.0018	0.0068		0.0326	0.0134	*
Pop% with at least college degree	0.3735	0.0617	***	0.2374	0.0369	***
Territory by Year FE	X			X		
Zip-code RE						

Observations are 4755 zip-years. Robust std err are reported.
Random effects cannot be estimated due to negative variance

significant, only represents a 0.5 percentage point increase in take-up rate. Based on a prior median take-up rate of 10%, the take-up rate will only increase to around 10.5%. This is a slightly bigger magnitude than those obtained in the log model, but still economically small, especially when compared to how responsive take-up rate is to PGA.

9.3 Regression Results on Different Shaking Intensities

The previous section estimates demand changes from experiencing any significant earthquakes with intensity higher than or equal to IV. A further examination of my shaking dataset shows that most of time zip-codes experienced intensity IV shakings (79%), and it is very rare that zip-codes experience intensity of VI or above shakings (3%). So in this section, I further divide the intensities into two intervals: intensity IV or above intensity IV.

Table 9.8 shows the set of results for model (1), and Table 9.9 shows the set of results for model (2).

It is quite obvious that shakings with an intensity V or above have larger impacts on insurance

Table 9.9: Effects of Earthquakes of Different Intensities on Take-Up Rate: Model Specification (2)

	(I) Pooled OLS			(II) Pooled WLS			(III) Zip-code RE		
	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
log(TUR in Year 2005)	0.8211	0.0372	***	0.8601	0.0069	***	0.8237	0.0369	***
Shaking (IV) in the current year (S0)	-0.0256	0.0107	*	-0.0170	0.0142		0.0025	0.0103	
Shaking (V) in the current year (S0)	0.0664	0.0228	**	0.0601	0.0270	*	0.0330	0.0192	.
Shaking (IV) in Year t-1 (S1)	0.0119	0.0191		-0.0042	0.0289		0.0034	0.0156	
Shaking (V) in Year t-1 (S1)	0.0473	0.0218	*	0.0309	0.0154	*	0.0423	0.0179	*
Shaking (IV) in Year t-2 (S2)	-0.0019	0.0101		-0.0073	0.0153		-0.0110	0.0098	
Shaking (V) in Year t-2 (S2)	0.0013	0.0173		0.0014	0.0283		-0.0094	0.0165	
Shaking (IV) in Year t-3 (S3)	0.0439	0.0190	*	0.0257	0.0232		0.0066	0.0138	
Shaking (V) in Year t-3 (S3)	0.0890	0.0197	***	0.0757	0.0343	*	0.0628	0.0162	***
PGA	0.5363	0.1031	***	0.3704	0.0520	***	0.5380	0.1035	***
log(Median Home Value)	-0.0046	0.0089		0.0499	0.0147	***	-0.0125	0.0088	
Pop% with at least college degree	0.4398	0.0936	***	0.2516	0.0408	***	0.4387	0.0940	***
Territory by Year FE	X			X			X		
Zip-code RE							X		

Observations are 4755 zip-years. Robust std err are reported.

take-up rates than shakings with an intensity of IV. In fact, an intensity V or above shaking in the current year now has a positive impact on the earthquake insurance take-up rate, with a magnitude of about 5%. An intensity V or above shaking in the previous year also has bigger impact on the insurance take-up, compared to the intensity IV shakings. Nonetheless, any effects disappear after the first year.

9.4 Conclusion

This chapter explores the potential effects of shaking experiences on demand for earthquake insurance. Risk perception has been found to affect disaster insurance adoption in prior literature, but how big a role experiences play in shaping and changing individuals' perception of risk remains unclear, as most earlier studies elicit risk perception based on survey questions. Recent literature on flood insurance demand has used flood losses to proxy risk perception, and find significant, though diminishing, effects over time. This study is the first to investigate shaking experience exclusively as a potential impact factor for insurance demand, controlling for other variables, including probabilistic seismic risk measures.

The residual effects from shaking experience (other than the effects of probabilistic seismic risk measures) seem small. I only find the coefficients of the 1-year-prior shaking indicator variables to be positive, with marginal significance. Shaking events that happened more than one year ago do not seem to have any leftover effect on the insurance take-up rate. Stronger shakings seem to have large effects, and strong shakings in the current year or the previous year both increase the take-up of earthquake insurance.

This result suggests that homeowners in California do not appear to be very sensitive to personal earthquake experiences. Even if they are, their experiences seem to lose importance very quickly. Possible reasons for such insensitivity may be that homeowners form their perceptions of earthquake risks mainly based on the relatively constant seismic risk levels assigned to each region, or that the earthquakes used in this study were not significant enough to have a meaningful impact on individual insurance adoption behaviors.

Chapter 10

Conclusion and Discussion

In this study I provide insights into the demand for catastrophe insurance by looking at a unique catastrophe insurance market. I first discuss insurers' geographic pricing schemes for seismic risk, then investigate a range of issues related to the demand for residential earthquake insurance by homeowners.

I come to four empirical conclusions. First, regarding geographic risk classification: the public insurer CEA offers cross-subsidized rates, while the private insurers seem to use finer geographic pricing schemes. Secondly, on the demand for the cross-subsidized CEA earthquake policies, I find a classic adverse selection phenomenon: individuals living in areas with higher objective seismic risk (PGA) are more likely to purchase CEA insurance policies, provided everything else is the same. Thirdly, as to the comparison of demand for CEA and private insurance, my results show that, on average, finer pricing by the private insurers mitigates the positive risk-demand correlation, but the magnitude is relatively small and the difference in demand patterns does not always go in the direction expected. Lastly, as to whether the demand for earthquake insurance is affected by recent, non-destructive earthquakes, I do not find any strong effects. Demand only increases slightly in the year after an earthquake, and the magnitude of change is very small compared to the change in demand with respect to different seismic risk levels as measured by PGA.

There are a few avenues for future research. First, I have not investigated whether the heterogeneity in demand responses to public vs. private insurers is related to the degree to which private insurers differentiate themselves from the CEA. It would be interesting to know the geographic variation of price differences between CEA and private insurers in greater details. This would allow testing of whether a greater difference results in more sorting of homeowners (low-risks go to private insurers, and the high-risks go to the CEA).

Second, the adverse selection phenomenon and demand patterns documented in this study are only a snapshot in time. When the panel data extends a few more years, we can observe if the current market equilibrium is relatively static or if the adverse selection will worsen due to more and more lower-risk people dropping out of earthquake coverage from the CEA, or altogether.

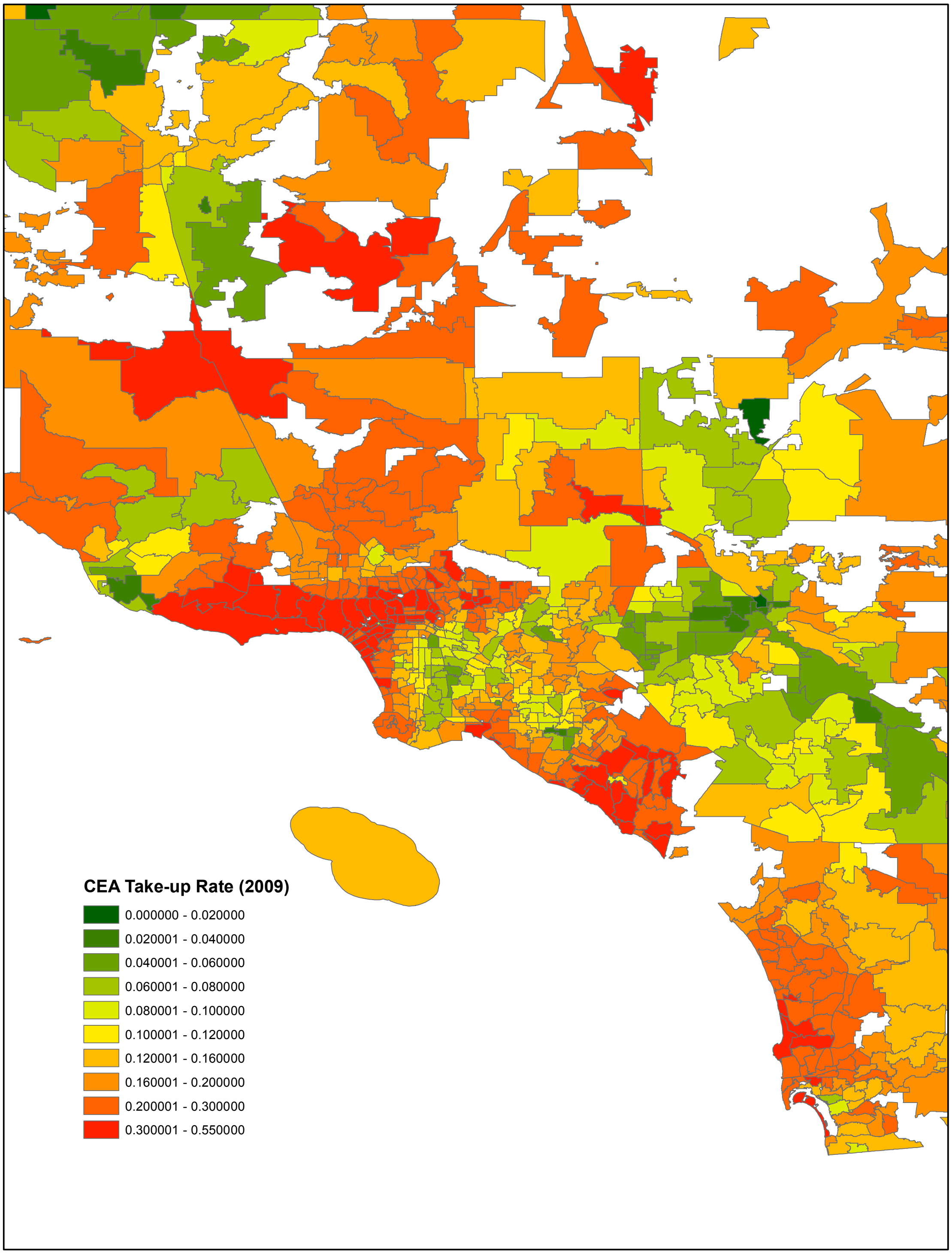
Another future research possibility would be to incorporate spatial models into the analysis of the effects of earthquake experience. So far I have only used dummy variables to represent whether or not an area was hit by an earthquake. I have not considered the difference between being close to the epicenter and being in the periphery of an earthquake. Some kind of distance measure may enable better indentification of changes in demand with respect to exposure to strong earthquakes.

