The Interaction Between Risk Classification and Adverse selection: Evidence from California's Residential Earthquake Insurance Market

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Abstract

A central concern for insurance markets is the possibility that limits to the ability to classify risk will lead to problems of adverse selection. This study investigates this issue in the context of California's residential earthquake insurance market. I first show that there is substantial variation in underlying seismic risk within areas where the semi-public insurer, the California Earthquake Authority (CEA) charges the same rate. 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. This finding raises the possibility that limited classification leads to inefficiencies in the earthquake-insurance market. However, the true extent of the inefficiency depends on how individuals respond to finer pricing. To investigate that issue, I 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 limited risk classification by the CEA does not severely undermine the efficiency of the market.

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1 Introduction

Adverse selection is a key concern for insurance markets. Under asymmetric information, the bad risks drive out the good risks, and markets could unravel (Akerlof, 1970). One way to deal with it is to offer different contracts and let consumers self-select (Rothschild and Stiglitz, 1976); Another way is through active risk classification by insurers.[1] Risk classification however, induces equity concerns when individuals face the risk of being classified unfavorably, and having to pay higher premiums, or be uninsured as a result. This efficiency-equity trade-off of risk classification has been discussed extensively both in theory and empirically. The overall welfare implications of risk classification are ambiguous.[2] In reality, governments often ban the use of certain information in underwriting out of fairness concern. One of the most debated examples is the pre-existing condition exclusions in health insurance in the U.S.[3] In catastrophe insurance markets, similar debates exist: whether insurance rate should be risk-based, or whether it should be more heavily regulated and uniformly-priced.[4] In order to determine how finely insurers should classify risks, we need to understand whether people react to private information that is not priced in the insurance contracts; and then if they do, to what degree can a more finely tuned classification scheme help improve the market efficiency.

This study considers the nature of selection issues and how they interact with risk classification in the market for residential earthquake insurance in California. The dominant insurer here is a semi-public organization called the California Earthquake Authority (CEA). The

[1] For example, in auto insurance industry, insurers typically price based on driver age, car type, zip-code, and so on.

[2] For theoretical work, see Crocker and Snow (1986, 2010). They state conditions under which classification increases or decreases social welfare. For empirical work, see Harrington and Doerpinghaus (1993) for a discussion of the efficiency consequences of rate classification restrictions in auto insurance industry; and Buchmueller and DiNardo (2002) on the topic of community rating and death spiral in health insurance markets.

[3] 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).

[4] Picard (2008) argues theoretically risk-based pricing Pareto-dominates uniform-pricing. However, empirical evidence of cross-subsidized rates and loss of efficiency is documented in the property insurance and flood insurance market in the U.S. (Nyce and Maroney, 2011; Cazjkowski et al., 2012). Government or regulators are especially reluctant to allow rates to increase: After the 2004 hurricane seasons in Florida, regulators have rejected the majority of insurers' requests to increase rates in coastal areas, citing concerns that the spikes in rates in some areas would be too high and not affordable for homeowners, although the rates were claimed to be justified by updated catastrophe models.

CEA uses a rather coarse geographic risk classification by drawing only 19 rating territories across California. Jaffee and Russell (2000) argue that the CEA rates are tempered due to political reasons and marketing concerns. As a consequence, worries arise about adverse selection in California's earthquake insurance market. Such worries are even more profound since there is no mandate on earthquake coverage for Californian homeowners.[5] If adverse selection exists and results in market inefficiency, then can the market condition be improved should insurers price more finely? To address this question, I consider the market dynamic between the public insurer (the CEA) and the private competitors who use finer geographic-risk-classification schemes. Whether the private insurers are able to get a better risk pool has implications for how much the efficiency loss due to limited classification could be alleviated by finer pricing.

To answer the above empirical questions, I utilize a dataset obtained from the California Department of Insurance consisting of zip-code level counts and coverages of homeowners' policies sold by CEA participating insurers vs. policies sold by non-CEA insurers, and those of earthquake policies sold by the CEA vs. policies sold by non-CEA insurers. In addition, I collect seismic risk data from the U.S. Geological Survey, and gather rate information on the CEA and other private underwriters from public filings with the California Department of Insurance.

I first investigate the pricing strategy of the CEA. The CEA is subjected to certain rate regulation, which requires actuarially-sound rates, but discourages too much rate discrimination.[6] I analyze quantitatively to what extent the CEA prices are based on underlying seismic risk, and to what degree cross-subsidization exists. My findings are that on average, the territory-level prices are risk-based and high correlation exists between CEA rate and

[5]A mandate is a powerful tool to eliminate adverse selection, and is often coupled with underwriting restrictions. For example, the individual mandate requires indivuals to purchase health insurance or pay a fine. Among other economists, Johathan Guber is an advocate of the individual mandate: "The health care reform could not work without requiring everyone to buy insurance... any alternative imposes much higher costs on those buying insurance in the new health insurance exchanges as the healthiest opt out and the less healthy face increased premiums." Another example is the National Flood Insurance Program (NFIP), which requires federally-regulated mortgage lenders to purchase flood insurance for property required or developed in Special Flood Hazard Areas (SFHAs) (Michel-Kerjan, 2010).

[6]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.

territory-average seismic risk; however, there is substantial risk variation within areas where the CEA charges a constant price. This evidence of cross-subsidization leaves us wondering whether people who live in higher-risk areas will be more likely to purchase the CEA policies, all else equal.

In order to test for evidence of adverse selection, I focus on the take-up rates of the CEA policies[7] by individuals with different risk but faced with the same price. In my demand function, I control for a host of socioeconomic and demographic factors, most of which affect demand in the way expected: areas with higher median home value, or a higher education level, are generally associated with higher take-up rates. For the main independent variable of interest, the seismic risk measure, I find a strong positive correlation between the zip-code level seismic risk and the zip-code level take-up rate of earthquake insurance 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%. This suggests the possibility of efficiency loss relative to the scenario where price segmentation is perfect and people with different risks purchase policies with different prices. Acknowledging that people act on the 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 would price at a finer level. Ideally, we would run an experiment of how people react to finer pricing. This is difficult in reality as it is quite impossible that the CEA suddenly changes its pricing strategy dramatically. However, the coexistence of the CEA and private insurers allows us to partly answer those questions.

The private insurers represent about 25% of California's residential earthquake insurance market. They generally use finer risk classification shemes. For example, GeoVera and Chartis, the 2^{nd} and 3^{rd} players[8] in California's residential earthquake insurance market, both have their rates varied at a more granular level than does the CEA. The opportunity for private market to "cherry-pick" lower-risk homeowners from the CEA was brought up long time ago by an official at the California Department of Insurance (CDI), who wrote,[9]

[7]Defined as the number of CEA earthquake policies divided by the number of CEA participating insurers' homeowners' policies.

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

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

"The CEA territories are very crude. They start out with rates based on expected costs in 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 of the private insurers getting a better risk pool than the CEA, I compare the demand patterns for these two types of insurers. I then compose a ratio variable to capture the results of such comparison. The variable is created using CEA's zip-code level earthquake market shares divided by its territory-averages: A ratio of 1 throughout a territory means that the CEA captures the same proportion of market everywhere within the territory, a higher ratio signifies a relative higher demand for the CEA policies. This measure makes it easy for interpretation: A positive slope of the ratio vs. risk means that the CEA has relatively larger market shares in high-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 private market. However, heterogeneity exists among different areas: the slopes of the risk-share correlation varies among 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. Some possible explanations could be that homeowners' risk levels are positively correlated with risk preferences (or any characteristics that drive up the demand for earthquake insurance but unobserved in the data), or that homeowners only engage in very limited comparison shopping when buying earthquake policies. Another explanation is from the insurers' perspective: the insurers may have employed other marketing tactics that are unrelated to risks. For example, the private insurers may focus more on higher-end homeowners because of a higher profit margin. In fact, this possibility seems confirmed by summary statistics which show that the coverage amount for house structure is on average higher for a private policy than for a CEA policy.

My study informs debates about government's role in risk classification in catastrophe insurance markets. Catastrophe insurance markets are characterized by strong government interventions.[10] Those markets often involve cross-subsized rates (Kunreuther and Michel-

GeoVera in 1998.

[10]Paudel (2012) conducts a comparative study of catastrophe insurance systems in ten countries; In the United States, Kousky (2011) summarizes 10 state insurance programs; Klein (2008, 2009) discusses the

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 and 2010). 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 the 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.

Methodology-wise, my choice to use "objective risk" in the adverse selection test differs 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).[11] By using objective risk directly, I avoid ambiguities of deductibles (or"pseudo-deductibles") and moral hazard issues, which makes for a cleaner test. In my case, the information setting is also quite unique: the insurers should have more information on seismic risk than the buyers do, but they just do not use all that information in pricing. The situation discribed 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 gender in determining the price.

Lastly, my study adds to the catastrophe insurance demand literature by emphasizing the role of objective risk. On the demand for catastrophic insurance, empirical research has found that it is generally price-inelastic (Athavale and Avila, 2011; Latourrette et al., 2010; Kunreuther and Michel-Kerjan, 2009), that it is significantly affected by income (Browne and Hoyt, 2000), and that it can be affected by mandatory requirement (Kriesel and Landry, 2004), subsidized rates, or guarantee fund provisions (Grace, Klein, and Kleindorfer, 2004), but not affected by information disclosure (Palm, 1981 and 1992). Another aspect of the literature considers how demand is more closely related to risk. Browne and Hoyt (2000) use flooding experience to proxy "risk perception", and find its effect on insurance demand

politics and regulations in Florida's homeowners' market

[11]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 literature uses subjective measurement such as self-evaluated health condition.

significant. Relatively few studies use "objective risk" in their demand analysis.[12] Even when they do, they generally do not have much variation in risk measure, and cannot isolate the risk variation from insurance price variation.[13] My study contributes to the existing literature by having enough risk variation (my dataset encompasses all areas in California and has risk measure at the zip-code level), and further isolating objective risk from all the other factors, price in particular.

The remainder of this paper proceeds as follows. In the next section, I offer background information on the California Earthquake Authority (CEA). Section 3 describes the data used in this study. Section 4 gives results. Last, Section 5 concludes and discusses directions for future study.

2 Background

California is highly vulnerable to earthquakes, as it sits on multiple fault lines, including the most famous and active San Andreas fault.[14] Historically, eight out of ten of the most costly earthquakes (based on estimated current exposures) in the United States happened in California. (Sources: U.S. Geological Survey and California Geological Survey.) Not surprisingly, California has the largest earthquake insurance market in the U.S, with \$1.6bn of direct premiums written in 2010, topping the second and third states[15] by a large margin. (Sources: Swiss Re and Insurance Information Institute.)

After the 1994 Northridge Earthquake, many insurers suffered big losses. After reevaluating their earthquake exposures, they decided that they could not risk selling earthquake policies any more. But because of the mandatory offer law in California,[16] they could not simply stop selling earthquake coverage without exiting the homeowners' market entirely. In-

[12]Earlier surveys on earthquake insurance demand 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 a limited geographic risk variation in their suvey sample.

[13]Athavale and Avila (2011) use only 5 categories of "objective risk" in the entirely State of Missouri. They find that insurers have taken that risk variation into account for pricing. Therefore, they have not examined whether "objective risk" still affects demand holding price constant.

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

[15]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.

[16]See Zanjani (2008): "California has a "mandatory offer" law, dating from 1985, requiring that earthquake coverage be offered along with homeowners insurance."

surers lobbied to repeal the mandatory offer 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 non-existent. The California Earthquake Authority (CEA) was established by lawmakers to take over earthquake exposures and to restore the homeowners' market. It became operational at the end of 1996. The CEA is a publicly managed, largely privately funded organization. As a publicly managed organization, its board members consist of the Governor, the Treasurer, and the 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 state premium tax), additional assessment on the industry, a layer of reinsurance, some revenue bond, and a further contingent policyholder assessment. The CEA's claim-paying capacity is claimed to be over \$9bn.[17]

The CEA represents a public-private partnership. Private insurers participate in the CEA program on a voluntary basis. Insurers holding roughly 70% of the California homeowners market joined the CEA (Jaffee and Russel, 2000). To date, there are 20 participating insurers.[18] A participating insurer agrees to offer CEA earthquake coverage to its homeowners' 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 the 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) should be the same as that of companion homeowner's policy, and a deductible of 15% 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 increases the maximum contents coverage limit to \$100,000 and the maximum loss of use limit to \$15,000; it also offers the option of a lower deductible of 10% on structural coverage.

[17]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).

[18]Insurers participate on a group basis. At the time of this study, there were 19 participating insurers. A complete list of CEA participating insurers can be found at http://www.earthquakeauthority.com.

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

Although a 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 its homeowners business. Alternatively, an insurer can be a specialist in the earthquake business, in which case, it underwrites and manages its own and only earthquake exposures. To summarize, the earthquake insurance market in California consists of the CEA, the non-CEA homeowners' insurers, and the 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 the continuing efforts by insurers, regulators, and policy makers, earthquake insurance take-up rates have fallen to a low point after 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 the long recurrence interval between events are likely to be contributing factors to the low demand. But there has been very few systematic analyses on the nature of demand and the earthquake insurance market in California, except the earlier surveys by Kunreuther et al. (1978) and Palms (1989-1995). In this study, the author intends to bridge the gap by using recent years' statewide data on earthquake insurance purchase, and to bring new insights to the current residential earthquake insurance market in California.

3 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 joined

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

at this level as well, which will be the unit of observation of this study.

3.1 Insurance Policy Count and Coverage Data

Zip-code level policy count and coverage data serve as our source of dependent variables that represent 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.[20] 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 (coverage limit for home structures) of homeowners' policies, a count of earthquake insurance policies, and the total value of coverage A of earthquake policies. Such data are available for the years 2005, 2007, and 2009. Please note that only homeowners' policies[21] are included in this study, any renters, condominium, mobile home, or dwelling fire policies are excluded.

Table 1 provides basic summary statistics on counts of homeowners' 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 parenthesis). Table 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 participating insurers' homeowners' policies;[22] 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).

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-

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

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

[22]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.

up rate of earthquake policies among homeowners in general delined.[23]

[Insert Table 1 here]

Table 2 provides summary statistics on the dollar amount of coverage limit for home structure (coverage A). The data is again divided into CEA and non-CEA insurers. The table reveals several interesting facts: first, the average coverage limit for home structure 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 limit is on average lower for CEA participating insurers than for non-CEA insurers. Third, the same pattern is true as regards to earthquake policies, and the gap in coverage limit values is even bigger between CEA and non-CEA insurers.

[Insert Table 2 here]

Table 3 provides summary statistics by zip-codes. 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, respectively. 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'.

[Insert Table 3 here]

3.2 Geological Data

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

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

[23]Except for the CEA from the year 2005-2007.

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 those 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 described above, a ground motion value[24] is assigned, given a certain exceedance probability (such as 10% in 50 years). The ground motion value can either be under certain spectral acceleration, or be the Peak Ground Acceleration (PGA).[25] Figure 1 shows the underlying seisimic 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 later.

3.3 Census Data

I extract zip-code level variables from the U.S. Census Bureau, and link them to the zip-code level insurance data. These census variables describe the population's demographic and socioeconomic profiles. It's 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 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 homeowners' purchase decision of earthquake insurance.

Table 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

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

[25]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). In an earthquake, damage to buildings and infrastructure is related more closely to ground motion, rather 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.

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 the 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.

[Insert Table 4 here]

3.4 Insurers Rating Schemes and Menus

The insurance premium data come from insurers' rate manuals, which are public information in California, and can be downloaded directly from the CDI website.[26] Table 5 lists the CEA's historical rates from 1999 to 2007.[27] For a basic earthquake coverage, there are in total 19 different rates based on the 19 CEA territories holding fixed 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 1. By just eye-balling, there are obvious cases where different levels of risk are lumped together into one single territory, such as Territory 27. Territory 27 expands to include the majority part of California (except the coastal areas).

[Insert Table 5 here]

Next to 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 6. Besides differences in rating schemes, insurers also provide different policy forms and different coverage menus. Table 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 are basing their rates on more finely divided geographic units. Especially GeoVera, who has pricing variations even within a zip-code. It is almost impossible to provide an exhaustive list of

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

[27] 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.

the earthquake policy rates for GeoVera, but I will illustrate its finer price-risk correlation in the next section.

4 Results

4.1 Geographic Risk Classification for Earthquake Risk in California

In this section I show in specifics 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 which come 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.

Although PGA can 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.[28] Those models take into account other factors that also correlate with expected losses: for example, house structure, soil type, distance to fault line, liquefaction potential, and so on. 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 2 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.[29] This is significant because if the rates are on average risk-based, then a relatively uniform rate suggests a

[28]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.

[29]According to the CEAs 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.

cross-subsidization from the lower-risks to the higher-risks.

[Insert Figure 2 here]

Proceeding demonstrated that the CEA's territory rates are 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 to classify risks by drawing territories, it is expected to pool homogenous PGA values together 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 3. Figure 3 tells us that the risk levels still vary wildly 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.

[Insert Figure 3 here]

Last, 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 pick 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 of base rates for houses with the same characteristics and located within the same zip-code.[30] I calculate the average of all possible rates for each zip-code. Figure 4 shows a set of scatterplots of the zip-code level GeoVera rates vs. PGA values by CEA territory. For all of the CEA territories, there are obvious positive correlations between GeoVera's rates and PGA values.