Lastly, if I had a more selective set of (stronger) earthquakes, or more frequent observations of demand for earthquake insurance (such as quarterly or monthly take-up rate), it would be possible to pick up effects from earthquakes that are not observed in the current dataset. Weaker earthquakes may have diluted impacts from disaster experience, and some possible short-term impacts may also have been unseen due to the long breaks in the current panel dataset.

Chapter 11

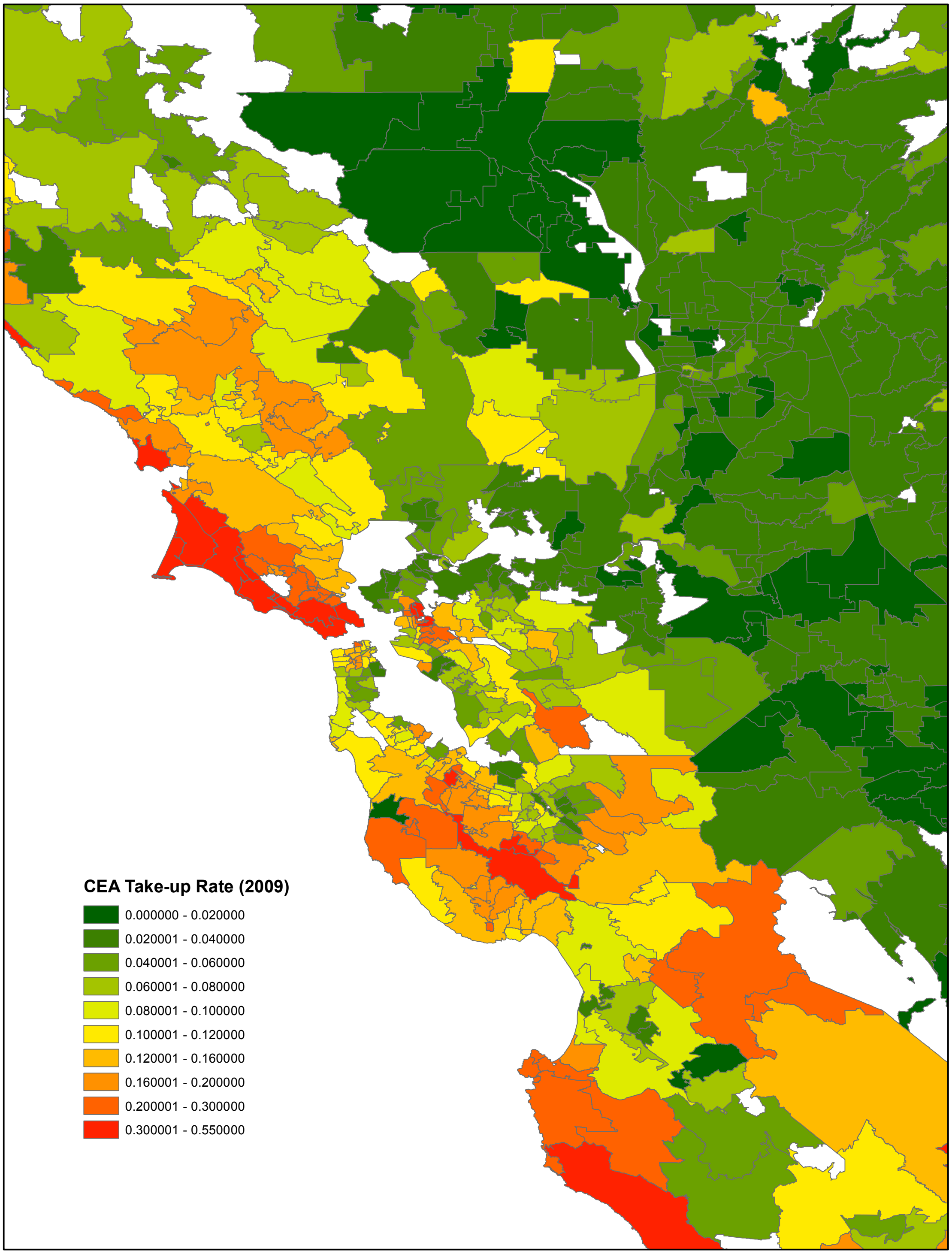
Appendices to Chapter 6 Demand for CEA Earthquake Insurance

Figure 11.1: CEA Take-up Rates in the Greater Los Angeles Area.



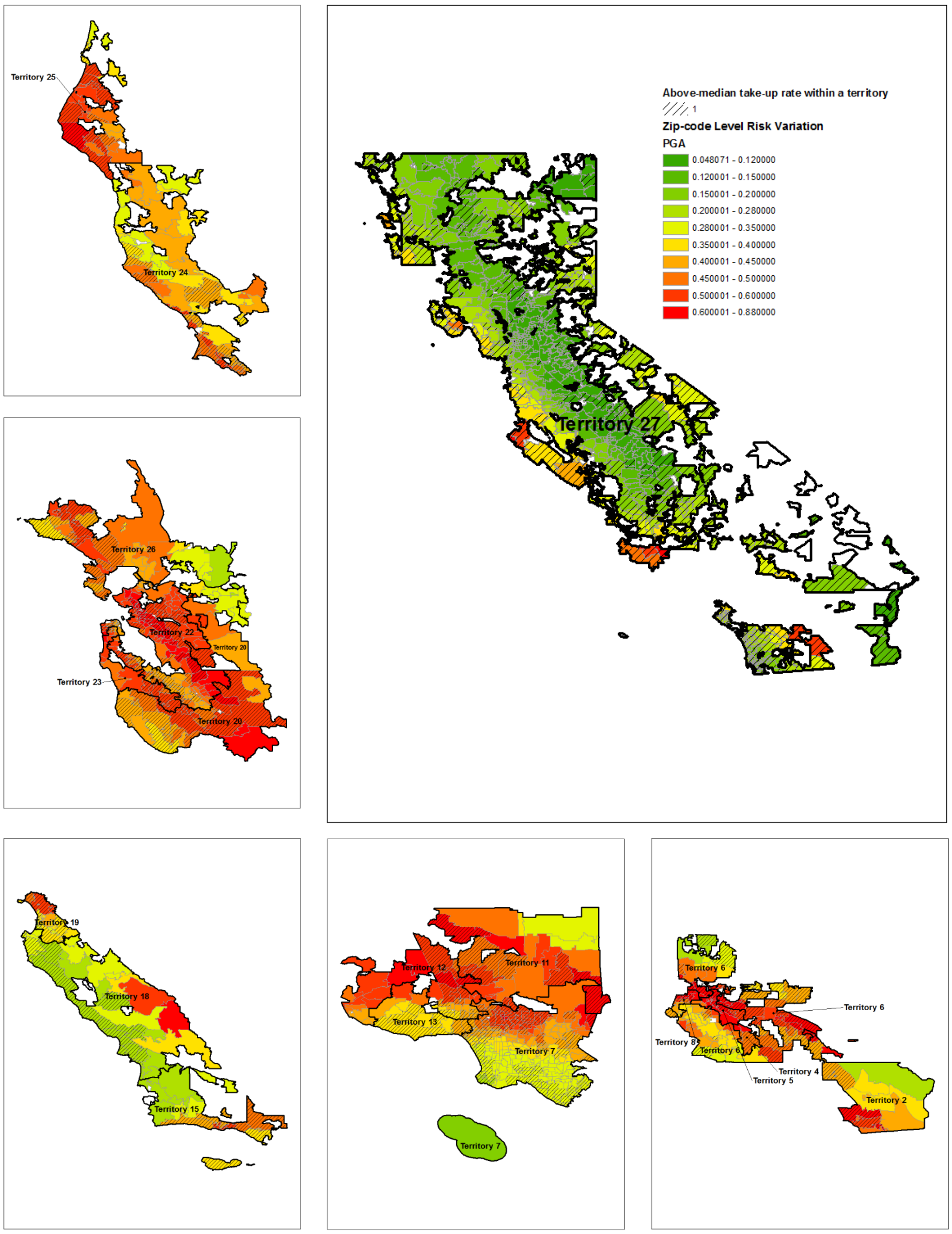
This is a zoom-in map from Figure 6.1.

Figure 11.2: CEA Take-up Rates in the San Francisco Bay Area.



This is a zoom-in map from Figure 6.1.

Figure 11.3: CEA Take-up Rate vs. PGA Correlation Maps.



Hatched areas represent above median take-up rate in that territory. PGA (the risk level) is defined by color ramp from green (lowest risk) to red (higher risk). Territory 27 almost occupies an entire map since it's the largest territory. Other territories are grouped into 5 remaining maps by their geographical vicinity.

Table 11.1: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate as Dependent Variable and Include Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.8418	0.0407	***	0.7279	0.0277	***	0.7362	0.0276	***
Log (Median Home Value)				0.0769	0.0063	***	0.0586	0.0066	***
Log (Median Household Income)				-0.0794	0.0063	***	-0.0392	0.0081	***
Pop% with At Least College Degree				0.2977	0.0153	***	0.2425	0.0196	***
Median Household Size							-0.0293	0.0057	***
Gender (female%)							-0.2835	0.0631	***
Median Age							0.0003	0.0004	
Pop% of Black or African American							-0.0095	0.0182	
Pop% of Asian							-0.0222	0.0132	.
Pop% of ther Races							0.0649	0.0315	*
Household with Children							-0.0380	0.0308	
Log (Population Per Square Mile)							0.0084	0.0012	***
Territory 2*PGA	0.3736	0.2182	.	0.2687	0.1449	.	0.1873	0.1401	
Territory 4*PGA	-0.1289	0.4959		0.0487	0.3289		0.0461	0.3174	
Territory 5*PGA	0.1244	0.2276		0.0164	0.1511		0.0207	0.1461	
Territory 6*PGA	0.2004	0.0595	***	0.1853	0.0395	***	0.1611	0.0383	***
Territory 7*PGA	0.2938	0.0438	***	0.2346	0.0292	***	0.2488	0.0284	***
Territory 8*PGA	0.0582	0.1248		-0.0400	0.0829		-0.0023	0.0802	
Territory 11*PGA	0.2739	0.1418	.	0.0680	0.0945		0.0315	0.0916	
Territory 12*PGA	-0.0045	0.1309		0.2024	0.0871	*	0.2470	0.0844	**
Territory 13*PGA	-0.1982	0.2395		0.2786	0.1592	.	0.2645	0.1539	.
Territory 15*PGA	0.7485	0.1176	***	0.3219	0.0788	***	0.3094	0.0761	***
Territory 18*PGA	-0.3619	0.2756		-0.2615	0.1827		-0.2145	0.1767	
Territory 19*PGA	0.1878	0.2484		0.1253	0.1648		0.1852	0.1592	
Territory 20*PGA	0.5302	0.1023	***	0.1471	0.0685	*	0.2249	0.0671	***
Territory 22*PGA	0.1587	0.0625	*	0.1902	0.0415	***	0.2367	0.0409	***
Territory 23*PGA	0.0249	0.2716		0.1798	0.1801		0.3666	0.1754	*
Territory 24*PGA	1.6739	0.3619	***	0.9085	0.2406	***	0.9202	0.2326	***
Territory 25*PGA	-0.1614	0.6119		-0.0248	0.4056		-0.1420	0.3914	
Territory 26*PGA	0.3978	0.1636	*	0.1813	0.1086	.	0.1842	0.1055	.
Territory 2	-0.1075	0.1243		-0.0113	0.0826		0.0450	0.0801	
Territory 4	0.1654	0.2748		0.1228	0.1823		0.1244	0.1759	
Territory 5	0.0237	0.1376		0.1083	0.0913		0.1122	0.0883	.
Territory 6	0.0790	0.0285	**	0.0948	0.0190	***	0.1051	0.0184	***
Territory 7	0.1083	0.0194	***	0.0643	0.0134	***	0.0598	0.0132	***
Territory 8	0.0777	0.0718		0.1279	0.0477	**	0.1041	0.0462	*
Territory 11	0.1117	0.0722		0.2112	0.0480	***	0.2374	0.0466	***
Territory 12	0.2196	0.0644	***	0.0647	0.0430		0.0419	0.0418	
Territory 13	0.4295	0.1008	***	0.1296	0.0671	.	0.1417	0.0649	*
Territory 15	-0.0142	0.0469		0.0744	0.0311	*	0.0912	0.0302	**
Territory 18	0.3900	0.0751	***	0.2924	0.0500	***	0.2898	0.0482	***
Territory 19	0.0467	0.1068		0.0345	0.0708		0.0141	0.0684	
Territory 20	-0.0820	0.0469	.	0.0302	0.0312		0.0035	0.0304	
Territory 22	0.0502	0.0353		-0.0633	0.0239	**	-0.0870	0.0237	***
Territory 23	0.1542	0.1438		-0.0525	0.0955		-0.1466	0.0931	
Territory 24	-0.4746	0.1529	**	-0.2666	0.1016	**	-0.2579	0.0982	**
Territory 25	0.2601	0.3304		0.1408	0.2191		0.2124	0.2115	
Territory 26	-0.0476	0.0754		0.0063	0.0500		0.0056	0.0487	
(Intercept)	-0.0442	0.0079	***	-0.2076	0.0849	*	-0.2393	0.1017	*
Observations	1636			1636			1636		
Adjusted R-squared	0.426			0.7479			0.7657		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 11.2: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate as Dependent Variable and Include Premium-Risk Interaction Terms)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
PGA*Ln(Premium Rate)	-0.4788	0.0577	***	-0.4390	0.0767	***	-0.4340	0.0591	***
PGA	0.4422	0.0319	***	0.3560	0.0384	***	0.3957	0.0329	***
Log (Premium Rate)	0.0717	0.0217	***	0.0646	0.0212	**	0.0607	0.0200	**
Log (Median Home Value)				0.0274	0.0338		0.0128	0.0258	
Log (Median Household Income)				-0.0631	0.0232	**	-0.0612	0.0248	*
Pop% with At Least College Degree				0.3180	0.0778	***	0.3149	0.0462	***
Median Household Size							0.0217	0.0231	
Gender (female%)							-0.2580	0.1074	*
Median Age							-0.0010	0.0010	
Pop% of Black or African American							-0.0268	0.0288	
Pop% of Asian							-0.1681	0.0419	***
Pop% of other races							-0.2076	0.0926	*
Household with Children							-0.1332	0.0682	.
Log (Population Per Square Mile)							0.0106	0.0024	***
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.2998			0.5765			0.62		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight. Standard errors are clustered at the territory level. Significance:*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Table 11.3: Demand for CEA Earthquake Insurance (Use CEA Coverage A Share as Dependent Variable)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.4446	0.0238	***	0.3528	0.0163	***	0.3585	0.0162	***
Log (Median Home Value)				0.0986	0.0069	***	0.0797	0.0073	***
Log (Median Household Income)				-0.0778	0.0070	***	-0.0300	0.0090	***
Pop% with At Least College Degree				0.2712	0.0169	***	0.2415	0.0219	***
Median Household Size							-0.0341	0.0064	***
Gender (female%)							-0.3751	0.0707	***
Median Age							0.0003	0.0005	
Pop% of Black or African American							0.0027	0.0202	
Pop% of Asian							-0.0237	0.0148	
Pop% of other races							0.1438	0.0349	***
Household with Children							-0.0376	0.0347	
Log (Population Per Square Mile)							0.0069	0.0013	***
Territory Fixed Effects	X			X			X		
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.3588			0.7062			0.725		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Table 11.4: Demand for CEA Earthquake Insurance (Use CEA Coverage A Share as Dependent Variable and Include Territory-Risk Interaction Terms)