[Insert Figure 4 here]

To summarize, the CEA rates are on average risk-based at the territory level, but there is large risk variation within a CEA pricing territory, which raises possibilies 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.

[30]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.

4.2 Demand for CEA Earthquake Insurance

4.2.1 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.

Figures 5-7 show 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 6) and the San Francisco Bay Area (Figure 7), 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 8 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' 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.

[Insert Figure 8]

[Insert Figure 9]

Figure 9 shows the risk-demand relationship for territory 27 (the largest CEA territory) 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 positive correlation between PGA and take-up rate is quite obvious, further confirming a positive risk-demand correlation.

4.2.2 Regression Framework

The previous section has explored the relationship between risk and demand through graphics. This section provides a more rigorous regression analysis. The main purpose here is to see 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:

$$\textit{Demand for CEA Earthquake Policies} = \beta_0 + \beta_1(\textit{Objective Risk}) + \beta_2 Ln\ (\textit{Home value}) + \beta_3 Ln\ (\textit{Income}) + \beta_4(\textit{Demographic characteristics}) + \beta_5(\textit{Territory}) + \epsilon$$

The main model is estimated using the take-up rate of CEA policies as the dependent variable.[31] Observations are at the zip-code level. 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.[32]

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, home 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

[31] an alternative dependent variable is the CEA coverage A take-up rate.

[32] An alternative is to use the number of CEA homeowners' policies as the weight for each zip-code. Author's calculation shows that using this alternative weighting scheme barely changes results.

measures of education level, average household size, racial composition, etc. *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.[33] In alternative versions of the main regression model, I interact these Territory dummies with PGA values, to allow for different slopes of risk-demand correlation in different territories.

4.2.3 Regression Results

Table 7 reports the weighted least square estimates for demand for earthquake insurance measured by the CEA take-up rate.

[Insert Table 7]

Objective Risk: The coefficient of PGA is highly significant and consistent in signs and magnitude (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. 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. To see more intuitively what a 0.2 change in PGA means in terms of change in expected loss: based on the scatter plot in Figure 2 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,[34] so an increase of 0.2 in PGA is roughly equivalant to doubling the CEA base rate, or doubling the expected loss.[35] To summarize, a coefficient of 0.35 means that the take-up rate could increase by 70% for 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.

[33]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.

[34]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.

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

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 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 increases by 20% to \$240,000, then the take-up rate of earthquake insurance increases 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 increases 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 increases 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 indicates that the higher the female population, the lower the demand, which contradicts prior research about females being more risk-adverse. The 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 increases from 2 members to 3 members, then the take-up rate of earthquake policies will 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.

Tables 8 is estimated including interaction terms of Territory dummies and PGA. Interaction terms allow for different effects of PGA on demand among territories. 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.[36]

4.3 Comparison of Demand for CEA and Private Earthquake Insurance

4.3.1 Geographic variation in the relative demand for CEA policies

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 classify risks, we can compare the demand for CEA and private earthquake insurance to see that whether the private sector gets a better risk pool through finer risk classification. Figure 10 includes two sets of risk-demand relationship 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.

[Insert Figure 10 here]

[36]The author also has tried alternative models for robustness check, using the CEA coverage A take-up as dependent variable. Results change very little, and that the effects of PGA on demand measured by coverage amount is on average slightly larger. Similar heterogeneity exists when estimated including interaction terms.

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 $(= \frac{\text{\# of CEA earthquake policies}}{\text{\# of total earthquake policies}})$. 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* $(= \frac{\text{CEA's earthquake market share}}{\text{territory average of the CEA's earthquake market share}})$.[37] How this variable changes within territory implies how the demand in private sector varies compared with that for the CEA. Figure 11 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.[38] 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.

[Insert Figure 11 here]

4.3.2 Regression Framework

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

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

[37]Another potential variable to measure the relative demand for CEA earthquake insurance is called *CEA share* $(= \frac{\text{\# of CEA earthquake policies/\# of total earthquake policies}}{\text{\# of CEA homeowners' policies/\# of total homeowners' policies}})$, 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.

[38]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 11.

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.

4.3.3 Regression Results

Table 9 reports the weighted least square estimates of coefficients. The only consistently significant coefficients are the Objective Risk Measure (PGA) and the CEA participating insurers' HO market share.

[Insert Table 9]

Objective Risk: The coefficient of PGA is significantly positive, with a maginitude 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. This is not a substantial size compared with the current statewide CEA earthquake market share of about 75%.

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, which is not surprising, since homeowners typically shop their home insurance first, and then weighing the options for an additional earthquake coverage. On the other hand, the variation in CEA participating insurers' homeowners' insurance market cannot 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 10 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.[39] This futher implies that a finer pricing does not necessarilty result in efficiency improvement, probably because homeowners' purchase decisions are affected by other factors besides a comparison of expected loss and price. While what those factors exactly are 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.

5 Conclusion and Discussion

This study investigates the consequences of limited risk classification by the semi-public insurer CEA in California's earthquake insurance market: how the limited risk classification interacts with selection from the homeowners, and to what extent limited classification causes inefficiencies. I first show that the CEA offers highly cross-subsidized rates, which raises concerns about adverse selection and consequent inefficiency issues.

I then find evidence of adverse selection against the CEA in the sense that 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 clear. 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 seismically active areas tend to be more risk-averse), then homeowners may not be responsive to finer pricing schemes at all.

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

[39]For robustness check, 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 as in Table 10.

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.

In the future, it may be worthwhile to quantify the efficiency loss due to limited risk classification here. It would also be interesting to explore reasons that consumers do/don't respond to finer risk classification, and to investigate what causes the geographic heterogeneity observed in this study. Another future study could focus particularly on investigating how risk perceptions toward disasters are shaped through experience, and how consumers use and update that piece of information in their insurance purchase decision. After collecting multiple years of earthquake insurance policy count data, some longitudinal study could also be conducted to understand the change in take-up rate.

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Table 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 number of total earthquake policies (both CEA and non-CEA) divided by the total number of homeowners' policies (both CEA and non-CEA).

**The CEA earthquake policy take-up rate is the number of CEA earthquake policies divided by the number of CEA homeowners' policies.

***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.

Table 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 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

Table 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.
Source: U.S. Census Bureau, 2007-2011 American Community Survey

Table 5: CEA Policy Base Rates (Per $1,000)

	CEA Rates 2007	CEA Rates 2005	CEA Rates 1999	Zip-code Counts	Population
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

Table 6: Comparison of insurance terms among CEA, GeoVera, and Chartis

	CEA		GeoVera		Chartis	
Program Types	**Base Limit**	**Increased Limit**	**Standard**	**Comprehensive**	**Basic**	**Broad**
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) 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) retrofitting discount For increased limits, add additional premiums		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) Apply construction debits and credits (based on year built, levels, grade under house, and foundation type) retrofitting discount Adjusted to deductible levels (Comprehensive product has 4 levels)		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) multiply by a contruction type/year built factor, and a number-of-stories factor retrofitting discount Coverage C and coverage D charge additional premiums (even for the basic levels)	

Table 7: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate as Dependent Variable)