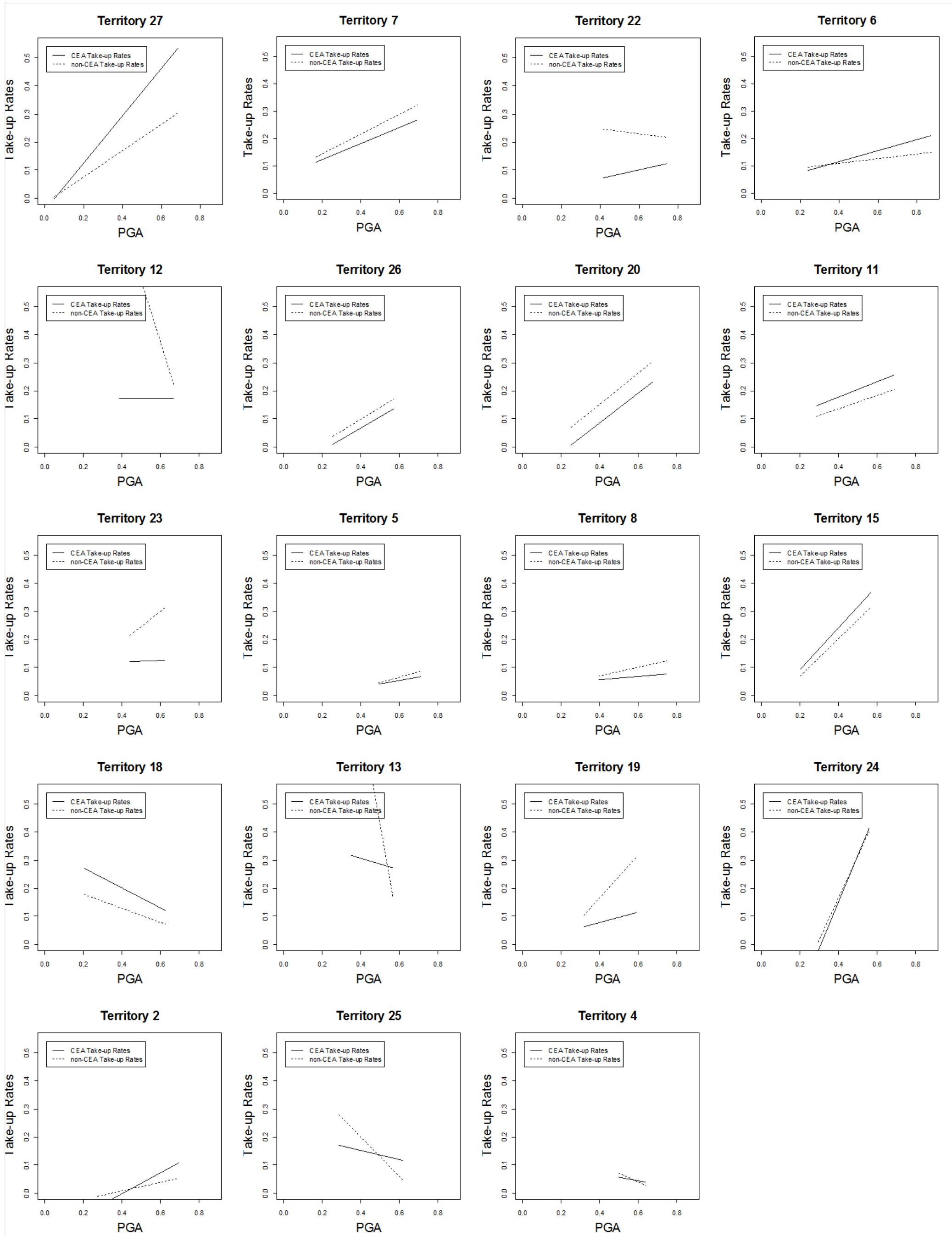
	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.8792	0.0425	***	0.7560	0.0288	***	0.7602	0.0288	***
Log (Median Home Value)				0.0840	0.0066	***	0.0642	0.0069	***
Log (Median Household Income)				-0.0819	0.0066	***	-0.0402	0.0084	***
Pop% with At Least College Degree				0.3029	0.0159	***	0.2614	0.0204	***
Median Household Size							-0.0270	0.0060	***
Gender (female%)							-0.2831	0.0658	***
Median Age							0.0003	0.0005	
Pop% of Black or African American							-0.0105	0.0190	
Pop% of Asian							-0.0279	0.0138	*
Pop% of other races							0.0863	0.0328	**
Household with Children							-0.0639	0.0321	*
Log (Population Per Square Mile)							0.0080	0.0012	***
Territory 2*PGA	0.3647	0.2279		0.2492	0.1506	.	0.1732	0.1461	
Territory 4*PGA	-0.1669	0.5180		0.0142	0.3418		0.0061	0.3309	
Territory 5*PGA	0.1393	0.2378		0.0303	0.1570		0.0430	0.1523	
Territory 6*PGA	0.2118	0.0621	***	0.1966	0.0410	***	0.1688	0.0399	***
Territory 7*PGA	0.3104	0.0458	***	0.2492	0.0304	***	0.2611	0.0296	***
Territory 8*PGA	0.0405	0.1303		-0.0635	0.0862		-0.0255	0.0836	
Territory 11*PGA	0.2788	0.1482	.	0.0571	0.0983		0.0149	0.0955	
Territory 12*PGA	0.0127	0.1367		0.2276	0.0906	*	0.2735	0.0880	**
Territory 13*PGA	-0.2627	0.2502		0.2327	0.1655		0.2215	0.1604	
Territory 15*PGA	0.8090	0.1228	***	0.3578	0.0819	***	0.3435	0.0793	***
Territory 18*PGA	-0.3590	0.2879		-0.2540	0.1899		-0.2134	0.1842	
Territory 19*PGA	0.2554	0.2595		0.1856	0.1713		0.2332	0.1659	
Territory 20*PGA	0.5533	0.1068	***	0.1485	0.0712	*	0.2176	0.0700	**
Territory 22*PGA	0.1731	0.0653	**	0.2080	0.0432	***	0.2528	0.0426	***
Territory 23*PGA	0.0188	0.2837		0.1810	0.1872		0.3769	0.1828	*
Territory 24*PGA	1.6764	0.3780	***	0.8737	0.2501	***	0.8731	0.2425	***
Territory 25*PGA	-0.1529	0.6392		-0.0072	0.4216		-0.1194	0.4080	
Territory 26*PGA	0.4298	0.1709	*	0.1995	0.1129	.	0.2059	0.1100	.
Territory 2	-0.0966	0.1299		0.0079	0.0859		0.0577	0.0835	
Territory 4	0.1930	0.2871		0.1521	0.1894		0.1557	0.1833	
Territory 5	0.0212	0.1437		0.1070	0.0949		0.1039	0.0921	
Territory 6	0.0791	0.0298	**	0.0946	0.0197	***	0.1052	0.0192	***
Territory 7	0.1106	0.0203	***	0.0622	0.0139	***	0.0575	0.0138	***
Territory 8	0.0923	0.0750		0.1438	0.0495	**	0.1187	0.0481	*
Territory 11	0.1117	0.0754		0.2179	0.0499	***	0.2457	0.0485	***
Territory 12	0.2174	0.0672	**	0.0540	0.0447		0.0293	0.0435	
Territory 13	0.4778	0.1053	***	0.1633	0.0698	*	0.1727	0.0677	*
Territory 15	-0.0188	0.0489		0.0734	0.0324	*	0.0886	0.0315	**
Territory 18	0.4014	0.0785	***	0.2973	0.0519	***	0.2943	0.0503	***
Territory 19	0.0245	0.1116		0.0113	0.0736		-0.0066	0.0713	
Territory 20	-0.0870	0.0490	.	0.0299	0.0325		0.0060	0.0317	
Territory 22	0.0473	0.0369		-0.0745	0.0249	**	-0.0976	0.0247	***
Territory 23	0.1650	0.1502		-0.0536	0.0993		-0.1538	0.0970	
Territory 24	-0.4666	0.1597	**	-0.2501	0.1056	*	-0.2384	0.1024	*
Territory 25	0.2613	0.3451		0.1346	0.2277		0.2037	0.2204	
Territory 26	-0.0559	0.0788		0.0005	0.0520		-0.0027	0.0508	
(Intercept)	-0.0457	0.0083	***	-0.2724	0.0883	**	-0.2998	0.1060	**
Observations	1636			1636			1636		
Adjusted R-squared	0.4264			0.7506			0.7669		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Chapter 12

Appendices to Chapter 7 Comparison of Demand for CEA and Private Earthquake Insurance

Figure 12.1: Comparison of Demand for CEA and non-CEA by Territory.



Y-axis is take-up rate, x-axis is PGA. The solid line is the best fitted line for the risk-demand relationship of the CEA. The dashed line is the best fitted line for the risk-demand relationship of the non-CEA insurers.)

Table 12.1: Relative Demand for CEA Earthquake Insurance (Use CEA EQ Share as Dependent Variable and Include Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.3646	0.0545	***	0.3610	0.0551	***	0.3390	0.0552	***
CEA PIs' HO market share	0.8692	0.0392	***	0.8752	0.0398	***	0.9427	0.0405	***
Log (Median Home Value)				0.0111	0.0129		0.0280	0.0133	*
Log (Median Household Income)				0.0288	0.0126	*	0.0287	0.0162	.
Pop% with At Least College Degree				-0.1553	0.0307	***	-0.1813	0.0396	***
Median Household Size							-0.0051	0.0114	
Gender (female%)							-0.1775	0.1258	
Median Age							-0.0033	0.0009	***
Pop% of Black or African American							0.1354	0.0366	***
Pop% of Asian							0.0814	0.0264	**
Pop% of other races							-0.1100	0.0630	.
Household with Children							0.0560	0.0614	
Log (Population Per Square Mile)							0.0059	0.0023	**
Territory 2*PGA	1.1634	0.2913	***	1.1457	0.2884	***	1.0250	0.2793	***
Territory 4*PGA	0.8273	0.6625		0.7468	0.6550		0.6411	0.6328	
Territory 5*PGA	0.1994	0.3042		0.2571	0.3011		0.1225	0.2916	
Territory 6*PGA	0.3020	0.0798	***	0.3089	0.0789	***	0.3238	0.0767	***
Territory 7*PGA	-0.0230	0.0586		-0.0027	0.0582		0.0244	0.0567	
Territory 8*PGA	-0.1711	0.1667		-0.1507	0.1652		-0.1482	0.1600	
Territory 11*PGA	-0.0119	0.1897		-0.0091	0.1883		0.0275	0.1827	
Territory 12*PGA	1.4651	0.1747	***	1.3987	0.1734	***	1.4245	0.1682	***
Territory 13*PGA	1.8515	0.3198	***	1.6934	0.3170	***	1.6209	0.3068	***
Territory 15*PGA	-0.1356	0.1569		-0.0613	0.1569		-0.0687	0.1517	
Territory 18*PGA	0.0543	0.3680		0.0274	0.3638		0.0484	0.3524	
Territory 19*PGA	-0.8381	0.3316	*	-0.8599	0.3279	**	-0.7581	0.3172	*
Territory 20*PGA	0.7262	0.1370	***	0.7958	0.1365	***	0.8442	0.1341	***
Territory 22*PGA	0.3961	0.0836	***	0.4045	0.0827	***	0.4065	0.0815	***
Territory 23*PGA	-0.5631	0.3626		-0.6025	0.3585	.	-0.6115	0.3495	.
Territory 24*PGA	0.6308	0.4831		0.8303	0.4788	.	0.8105	0.4637	.
Territory 25*PGA	0.9794	0.8169		0.9683	0.8072		0.8317	0.7801	
Territory 26*PGA	0.1156	0.2184		0.1412	0.2162		0.1551	0.2103	
Territory 2	-0.4429	0.1663	**	-0.4381	0.1646	**	-0.3419	0.1598	*
Territory 4	-0.4116	0.3672		-0.3730	0.3631		-0.3008	0.3507	
Territory 5	-0.0296	0.1839		-0.0719	0.1820		-0.0041	0.1763	
Territory 6	-0.0808	0.0383	*	-0.0926	0.0380	*	-0.0989	0.0368	**
Territory 7	-0.0560	0.0264	*	-0.0651	0.0268	*	-0.1109	0.0268	***
Territory 8	0.1227	0.0960		0.0974	0.0950		0.0700	0.0922	
Territory 11	0.0187	0.0965		0.0088	0.0955		-0.0219	0.0928	
Territory 12	-0.7611	0.0860	***	-0.7320	0.0855	***	-0.7629	0.0833	***
Territory 13	-0.7338	0.1347	***	-0.6587	0.1337	***	-0.6349	0.1296	***
Territory 15	0.0681	0.0626		0.0398	0.0620		0.0492	0.0603	
Territory 18	0.0286	0.1003		0.0368	0.0995		0.0493	0.0962	
Territory 19	0.3360	0.1427	*	0.3353	0.1409	*	0.2890	0.1364	*
Territory 20	-0.3533	0.0627	***	-0.3872	0.0622	***	-0.4259	0.0606	***
Territory 22	-0.2631	0.0479	***	-0.2588	0.0481	***	-0.3020	0.0478	***
Territory 23	0.2835	0.1921		0.3176	0.1901	.	0.2835	0.1856	
Territory 24	-0.1848	0.2041		-0.2548	0.2022		-0.2205	0.1958	
Territory 25	-0.4625	0.4411		-0.4487	0.4359		-0.3684	0.4215	
Territory 26	-0.0810	0.1007		-0.0957	0.0995		-0.1096	0.0971	
(Intercept)	0.3454	0.0283	***	-0.0721	0.1691		-0.1567	0.2033	
Observations	1636			1636			1636		
Adjusted R-squared	0.3367			0.3525			0.3966		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 12.2: Relative Demand for CEA Earthquake Insurance (Use CEA EQ Cov A Share as Dependent Variable)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.4446	0.0238	***	0.3528	0.0163	***	0.3585	0.0162	***
Log (Median Home Value)				0.0986	0.0069	***	0.0797	0.0073	***
Log (Median Household Income)				-0.0778	0.0070	***	-0.0300	0.0090	***
Pop% with At Least College Degree				0.2712	0.0169	***	0.2415	0.0219	***
Median Household Size							-0.0341	0.0064	***
Gender (female%)							-0.3751	0.0707	***
Median Age							0.0003	0.0005	
Pop% of Black or African American							0.0027	0.0202	
Pop% of Asian							-0.0237	0.0148	
Pop% of other races							0.1438	0.0349	***
Household with Children							-0.0376	0.0347	
Log (Population Per Square Mile)							0.0069	0.0013	***
Territory Fixed Effects	X			X			X		
(Intercept)	X			X			X		
Observations	1636			1636			1636		
Adjusted R-squared	0.3588			0.7062			0.725		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 12.3: Relative Demand for CEA Earthquake Insurance (Use CEA EQ Cov A Share as Dependent Variable with Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.4572	0.0685	***	0.4823	0.0696	***	0.4290	0.0693	***
Log (Median Home Value)				-0.0427	0.0159	**	-0.0079	0.0165	
Log (Median Household Income)				0.0678	0.0159	***	0.0487	0.0203	*
Pop% with At Least College Degree				-0.0882	0.0386	*	-0.0344	0.0491	
Median Household Size							0.0200	0.0144	
Gender (female%)							-0.0490	0.1583	
Median Age							-0.0041	0.0011	***
Pop% of Black or African American							0.2250	0.0457	***
Pop% of Asian							0.0223	0.0332	
Pop% of other races							-0.1109	0.0789	
Household with Children							0.0790	0.0773	
Log (Population Per Square Mile)							0.0038	0.0029	
Territory 2*PGA	1.1930	0.3672	**	1.1746	0.3646	**	1.0572	0.3514	**
Territory 4*PGA	1.2399	0.8348		1.1232	0.8274		0.8638	0.7960	
Territory 5*PGA	-0.1803	0.3832		-0.1043	0.3802		-0.2290	0.3663	
Territory 6*PGA	0.1857	0.1001	.	0.2015	0.0993	*	0.2450	0.0959	*
Territory 7*PGA	-0.0693	0.0738		-0.0325	0.0735		0.0177	0.0713	
Territory 8*PGA	-0.1686	0.2100		-0.1883	0.2087		-0.2262	0.2012	
Territory 11*PGA	-0.0419	0.2387		-0.0124	0.2379		0.0763	0.2297	
Territory 12*PGA	1.1094	0.2203	***	1.0011	0.2192	***	1.0433	0.2116	***
Territory 13*PGA	1.1269	0.4032	**	0.9800	0.4006	*	0.9011	0.3859	*
Territory 15*PGA	-0.2094	0.1979		-0.0609	0.1984		-0.0895	0.1908	
Territory 18*PGA	-0.0599	0.4639		-0.1306	0.4598		-0.1424	0.4431	
Territory 19*PGA	-0.9045	0.4182	*	-0.8777	0.4146	*	-0.8144	0.3992	*
Territory 20*PGA	0.6653	0.1722	***	0.7746	0.1723	***	0.8161	0.1684	***
Territory 22*PGA	0.4227	0.1052	***	0.4163	0.1045	***	0.3885	0.1025	***
Territory 23*PGA	-0.5320	0.4572		-0.6210	0.4532		-0.5586	0.4399	
Territory 24*PGA	0.6780	0.6092		0.8167	0.6053		0.6852	0.5834	
Territory 25*PGA	1.0225	1.0300		0.9466	1.0205		0.8353	0.9816	
Territory 26*PGA	0.0894	0.2754		0.1627	0.2734	.	0.1664	0.2646	
Territory 2	-0.3635	0.2093	.	-0.3646	0.2079	.	-0.3000	0.2008	
Territory 4	-0.6905	0.4626		-0.6442	0.4586		-0.4875	0.4411	
Territory 5	0.0465	0.2316		-0.0043	0.2298		0.0317	0.2215	
Territory 6	-0.0593	0.0479		-0.0740	0.0478		-0.1042	0.0461	*
Territory 7	-0.0429	0.0327		-0.0337	0.0336		-0.0928	0.0331	**
Territory 8	-0.0413	0.1208		-0.0366	0.1199		-0.0568	0.1158	
Territory 11	0.0940	0.1215	.	0.0728	0.1207		0.0000	0.1167	
Territory 12	-0.9737	0.1083	***	-0.9048	0.1081	***	-0.9518	0.1047	***
Territory 13	-0.7841	0.1696	***	-0.7047	0.1689	***	-0.6924	0.1628	***
Territory 15	0.1070	0.0789		0.0780	0.0783		0.0825	0.0757	
Territory 18	0.1134	0.1265		0.1591	0.1258		0.1744	0.1210	
Territory 19	0.1962	0.1798		0.2015	0.1781		0.1608	0.1715	
Territory 20	-0.4719	0.0790	***	-0.5125	0.0786	***	-0.5573	0.0762	***
Territory 22	-0.5389	0.0595	***	-0.5100	0.0602	***	-0.5384	0.0593	***
Territory 23	0.0845	0.2421		0.1613	0.2403		0.0936	0.2334	
Territory 24	-0.3493	0.2574		-0.3698	0.2556		-0.2978	0.2463	
Territory 25	-0.5247	0.5562		-0.4564	0.5512		-0.3834	0.5304	
Territory 26	-0.1591	0.1270		-0.1803	0.1258		-0.1911	0.1222	
(Intercept)	1.0135	0.0133	***	0.8283	0.2137	***	0.6567	0.2550	*
Observations	1636			1636			1636		
Adjusted R-squared	0.6299			0.6368			0.6647		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight

Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 12.4: Relative Demand for CEA Earthquake Insurance (Use Alternative CEA Share as Dependent Variable)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.2173	0.0337	***	0.2503	0.0335	***	0.2544	0.0327	***
Log (Median Home Value)				-0.0493	0.0142	***	-0.0177	0.0147	
Log (Median Household Income)				0.0761	0.0143	***	0.0706	0.0182	***
Pop% with At Least College Degree				-0.1268	0.0347	***	-0.1168	0.0442	**
Median Household Size							-0.0045	0.0129	
Gender (female%)							-0.1878	0.1429	
Median Age							-0.0039	0.0010	***
Pop% of Black or African American							0.1974	0.0408	***
Pop% of Asian							0.0448	0.0299	
Pop% of other races							-0.0759	0.0704	
Household with Children							0.1430	0.0701	*
Log (Population Per Square Mile)							0.0051	0.0026	*
Territory Fixed Effects	0.1051	0.0400	**	0.0705	0.0397	.	0.0810	0.0382	*
(Intercept)	-0.1706	0.0519	**	-0.2132	0.0516	***	-0.1911	0.0495	***
Observations	1636			1636			1636		
Adjusted R-squared	0.5883			0.6051			0.6403		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 12.5: Relative Demand for CEA Earthquake Insurance (Use Alternative CEA Share as Dependent Variable with Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.3739	0.0621	***	0.4223	0.0625	***	0.3753	0.0619	***
Log (Median Home Value)				-0.0544	0.0143	***	-0.0226	0.0148	
Log (Median Household Income)				0.0621	0.0143	***	0.0563	0.0181	**
Pop% with At Least College Degree				-0.0957	0.0347	**	-0.0967	0.0439	*
Median Household Size							-0.0022	0.0129	
Gender (female%)							-0.1314	0.1415	
Median Age							-0.0038	0.0010	***
Pop% of Black or African American							0.1849	0.0408	***
Pop% of Asian							0.0442	0.0296	
Pop% of other races							-0.0945	0.0705	
Household with Children							0.1326	0.0690	
Log (Population Per Square Mile)							0.0056	0.0026	*
Territory 2*PGA	1.4657	0.3330	***	1.4836	0.3274	***	1.3533	0.3140	***
Territory 4*PGA	1.2347	0.7569		1.1275	0.7430		0.8847	0.7112	
Territory 5*PGA	-0.0387	0.3474		0.0276	0.3414		-0.1016	0.3273	
Territory 6*PGA	0.1878	0.0908	*	0.2010	0.0892	*	0.2411	0.0857	**
Territory 7*PGA	-0.0700	0.0669		-0.0338	0.0660		0.0160	0.0637	
Territory 8*PGA	-0.0407	0.1904		-0.0361	0.1874		-0.0513	0.1797	
Territory 11*PGA	-0.1818	0.2165	.	-0.1091	0.2136		-0.0303	0.2052	
Territory 12*PGA	1.0402	0.1997	***	0.9266	0.1969	***	0.9661	0.1891	***
Territory 13*PGA	1.4470	0.3655	***	1.2634	0.3598	***	1.1757	0.3448	***
Territory 15*PGA	-0.1646	0.1794		0.0322	0.1781		0.0111	0.1705	
Territory 18*PGA	-0.0543	0.4206		-0.1247	0.4129		-0.1250	0.3959	
Territory 19*PGA	-0.7392	0.3792	.	-0.6972	0.3723	.	-0.5990	0.3567	.
Territory 20*PGA	0.5407	0.1561	***	0.6983	0.1547	***	0.7599	0.1504	***
Territory 22*PGA	0.3448	0.0954	***	0.3299	0.0938	***	0.3310	0.0915	***
Territory 23*PGA	-0.4722	0.4145		-0.5662	0.4070		-0.4922	0.3930	
Territory 24*PGA	0.4837	0.5523		0.7224	0.5436	***	0.6466	0.5212	
Territory 25*PGA	0.9102	0.9339		0.8225	0.9164		0.6922	0.8771	
Territory 26*PGA	0.0428	0.2496		0.1444	0.2455	.	0.1317	0.2364	
Territory 2	-0.5632	0.1897	**	-0.5894	0.1867	**	-0.5108	0.1794	**
Territory 4	-0.7021	0.4194	.	-0.6689	0.4118		-0.5208	0.3941	
Territory 5	-0.0251	0.2099		-0.0715	0.2064		-0.0237	0.1979	
Territory 6	-0.0318	0.0435		-0.0431	0.0429		-0.0687	0.0412	.
Territory 7	-0.0314	0.0296		-0.0110	0.0302		-0.0653	0.0296	*
Territory 8	-0.0836	0.1095		-0.0858	0.1077		-0.1136	0.1034	
Territory 11	0.1873	0.1102	.	0.1494	0.1084		0.0879	0.1043	
Territory 12	-0.8699	0.0982	***	-0.7881	0.0971	***	-0.8307	0.0936	***
Territory 13	-0.8853	0.1538	***	-0.7725	0.1516	***	-0.7507	0.1455	***
Territory 15	0.0773	0.0715		0.0415	0.0704		0.0486	0.0677	
Territory 18	0.0945	0.1147		0.1509	0.1129		0.1672	0.1081	
Territory 19	0.1411	0.1630		0.1483	0.1600		0.0963	0.1533	
Territory 20	-0.3953	0.0716	***	-0.4441	0.0706	***	-0.4941	0.0681	***
Territory 22	-0.4500	0.0539	***	-0.4013	0.0540	***	-0.4442	0.0530	***
Territory 23	0.0669	0.2195		0.1662	0.2158		0.0956	0.2085	
Territory 24	-0.2647	0.2334		-0.3123	0.2296		-0.2599	0.2201	
Territory 25	-0.4734	0.5043		-0.3966	0.4950		-0.3145	0.4739	
Territory 26	-0.1236	0.1151		-0.1487	0.1130		-0.1518	0.1092	
(Intercept)	1.0401	0.0121	***	1.0646	0.1919	***	0.8505	0.2278	***
Observations	1636			1636			1636		
Adjusted R-squared	0.6073			0.6220			0.6545		