Variable	(1) Estimate	(1) Std. Error		(2) Estimate	(2) Std. Error		(3) Estimate	(3) Std. Error		(4) Estimate	(4) Std. Error		(5) Estimate	(5) Std. Error	
Objective Risk Measure (PGA)	0.4233	0.0228	***	0.3268	0.0171	***	0.3368	0.0157	***	0.3421	0.0156	***	0.3453	0.0156	***
Log (Median Value of Owner-Occupied Homes)				0.1382	0.0038	***	0.0910	0.0067	***	0.0852	0.0067	***	0.0736	0.0070	***
Log (Median Household Income)							-0.0750	0.0067	***	-0.0565	0.0073	***	-0.0288	0.0087	***
Population with At Least College Degree (%)							0.2666	0.0163	***	0.2178	0.0194	***	0.2231	0.0210	***
Median Household Size										-0.0202	0.0035	***	-0.0362	0.0062	***
Gender (female%)										-0.2789	0.0648	***	-0.3741	0.0680	***
Median Age													0.0003	0.0005	
Percentage of Black or African American													0.0032	0.0194	
Percentage of Asian													-0.0180	0.0142	
Percentage of other races													0.1215	0.0335	***
Household with Children under 18 Years Old													-0.0127	0.0333	
Log (Population Per Square Mile)													0.0074	0.0012	***
Territory 2	-0.2104	0.0271	***	-0.0978	0.0203	***	-0.1144	0.0187	***	-0.1106	0.0185	***	-0.1130	0.0182	***
Territory 4	-0.2136	0.0352	***	-0.0732	0.0263	**	-0.0984	0.0243	***	-0.0987	0.0240	***	-0.1009	0.0236	***
Territory 5	-0.2306	0.0195	***	-0.1464	0.0147	***	-0.1519	0.0135	***	-0.1428	0.0134	***	-0.1518	0.0132	***
Territory 6	-0.0961	0.0094	***	-0.0516	0.0071	***	-0.0434	0.0066	***	-0.0431	0.0065	***	-0.0476	0.0065	***
Territory 7	-0.0178	0.0073	*	-0.0654	0.0055	***	-0.0517	0.0054	***	-0.0432	0.0054	***	-0.0535	0.0056	***
Territory 8	-0.2017	0.0179	***	-0.1851	0.0133	***	-0.1572	0.0123	***	-0.1533	0.0122	***	-0.1651	0.0121	***
Territory 11	-0.0379	0.0157	*	-0.0078	0.0116		0.0057	0.0108		0.0077	0.0106		0.0077	0.0105	
Territory 12	-0.0622	0.0122	***	-0.0915	0.0091	***	-0.0757	0.0084	***	-0.0717	0.0083	***	-0.0818	0.0083	***
Territory 13	0.0963	0.0163	***	0.0130	0.0123		0.0290	0.0113	*	0.0334	0.0112	**	0.0312	0.0110	**
Territory 15	0.0306	0.0177	.	-0.0217	0.0132	.	-0.0073	0.0123		-0.0057	0.0121		-0.0004	0.0119	
Territory 18	0.1063	0.0161	***	0.0465	0.0121	***	0.0579	0.0112	***	0.0554	0.0111	***	0.0651	0.0110	***
Territory 19	-0.1279	0.0207	***	-0.1537	0.0154	***	-0.1310	0.0143	***	-0.1254	0.0141	***	-0.1348	0.0140	***
Territory 20	-0.1101	0.0131	***	-0.1547	0.0098	***	-0.1294	0.0091	***	-0.1281	0.0090	***	-0.1287	0.0089	***
Territory 22	-0.1691	0.0105	***	-0.2243	0.0079	***	-0.2186	0.0073	***	-0.2141	0.0072	***	-0.2239	0.0075	***
Territory 23	-0.1308	0.0161	***	-0.2223	0.0122	***	-0.2124	0.0112	***	-0.2069	0.0111	***	-0.2144	0.0113	***
Territory 24	-0.0247	0.0176		-0.0992	0.0132	***	-0.1020	0.0122	***	-0.1019	0.0120	***	-0.0942	0.0120	***
Territory 25	-0.1296	0.0309	***	-0.0949	0.0229	***	-0.1226	0.0211	***	-0.1301	0.0209	***	-0.1160	0.0207	***
Territory 26	-0.1343	0.0129	***	-0.1514	0.0096	***	-0.1385	0.0089	***	-0.1400	0.0088	***	-0.1431	0.0087	***
(Intercept)	0.0309	0.0052	***	-1.7047	0.0477	***	-0.3564	0.0898	***	-0.2756	0.0973	**	-0.4209	0.1084	***
Observations	1636			1636			1636			1636			1636		
Adjusted R-squared	0.3581			0.648			0.7025			0.7108			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
Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $P < 0.1$

Table 8: Demand for CEA Earthquake Insurance (Use CEA Take-up Rate as Dependent Variable and Include Interaction Terms)

Variable	(1) Estimate	(1) Std. Error		(2) Estimate	(2) Std. Error		(3) Estimate	(3) Std. Error		(4) Estimate	(4) Std. Error		(5) Estimate	(5) Std. Error	
Territory 27*PGA	0.8418	0.0407	***	0.6515	0.0307	***	0.7279	0.0277	***	0.7354	0.0275	***	0.7362	0.0276	***
Log (Median Value of Owner-Occupied Homes)				0.1337	0.0037	***	0.0769	0.0063	***	0.0718	0.0063	***	0.0586	0.0066	***
Log (Median Household Income)							-0.0794	0.0063	***	-0.0590	0.0068	***	-0.0392	0.0081	***
Population with At Least College Degree (%)							0.2977	0.0153	***	0.2356	0.0180	***	0.2425	0.0196	***
Median Household Size										-0.0228	0.0033	***	-0.0293	0.0057	***
Gender (female%)										-0.1596	0.0603	**	-0.2835	0.0631	***
Median Age													0.0003	0.0004	
Percentage of Black or African American													-0.0095	0.0182	
Percentage of Asian													-0.0222	0.0132	.
Percentage of ther Races													0.0649	0.0315	*
Household with Children under 18 Years Old													-0.0380	0.0308	
Log (Population Per Square Mile)													0.0084	0.0012	***
Territory 2*PGA	0.3736	0.2182	.	0.1216	0.1621		0.2687	0.1449	.	0.2628	0.1426	.	0.1873	0.1401	
Territory 4*PGA	-0.1289	0.4959		-0.1584	0.3681		0.0487	0.3289		0.0926	0.3237		0.0461	0.3174	
Territory 5*PGA	0.1244	0.2276		0.1720	0.1690		0.0164	0.1511		0.0023	0.1488		0.0207	0.1461	
Territory 6*PGA	0.2004	0.0595	***	0.2107	0.0442	***	0.1853	0.0395	***	0.1775	0.0389	***	0.1611	0.0383	***
Territory 7*PGA	0.2938	0.0438	***	0.2806	0.0325	***	0.2346	0.0292	***	0.2378	0.0288	***	0.2488	0.0284	***
Territory 8*PGA	0.0582	0.1248		-0.0764	0.0927		-0.0400	0.0829		-0.0279	0.0816		-0.0023	0.0802	
Territory 11*PGA	0.2739	0.1418	.	-0.0544	0.1057		0.0680	0.0945		0.0728	0.0931		0.0315	0.0916	
Territory 12*PGA	-0.0045	0.1309		0.0782	0.0972		0.2024	0.0871	*	0.1873	0.0858	*	0.2470	0.0844	**
Territory 13*PGA	-0.1982	0.2395		0.0596	0.1779		0.2786	0.1592	.	0.2671	0.1567	.	0.2645	0.1539	.
Territory 15*PGA	0.7485	0.1176	***	0.3318	0.0880	***	0.3219	0.0788	***	0.3314	0.0776	***	0.3094	0.0761	***
Territory 18*PGA	-0.3619	0.2756		-0.3177	0.2046		-0.2615	0.1827		-0.2410	0.1799		-0.2145	0.1767	
Territory 19*PGA	0.1878	0.2484		0.0359	0.1845		0.1253	0.1648		0.1410	0.1622		0.1852	0.1592	
Territory 20*PGA	0.5302	0.1023	***	0.1490	0.0767	.	0.1471	0.0685	*	0.1825	0.0676	**	0.2249	0.0671	***
Territory 22*PGA	0.1587	0.0625	*	0.2319	0.0464	***	0.1902	0.0415	***	0.2101	0.0410	***	0.2367	0.0409	***
Territory 23*PGA	0.0249	0.2716		0.1113	0.2016		0.1798	0.1801		0.2158	0.1776		0.3666	0.1754	*
Territory 24*PGA	1.6739	0.3619	***	1.0163	0.2693	***	0.9085	0.2406	***	0.9877	0.2370	***	0.9202	0.2326	***
Territory 25*PGA	-0.1614	0.6119		-0.0147	0.4543		-0.0248	0.4056		-0.0107	0.3992		-0.1420	0.3914	
Territory 26*PGA	0.3978	0.1636	*	0.1515	0.1216		0.1813	0.1086	.	0.1927	0.1069	.	0.1842	0.1055	.
Territory 2	-0.1075	0.1243		0.0725	0.0924		-0.0113	0.0826		0.0011	0.0813		0.0450	0.0801	
Territory 4	0.1654	0.2748		0.2487	0.2040		0.1228	0.1823		0.0997	0.1794		0.1244	0.1759	
Territory 5	0.0237	0.1376		0.0032	0.1021		0.1083	0.0913		0.1291	0.0900	.	0.1122	0.0883	.
Territory 6	0.0790	0.0285	**	0.0582	0.0212	**	0.0948	0.0190	***	0.1012	0.0187	***	0.1051	0.0184	***
Territory 7	0.1083	0.0194	***	0.0133	0.0146		0.0643	0.0134	***	0.0739	0.0132	***	0.0598	0.0132	***
Territory 8	0.0777	0.0718		0.0994	0.0533	.	0.1279	0.0477	**	0.1285	0.0469	**	0.1041	0.0462	*
Territory 11	0.1117	0.0722		0.2403	0.0537	***	0.2112	0.0480	***	0.2141	0.0472	***	0.2374	0.0466	***
Territory 12	0.2196	0.0644	***	0.0888	0.0479	.	0.0647	0.0430		0.0793	0.0423	.	0.0419	0.0418	
Territory 13	0.4295	0.1008	***	0.1857	0.0751	*	0.1296	0.0671	.	0.1413	0.0661	*	0.1417	0.0649	*
Territory 15	-0.0142	0.0469		0.0370	0.0348		0.0744	0.0311	*	0.0748	0.0307	*	0.0912	0.0302	**
Territory 18	0.3900	0.0751	***	0.2782	0.0559	***	0.2924	0.0500	***	0.2864	0.0492	***	0.2898	0.0482	***
Territory 19	0.0467	0.1068		0.0290	0.0793		0.0345	0.0708		0.0363	0.0697		0.0141	0.0684	
Territory 20	-0.0820	0.0469	.	-0.0159	0.0349		0.0302	0.0312		0.0187	0.0308		0.0035	0.0304	
Territory 22	0.0502	0.0353		-0.1113	0.0266	***	-0.0633	0.0239	**	-0.0660	0.0236	**	-0.0870	0.0237	***
Territory 23	0.1542	0.1438		-0.0465	0.1069		-0.0525	0.0955		-0.0607	0.0943		-0.1466	0.0931	
Territory 24	-0.4746	0.1529	**	-0.3272	0.1136	**	-0.2666	0.1016	**	-0.2979	0.1001	**	-0.2579	0.0982	**
Territory 25	0.2601	0.3304		0.1471	0.2453		0.1408	0.2191		0.1286	0.2156		0.2124	0.2115	
Territory 26	-0.0476	0.0754		-0.0121	0.0560		0.0063	0.0500		0.0011	0.0492		0.0056	0.0487	
(Intercept)	-0.0442	0.0079	***	-1.7058	0.0464	***	-0.2076	0.0849	*	-0.2067	0.0908	*	-0.2393	0.1017	*
Observations	1636			1636			1636			1636			1636		
Adjusted R-squared	0.426			0.6837			0.7479			0.7559			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 9: Relative Demand for CEA Earthquake Insurance (Use CEA EQ share as Dependent Variable)

	(1)			(2)			(3)			(4)			(5)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Objective Risk Measure (PGA)	0.2712	0.0302	***	0.2875	0.0303	***	0.2809	0.0301	***	0.2690	0.0300	***	0.2822	0.0298	***
CEA participating insurers' HO market share	0.8641	0.0402	***	0.8907	0.0406	***	0.8743	0.0409	***	0.9048	0.0412	***	0.9499	0.0415	***
Log (Median Value of Owner-Occupied Homes)				-0.0266	0.0068	***	0.0105	0.0131		0.0113	0.0131		0.0254	0.0136	*
Log (Median Household Income)							0.0435	0.0128	***	0.0186	0.0140		0.0444	0.0166	**
Population with At Least College Degree (%)							-0.1808	0.0313	***	-0.0836	0.0379	*	-0.2018	0.0406	***
Median Household Size										0.0296	0.0069	***	-0.0076	0.0117	
Gender (female%)										-0.1195	0.1244		-0.2116	0.1296	
Median Age													-0.0034	0.0009	***
Percentage of Black or African American													0.1480	0.0374	***
Percentage of Asian													0.0837	0.0272	**
Percentage of other races													-0.0969	0.0640	
Household with Children under 18 Years Old													0.0636	0.0636	
Log (Population Per Square Mile)													0.0050	0.0023	*
Territory 2	0.0370	0.0369		0.0217	0.0369		0.0303	0.0366		0.0276	0.0364		0.0628	0.0356	.
Territory 4	-0.1224	0.0463	**	-0.1487	0.0465	**	-0.1303	0.0463	**	-0.1227	0.0461	**	-0.1119	0.0449	*
Territory 5	-0.0896	0.0259	***	-0.1039	0.0260	***	-0.1006	0.0258	***	-0.1057	0.0257	***	-0.1101	0.0252	***
Territory 6	-0.0839	0.0126	***	-0.0910	0.0127	***	-0.0963	0.0127	***	-0.0935	0.0126	***	-0.0916	0.0125	***
Territory 7	-0.1877	0.0109	***	-0.1820	0.0109	***	-0.1907	0.0111	***	-0.2005	0.0114	***	-0.2223	0.0117	***
Territory 8	-0.1414	0.0236	***	-0.1446	0.0235	***	-0.1623	0.0235	***	-0.1647	0.0234	***	-0.1847	0.0231	***
Territory 11	-0.1389	0.0206	***	-0.1446	0.0206	***	-0.1525	0.0205	**	-0.1544	0.0204	***	-0.1626	0.0200	***
Territory 12	-0.2005	0.0162	***	-0.1964	0.0162	***	-0.2069	0.0162	***	-0.2118	0.0161	***	-0.2219	0.0159	***
Territory 13	-0.0940	0.0215	***	-0.0792	0.0217	***	-0.0887	0.0216	***	-0.0921	0.0215	***	-0.0916	0.0210	***
Territory 15	-0.0985	0.0233	***	-0.0891	0.0233	***	-0.1003	0.0233	**	-0.1006	0.0232	***	-0.0912	0.0227	***
Territory 18	-0.0456	0.0212	*	-0.0347	0.0213		-0.0440	0.0214	*	-0.0407	0.0213	.	-0.0227	0.0209	
Territory 19	-0.1485	0.0275	***	-0.1459	0.0274	***	-0.1613	0.0273	***	-0.1685	0.0272	***	-0.1627	0.0269	***
Territory 20	-0.1693	0.0176	***	-0.1629	0.0176	***	-0.1780	0.0176	***	-0.1801	0.0175	***	-0.1938	0.0173	***
Territory 22	-0.2111	0.0143	***	-0.2031	0.0144	***	-0.2058	0.0142	***	-0.2116	0.0143	***	-0.2457	0.0147	***
Territory 23	-0.1718	0.0218	***	-0.1577	0.0220	***	-0.1625	0.0218	***	-0.1760	0.0219	***	-0.1988	0.0220	***
Territory 24	-0.0504	0.0232	*	-0.0366	0.0233		-0.0363	0.0232		-0.0320	0.0231	***	-0.0077	0.0229	
Territory 25	-0.0979	0.0406	*	-0.1057	0.0405	**	-0.0884	0.0403	*	-0.0789	0.0401	*	-0.0786	0.0394	*
Territory 26	-0.1680	0.0172	***	-0.1663	0.0171	***	-0.1743	0.0170	***	-0.1681	0.0170	***	-0.1793	0.0167	***
(Intercept)	0.3657	0.0280	***	0.6812	0.0854	***	-0.2044	0.1710		-0.0110	0.1869		-0.2940	0.2071	
Observations	1636			1636			1636			1636			1636		
Adjusted R-squared	0.2793			0.2856			0.3003			0.3079			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

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

Table 10: Relative Demand for CEA Earthquake Insurance (Use CEA EQ share as Dependent Variable and Include Interaction Terms)