Note: The observations are 1636 zip-codes in California. All regressions are estimated using weighted least square method, with the number of homeowners' policies in each zip-code being the weight
Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Chapter 13

Appendices to Chapter 8 Discrete Choice Modeling

Table 13.1: Choosing CEA HO vs. nonCEA HO

	(1)			(2)			(4)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.4659	0.0116	***	0.3042	0.0118	***	0.3957	0.0121	***
Log (Median Home Value)				0.3855	0.0049	***	0.3181	0.0053	***
Log (Median Household Income)				-0.1742	0.0050	***	-0.1939	0.0067	***
Pop% with At Least College Degree				-0.3987	0.0122	***	-0.8856	0.0162	***
Median Household Size							-0.0300	0.0048	***
Gender (female%)							-0.1689	0.0498	**
Median Age							0.0059	0.0004	***
Pop% of Black or African American							-0.7912	0.0150	***
Pop% of Asian							0.3980	0.0117	***
Pop% other races							-0.5958	0.0254	***
Household with Children							-0.2036	0.0258	***
Log (Population Per Square Mile)							0.0077	0.0009	***
(Intercept)	X			X			X		
Territory fix effects	X			X			X		
AIC	6519297			6512508			6500935		
-2 log likelihood	6519257			6512462			6500873		

Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Table 13.2: Choosing CEA EQ vs. Otherwise (Conditional on Having Chosen CEA HO)

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	3.3220	0.0157	***	2.7356	0.0164	***	2.9078	0.0168	***
Log (Median Home Value)				0.9817	0.0078	***	0.8135	0.0084	***
Log (Median Household Income)				-0.5272	0.0071	***	-0.0704	0.0104	***
Pop% with At Least College Degree				1.7378	0.0176	***	1.0534	0.0243	***
Median Household Size							-0.4240	0.0075	***
Gender (female%)							-2.9920	0.0825	***
Median Age							0.0062	0.0005	***
Pop% of Black or African American							0.0588	0.0234	*
Pop% of Asian							-0.0082	0.0159	
Pop% of other races							0.9021	0.0400	***
Household with Children							0.4310	0.0357	***
Log (Population Per Square Mile)							0.0705	0.0015	***
Territory fixed effects	X			X			X		
(Intercept)	X			X			X		
AIC	3314630			3192486			3184213		
-2 log likelihood	3314590			3192440			3184151		

Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 13.3: Choosing CEA EQ vs. Private EQ

	(1)			(2)			(3)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	1.5719	0.0288	***	1.4252	0.0298	***	1.4302	0.0304	***
Log (Median Home Value)				0.0184	0.0142		0.0882	0.0151	***
Log (Median Household Income)				0.1905	0.0121	***	0.2652	0.0185	***
Pop% At Least College Degree				-1.1211	0.0308	***	-1.4977	0.0417	***
Median Household Size							-0.1431	0.0137	***
Gender (female%)							0.7007	0.1422	***
Median Age							-0.0094	0.0008	***
Pop% of Black or African American							0.0284	0.0455	
Pop% of Asian							0.7087	0.0292	***
Pop% of other races							-0.0543	0.0717	
Household with Children							0.5414	0.0619	***
Log (Population Per Square Mile)							0.0312	0.0028	***
Territory fix effects	X			X			X		
(Intercept)	X			X			X		
AIC	5381803			5182232			5168303		
-2 log likelihood	5381723			5182140			5168179		

Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 13.4: Choosing no EQ vs. Private EQ

	(1)			(3)			(5)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	-1.8361	0.0258	***	-1.3343	0.0267	***	-1.4991	0.0272	***
Log (Median Home Value)				-1.0255	0.0127	***	-0.7801	0.0134	***
Log (Median Household Income)				0.7622	0.0108	***	0.3948	0.0163	***
Pop% with At Least College Degree				-2.8574	0.0273	***	-2.4182	0.0366	***
Median Household Size							0.2876	0.0120	***
Gender (female%)							3.6175	0.1262	***
Median Age							-0.0184	0.0007	***
Pop% of Black or African American							0.1398	0.0407	
Pop% of Asian							0.6426	0.0260	***
Pop% of other races							-0.7718	0.0637	***
Household with Children							0.0501	0.0550	
Log (Population Per Square Mile)							-0.0408	0.0025	***
Territory fix effects	X			X			X		
(Intercept)	X			X			X		

Significance: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, .$p < 0.1$

Table 13.5: Odds Ratio of Choosing CEA HO vs. nonCEA HO (Include Territory-Risk Interaction Terms)

		(1)			(2)			(3)	
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Territory 27*PGA	1.663	1.597	1.732	1.224	1.174	1.276	1.806	1.729	1.887
Territory 2*PGA	1.656	1.351	2.031	1.301	1.061	1.596	1.415	1.151	1.738
Territory 4*PGA	0.047	0.029	0.076	0.049	0.030	0.080	0.147	0.090	0.240
Territory 5*PGA	5.315	4.253	6.643	5.481	4.378	6.862	6.905	5.510	8.652
Territory 6*PGA	2.513	2.341	2.699	2.449	2.279	2.631	2.413	2.244	2.596
Territory 7*PGA	1.979	1.848	2.119	1.848	1.724	1.981	1.624	1.513	1.743
Territory 8*PGA	0.388	0.339	0.443	0.414	0.362	0.473	0.425	0.371	0.487
Territory 11*PGA	4.170	3.599	4.832	2.659	2.298	3.079	2.139	1.842	2.468
Territory 12*PGA	0.944	0.814	1.095	1.176	1.013	1.363	0.993	0.855	1.154
Territory 13*PGA	0.305	0.237	0.393	0.326	0.253	0.419	0.312	0.242	0.402
Territory 15*PGA	1.105	0.972	1.255	0.562	0.495	0.639	0.636	0.559	0.723
Territory 18*PGA	2.795	2.089	3.738	3.492	2.613	4.666	6.076	4.527	8.157
Territory 19*PGA	1.507	1.131	2.006	1.031	0.773	1.373	1.253	0.940	1.670
Territory 20*PGA	6.229	5.493	7.065	3.805	3.355	4.314	4.250	3.743	4.826
Territory 22*PGA	0.417	0.383	0.453	0.475	0.437	0.517	0.488	0.447	0.532
Territory 23*PGA	1.320	0.933	1.867	1.745	1.232	2.471	0.597	0.418	0.852
Territory 24*PGA	2.594	1.783	3.774	2.167	1.485	3.162	5.432	3.700	7.973
Territory 25*PGA	0.870	0.451	1.679	1.320	0.684	2.546	1.176	0.606	2.284
Territory 26*PGA	2.367	1.973	2.839	1.521	1.269	1.822	1.629	1.354	1.960
Log (Median Home Value)				1.463	1.448	1.477	1.357	1.342	1.371
Log (Median Household Income)				0.855	0.846	0.863	0.812	0.801	0.824
Pop% with At Least College Degree				0.656	0.639	0.672	0.413	0.400	0.427
Median Household Size							1.000	0.991	1.010
Gender (female%)							0.929	0.839	1.027
Median Age							1.005	1.004	1.006
Pop% of Black or African American							0.483	0.469	0.499
Pop% of Asian							1.445	1.411	1.479
Pop% of other races							0.452	0.429	0.476
Household with Children							0.774	0.735	0.815
Log (Population Per Square Mile)							1.008	1.006	1.001