	(1)			(2)			(3)			(4)			(5)		
Variable	Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error		Estimate	Std. Error	
Territory 27*PGA	0.3646	0.0545	***	0.4003	0.0550	***	0.3610	0.0551	***	0.3347	0.0554	***	0.3390	0.0552	***
CEA participating insurers' HO market share	0.8692	0.0392	***	0.8942	0.0395	***	0.8752	0.0398	***	0.9051	0.0401	***	0.9427	0.0405	***
Log (Median Value of Owner-Occupied Homes)				-0.0270	0.0067	***	0.0111	0.0129		0.0133	0.0129		0.0280	0.0133	*
Log (Median Household Income)							0.0288	0.0126	*	0.0043	0.0137		0.0287	0.0162	.
Population with At Least College Degree (%)							-0.1553	0.0307	***	-0.0626	0.0369	.	-0.1813	0.0396	***
Median Household Size										0.0293	0.0067	***	-0.0051	0.0114	
Gender (female%)										-0.0689	0.1212		-0.1775	0.1258	
Median Age													-0.0033	0.0009	***
Percentage of Black or African American													0.1354	0.0366	***
Percentage of Asian													0.0814	0.0264	**
Percentage of ther Races													-0.1100	0.0630	.
Household with Children under 18 Years Old													0.0560	0.0614	
Log (Population Per Square Mile)													0.0059	0.0023	**
Territory 2*PGA	1.1634	0.2913	***	1.2111	0.2902	***	1.1457	0.2884	***	1.1481	0.2868	***	1.0250	0.2793	***
Territory 4*PGA	0.8273	0.6625		0.8498	0.6594		0.7468	0.6550		0.6995	0.6514		0.6411	0.6328	
Territory 5*PGA	0.1994	0.3042		0.1804	0.3028		0.2571	0.3011		0.2780	0.2995		0.1225	0.2916	
Territory 6*PGA	0.3020	0.0798	***	0.2948	0.0795	***	0.3089	0.0789	***	0.3143	0.0785	***	0.3238	0.0767	***
Territory 7*PGA	-0.0230	0.0586		-0.0227	0.0584		-0.0027	0.0582		-0.0051	0.0579		0.0244	0.0567	
Territory 8*PGA	-0.1711	0.1667		-0.1392	0.1662		-0.1507	0.1652		-0.1583	0.1643		-0.1482	0.1600	
Territory 11*PGA	-0.0119	0.1897		0.0468	0.1894		-0.0091	0.1883		-0.0313	0.1874		0.0275	0.1827	
Territory 12*PGA	1.4651	0.1747	***	1.4487	0.1739	***	1.3987	0.1734	***	1.4150	0.1725	***	1.4245	0.1682	***
Territory 13*PGA	1.8515	0.3198	***	1.8051	0.3185	***	1.6934	0.3170	***	1.7158	0.3152	***	1.6209	0.3068	***
Territory 15*PGA	-0.1356	0.1569		-0.0522	0.1576		-0.0613	0.1569		-0.0617	0.1561		-0.0687	0.1517	
Territory 18*PGA	0.0543	0.3680		0.0403	0.3663		0.0274	0.3638		0.0029	0.3618		0.0484	0.3524	
Territory 19*PGA	-0.8381	0.3316	*	-0.8091	0.3302	*	-0.8509	0.3279	**	-0.8856	0.3261	**	-0.7581	0.3172	*
Territory 20*PGA	0.7262	0.1370	***	0.7957	0.1375	***	0.7958	0.1365	***	0.7391	0.1363	***	0.8442	0.1341	***
Territory 22*PGA	0.3961	0.0836	***	0.3846	0.0833	***	0.4045	0.0827	***	0.3928	0.0825	***	0.4065	0.0815	***
Territory 23*PGA	-0.5631	0.3626		-0.5815	0.3609		-0.6025	0.3585	.	-0.6012	0.3572	.	-0.6115	0.3495	.
Territory 24*PGA	0.6308	0.4831		0.7587	0.4819		0.8303	0.4788	.	0.7509	0.4767		0.8105	0.4637	.
Territory 25*PGA	0.9794	0.8169		0.9505	0.8131		0.9683	0.8072		0.9716	0.8027		0.8317	0.7801	
Territory 26*PGA	0.1156	0.2184		0.1614	0.2177		0.1412	0.2162		0.1233	0.2151		0.1561	0.2103	
Territory 2	-0.4429	0.1663	**	-0.4728	0.1656	**	-0.4381	0.1646	**	-0.4505	0.1637	**	-0.3419	0.1598	*
Territory 4	-0.4116	0.3672		-0.4381	0.3655		-0.3730	0.3631		-0.3486	0.3611		-0.3008	0.3507	
Territory 5	-0.0296	0.1839		-0.0194	0.1830		-0.0719	0.1820		-0.0994	0.1811		-0.0041	0.1763	
Territory 6	-0.0808	0.0383	*	-0.0739	0.0381	.	-0.0926	0.0380	*	-0.1003	0.0379	**	-0.0989	0.0368	**
Territory 7	-0.0560	0.0264	*	-0.0401	0.0266		-0.0651	0.0268	*	-0.0820	0.0270	**	-0.1109	0.0268	***
Territory 8	0.1227	0.0960		0.1143	0.0956		0.0974	0.0950		0.0895	0.0945		0.0700	0.0922	
Territory 11	0.0187	0.0965		-0.0046	0.0962		0.0088	0.0955		0.0094	0.0950		-0.0219	0.0928	
Territory 12	-0.7611	0.0860	***	-0.7374	0.0858	***	-0.7320	0.0855	***	-0.7535	0.0852	***	-0.7629	0.0833	***
Territory 13	-0.7338	0.1347	***	-0.6891	0.1345	***	-0.6587	0.1337	***	-0.6798	0.1330	***	-0.6349	0.1296	***
Territory 15	0.0681	0.0626		0.0564	0.0624		0.0398	0.0620		0.0321	0.0617		0.0492	0.0603	
Territory 18	0.0286	0.1003		0.0514	0.1000		0.0368	0.0995		0.0405	0.0990		0.0493	0.0962	
Territory 19	0.3360	0.1427	*	0.3371	0.1420	*	0.3353	0.1409	*	0.3309	0.1402	*	0.2890	0.1364	*
Territory 20	-0.3533	0.0627	***	-0.3665	0.0624	***	-0.3872	0.0622	***	-0.3727	0.0619	***	-0.4259	0.0606	***
Territory 22	-0.2631	0.0479	***	-0.2360	0.0482	***	-0.2588	0.0481	***	-0.2679	0.0479	***	-0.3020	0.0478	***
Territory 23	0.2835	0.1921		0.3200	0.1914	.	0.3176	0.1901	.	0.2945	0.1896		0.2835	0.1856	
Territory 24	-0.1848	0.2041		-0.2140	0.2033		-0.2548	0.2022		-0.2257	0.2013		-0.2205	0.1958	
Territory 25	-0.4625	0.4411		-0.4423	0.4391		-0.4487	0.4359		-0.4498	0.4336		-0.3684	0.4215	
Territory 26	-0.0810	0.1007		-0.0889	0.1002		-0.0957	0.0995		-0.0901	0.0990		-0.1096	0.0971	
(Intercept)	0.3454	0.0283	***	0.6635	0.0841	***	-0.0721	0.1691		0.0783	0.1826		-0.1567	0.2033	
Observations	1636			1636			1636			1636			1636		
Adjusted R-squared	0.3367			0.3429			0.3525			0.3598			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: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $P < 0.1$

Figure 1: PGA and CEA territories. PGA values are classified into 20 levels, represented by 20 colors produced by 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).

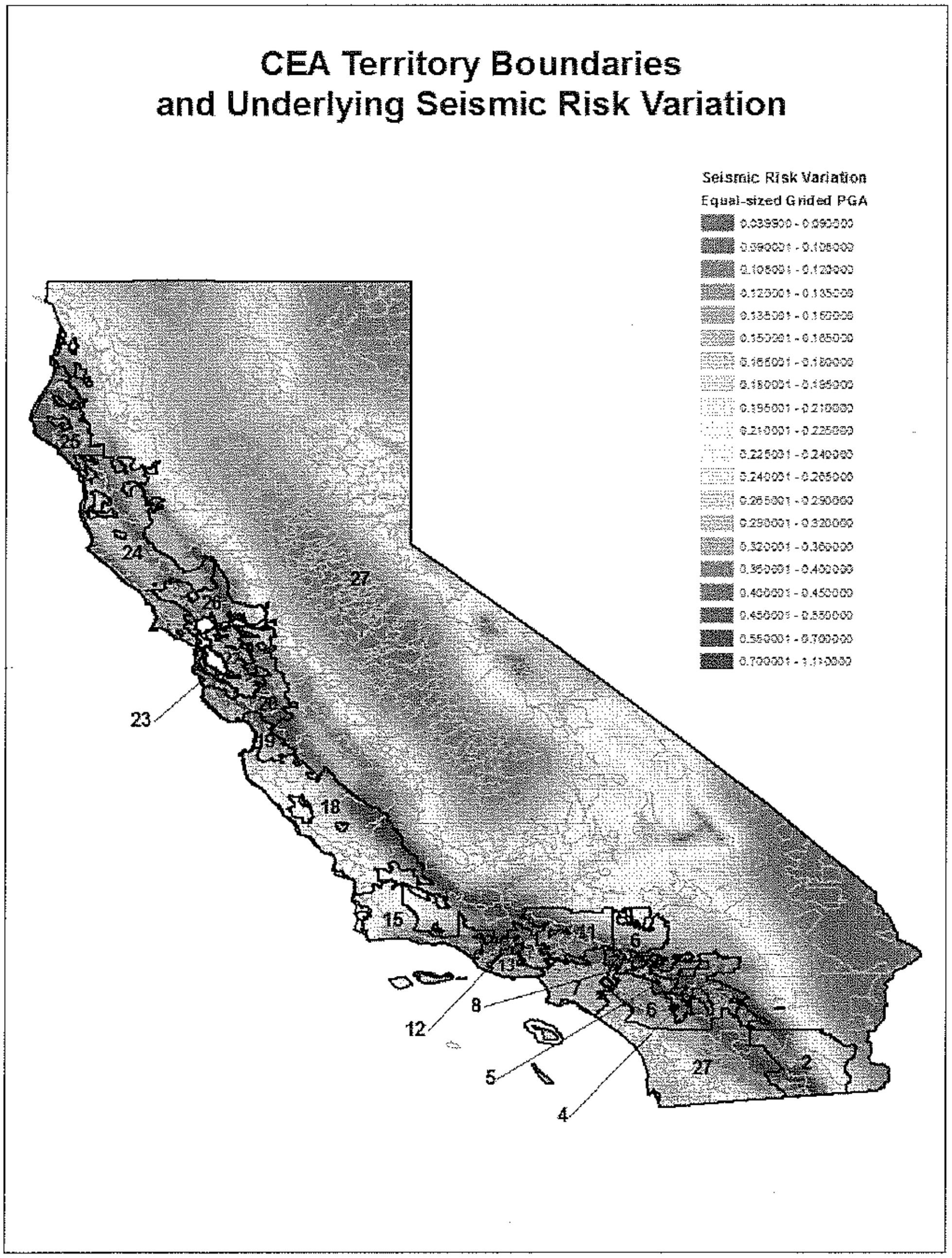

Figure 2: CEA rates vs. PGA by territory. The territory-level PGAs are calculated as a weighted average of zip-code-level PGAs. The weights are the number of CEA policies in each zip-code. The CEA rates are for policies with base limit, the same as those in Table 5.

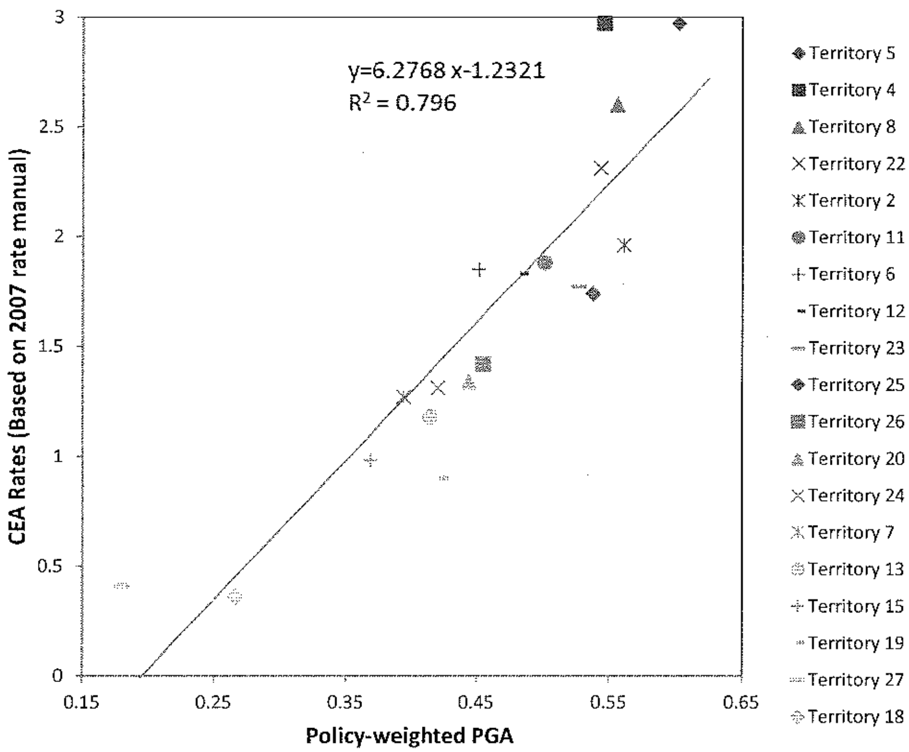

Figure 3: PGA Distributions by the CEA Territory. Each boxplot represents PGA distributions in one CEA territory, so that there are in total 19 boxplots. Territories are ranged by their median PGA values.

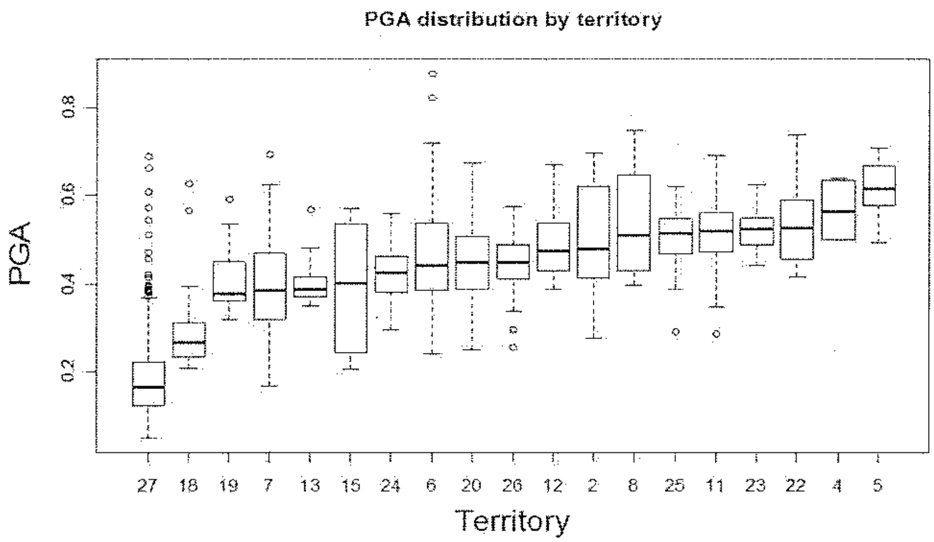

Figure 4: GeoVera Rates vs. PGA by the CEA Territory. Territories are ranged by total population. Each dot represents a zip-code.The size of a zip-code is proportional to the total number of homeowners' policies in that zip-code. The fitted line is weighted by the size of each zip-code (weights also based on the number of total homeowners' policies).

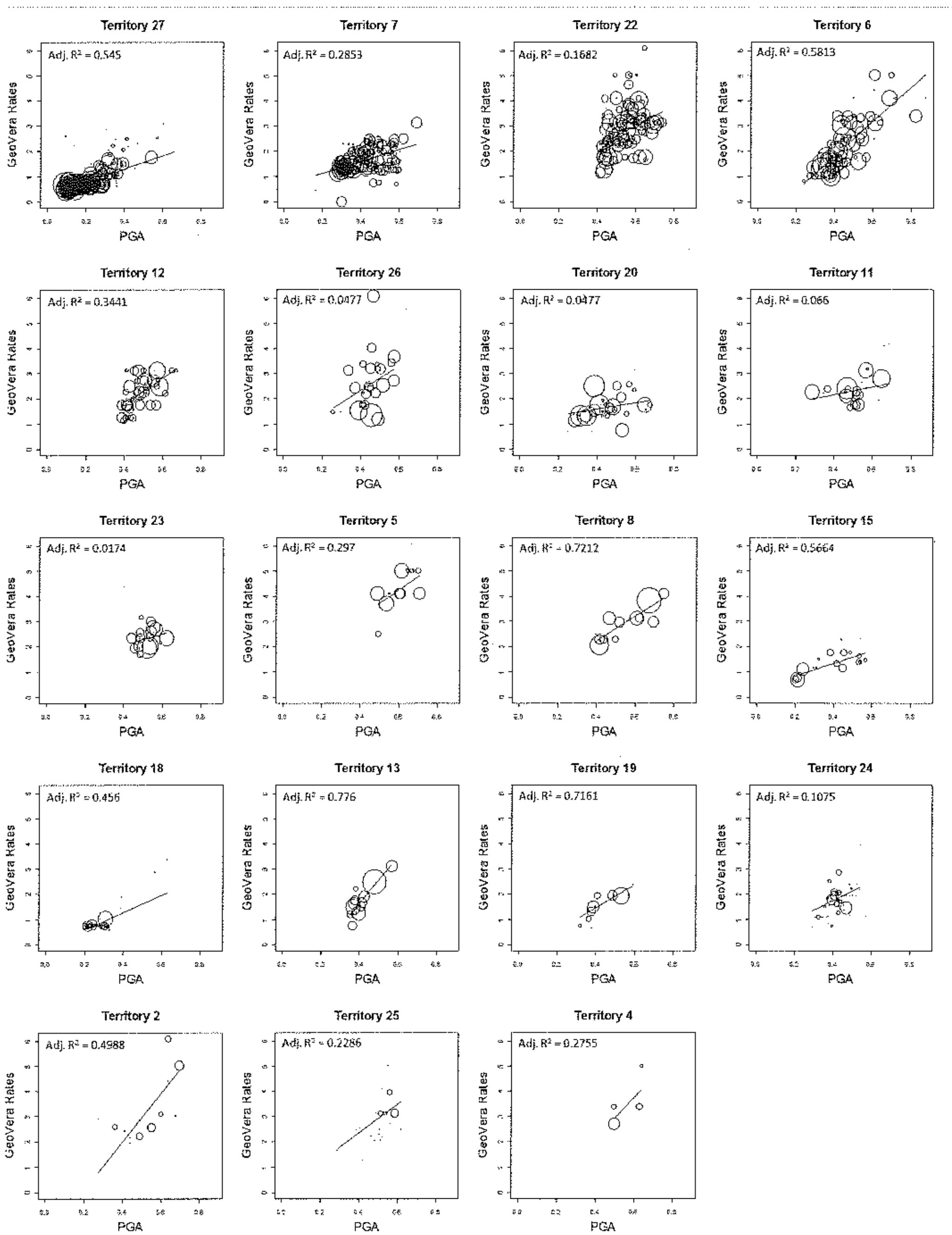

Figure 5: CEA take-up rates in California. Zip-code level CEA take-up rates range from 0 to 55%. These take-up rates are classified into 10 categories, represented by 10 colors produced by a graduant from green to red. Green zones have the lowest take-up rates, and red zones have the highest take-up rates. The categories do not necessarily have equal intervals. They are drawn with the idea that each category has similar number of observations (zip-codes). Though some categories still have significantly fewer observations than others.