Table 13.6: Conditional Odds Ratio of Choosing CEA EQ vs. Otherwise (Include Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Territory 27*PGA	930.107	875.417	988.215	514.605	482.220	549.166	669.747	626.094	716.444
Territory 2*PGA	24253.107	9567.240	61482.017	2346.312	987.128	5576.965	444.078	191.751	1028.442
Territory 4*PGA	0.061	0.016	0.233	0.270	0.070	1.040	0.243	0.063	0.937
Territory 5*PGA	11.596	6.569	20.473	5.650	3.086	10.344	5.050	2.744	9.293
Territory 6*PGA	5.288	4.736	5.906	5.928	5.278	6.659	4.837	4.294	5.448
Territory 7*PGA	6.205	5.716	6.735	4.100	3.763	4.468	5.004	4.585	5.462
Territory 8*PGA	2.960	2.250	3.893	0.977	0.742	1.287	1.379	1.042	1.825
Territory 11*PGA	5.747	4.627	7.136	0.867	0.681	1.105	0.722	0.564	0.925
Territory 12*PGA	1.063	0.878	1.287	6.298	5.205	7.621	10.627	8.757	12.897
Territory 13*PGA	0.409	0.307	0.544	18.044	13.534	24.056	17.905	13.374	23.972
Territory 15*PGA	98.140	82.122	117.284	2.654	2.206	3.193	2.113	1.758	2.540
Territory 18*PGA	0.129	0.089	0.187	0.091	0.060	0.138	0.093	0.060	0.143
Territory 19*PGA	10.780	6.846	16.974	6.768	4.228	10.833	19.637	12.212	31.576
Territory 20*PGA	171.571	143.682	204.875	17.458	14.339	21.255	35.823	29.406	43.641
Territory 22*PGA	6.027	5.325	6.822	6.899	6.085	7.822	11.379	10.004	12.944
Territory 23*PGA	1.186	0.782	1.799	4.261	2.739	6.627	39.579	25.639	61.099
Territory 24*PGA	83283.023	49305.948	140673.939	116.991	68.903	198.641	131.184	76.769	224.169
Territory 25*PGA	0.253	0.101	0.635	1.115	0.442	2.813	0.315	0.126	0.788
Territory 26*PGA	144.879	105.837	198.324	51.172	36.672	71.407	48.371	34.664	67.498
Log (Median Home Value)				2.272	2.236	2.309	1.890	1.858	1.923
Log (Median Household Income)				0.540	0.532	0.548	0.818	0.801	0.836
Pop% with At Least College Degree				8.504	8.203	8.815	3.954	3.763	4.154
Median Household Size							0.689	0.679	0.700
Gender (female%)							0.119	0.101	0.141
Median Age							1.006	1.005	1.007
Pop% of Black or African American							0.947	0.904	0.993
Pop% of Asian							0.950	0.920	0.981
Pop% of other races							1.585	1.460	1.720
Household with Children							1.207	1.124	1.297
Log (Population Per Square Mile)							1.097	1.093	1.100

Table 13.7: Odds Ratio of Choosing CEA EQ vs. Private EQ (Include Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Territory 27*PGA	3.234	2.884	3.627	4.214	3.692	4.811	5.548	4.862	6.331
Territory 2*PGA	137.965	34.939	544.790	103.337	28.962	368.706	47.040	13.673	161.839
Territory 4*PGA	3.614	0.317	41.252	2.660	0.233	30.438	1.726	0.150	19.886
Territory 5*PGA	2.853	1.124	7.243	4.081	1.492	11.162	2.324	0.837	6.451
Territory 6*PGA	5.383	4.395	6.593	6.191	4.959	7.728	8.206	6.541	10.295
Territory 7*PGA	0.783	0.668	0.918	0.829	0.699	0.982	0.820	0.692	0.971
Territory 8*PGA	0.394	0.248	0.626	0.564	0.353	0.901	0.617	0.383	0.994
Territory 11*PGA	2.432	1.625	3.638	4.972	3.109	7.952	4.941	3.070	7.951
Territory 12*PGA	60.588	46.549	78.862	30.499	23.366	39.809	33.341	25.483	43.624
Territory 13*PGA	88.191	58.154	133.740	33.255	21.719	50.917	25.136	16.286	38.795
Territory 15*PGA	0.456	0.328	0.633	0.768	0.543	1.087	0.649	0.460	0.915
Territory 18*PGA	3.526	1.667	7.460	11.095	4.818	25.552	13.878	5.917	32.547
Territory 19*PGA	0.182	0.088	0.376	0.132	0.062	0.283	0.279	0.129	0.604
Territory 20*PGA	7.859	5.719	10.798	25.930	17.954	37.450	28.245	19.486	40.940
Territory 22*PGA	2.266	1.844	2.784	2.458	1.986	3.044	3.054	2.455	3.797
Territory 23*PGA	0.153	0.075	0.314	0.101	0.047	0.220	0.046	0.021	0.099
Territory 24*PGA	6.937	2.963	16.240	37.690	15.602	91.049	45.092	18.959	107.243
Territory 25*PGA	30.655	5.412	173.643	27.682	4.838	158.380	7.172	1.313	39.189
Territory 26*PGA	4.241	2.443	7.365	5.483	3.021	9.951	4.202	2.333	7.569
Log (Median Home Value)				1.025	0.995	1.055	1.076	1.044	1.110
Log (Median Household Income)				1.054	1.028	1.081	1.062	1.022	1.103
Pop% with At Least College Degree				0.418	0.392	0.445	0.305	0.280	0.332
Median Household Size							0.924	0.899	0.950
Gender (female%)							3.343	2.501	4.469
Median Age							0.992	0.990	0.994
Pop% of Black or African American							1.015	0.925	1.114
Pop% of Asian							1.944	1.832	2.062
Pop% of other races							0.719	0.621	0.833
Household with Children							1.605	1.417	1.819
Log (Population Per Square Mile)							1.048	1.042	1.054

Table 13.8: Odds Ratio of Choosing No EQ vs. Private EQ (Include Territory-Risk Interaction Terms)

	(1)			(2)			(3)		
Effect	Estimate	95% Wald CL		Estimate	95% Wald CL		Estimate	95% Wald CL	
Territory 27*PGA	0.003	0.003	0.004	0.008	0.007	0.009	0.007	0.006	0.008
Territory 2*PGA	0.004	0.001	0.010	0.027	0.011	0.071	0.069	0.027	0.173
Territory 4*PGA	166.351	21.122	1310.154	28.205	3.573	222.672	14.151	1.781	112.438
Territory 5*PGA	0.128	0.060	0.272	0.372	0.163	0.847	0.224	0.097	0.519
Territory 6*PGA	0.790	0.659	0.949	0.808	0.661	0.987	1.260	1.027	1.546
Territory 7*PGA	0.107	0.092	0.124	0.185	0.158	0.217	0.157	0.134	0.184
Territory 8*PGA	0.169	0.115	0.248	0.672	0.454	0.994	0.529	0.355	0.788
Territory 11*PGA	0.322	0.223	0.464	4.347	2.837	6.660	5.416	3.521	8.330
Territory 12*PGA	123.953	100.053	153.561	10.986	8.809	13.700	7.690	6.160	9.599
Territory 13*PGA	1192.491	826.831	1719.863	8.416	5.775	12.264	6.383	4.358	9.348
Territory 15*PGA	0.005	0.004	0.007	0.366	0.267	0.503	0.381	0.278	0.522
Territory 18*PGA	18.743	9.386	37.427	83.179	38.275	180.765	87.610	39.619	193.737
Territory 19*PGA	0.014	0.008	0.025	0.017	0.009	0.031	0.012	0.006	0.022
Territory 20*PGA	0.037	0.028	0.049	1.414	1.019	1.962	0.733	0.526	1.021
Territory 22*PGA	0.443	0.371	0.528	0.402	0.333	0.484	0.304	0.251	0.368
Territory 23*PGA	0.111	0.060	0.206	0.019	0.010	0.037	0.001	0.001	0.002
Territory 24*PGA	0.000	0.000	0.000	0.333	0.152	0.731	0.291	0.135	0.624
Territory 25*PGA	143.409	30.732	669.211	29.003	6.141	136.975	27.478	6.074	124.313
Territory 26*PGA	0.025	0.016	0.041	0.099	0.059	0.166	0.082	0.050	0.137
Log (Median Home Value)				0.423	0.412	0.434	0.540	0.525	0.555
Log (Median Household Income)				2.021	1.976	2.066	1.372	1.327	1.419
Pop% with At Least College Degree				0.050	0.047	0.053	0.090	0.083	0.097
Median Household Size							1.341	1.308	1.374
Gender (female%)							26.298	20.338	34.005
Median Age							0.984	0.983	0.986
Pop% of Black or African American							1.253	1.152	1.362
Pop% of Asian							1.919	1.820	2.022
Pop% of other races							0.585	0.513	0.666
Household with Children							1.298	1.161	1.450
Log (Population Per Square Mile)							0.953	0.948	0.958

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