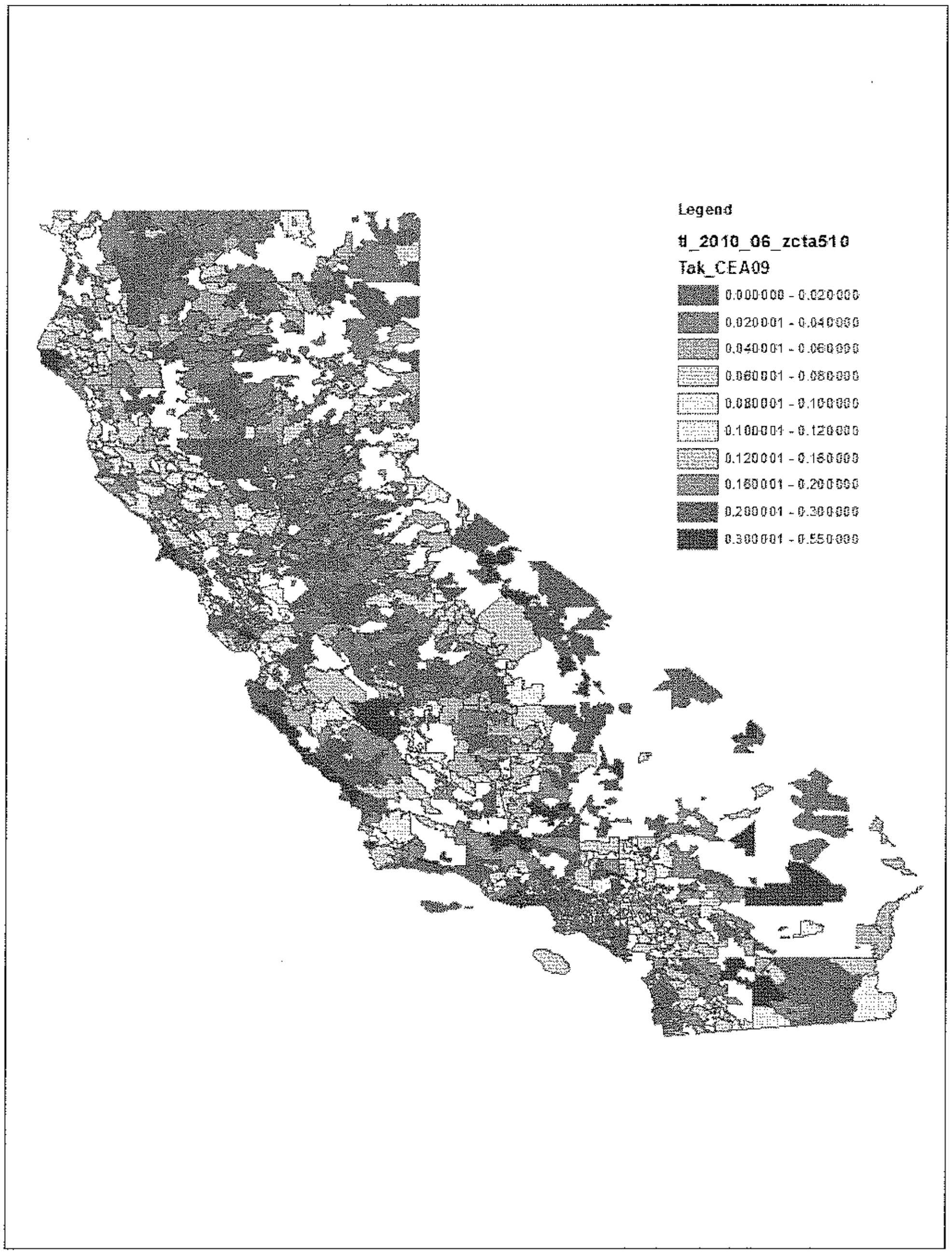

Figure 6: CEA take-up rates in the Greater Los Angeles Area. This is a zoom-in map from Figure 5.

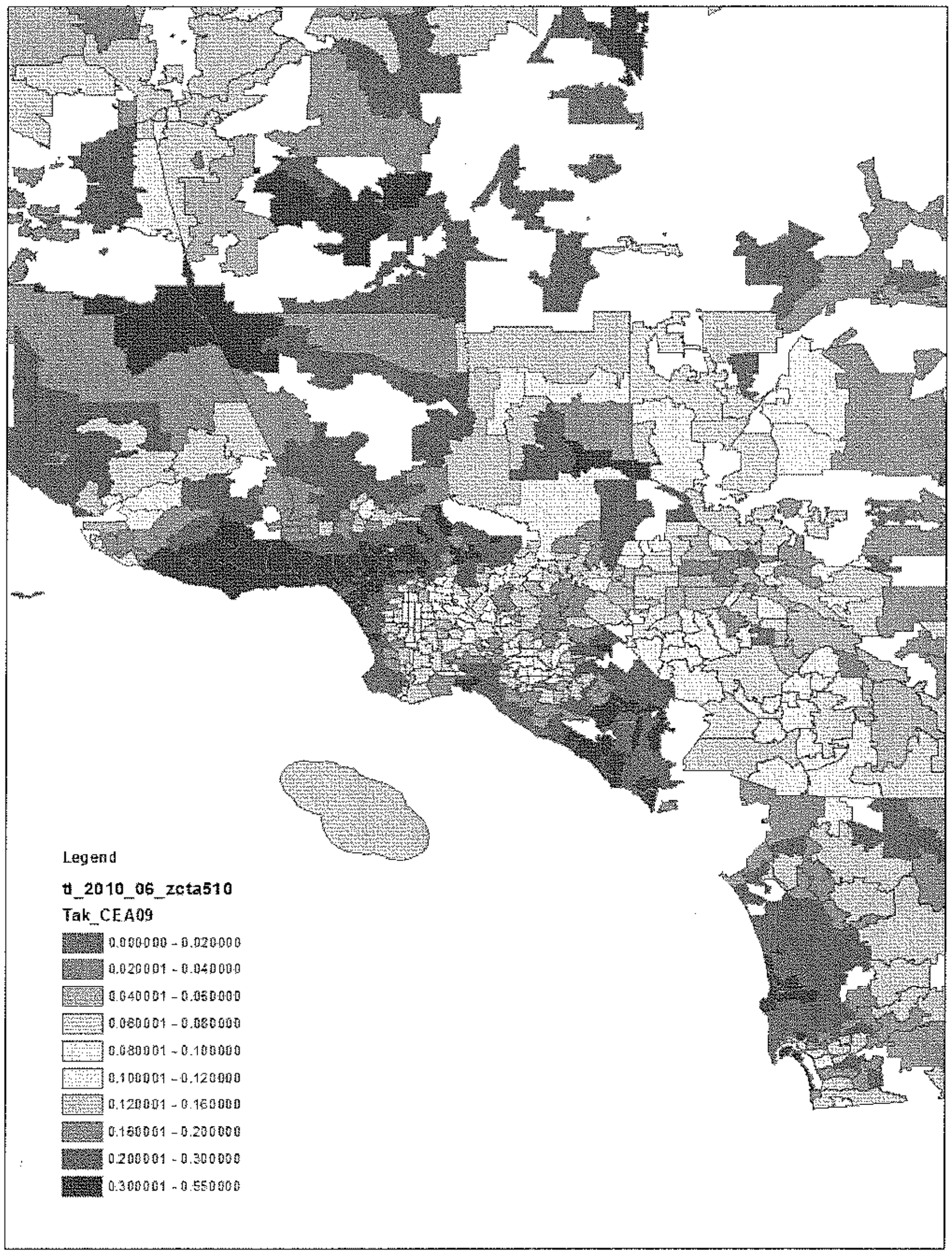

Figure 7: CEA take-up rates in the San Francisco Bay Area. This is a zoom-in map from Figure 5.

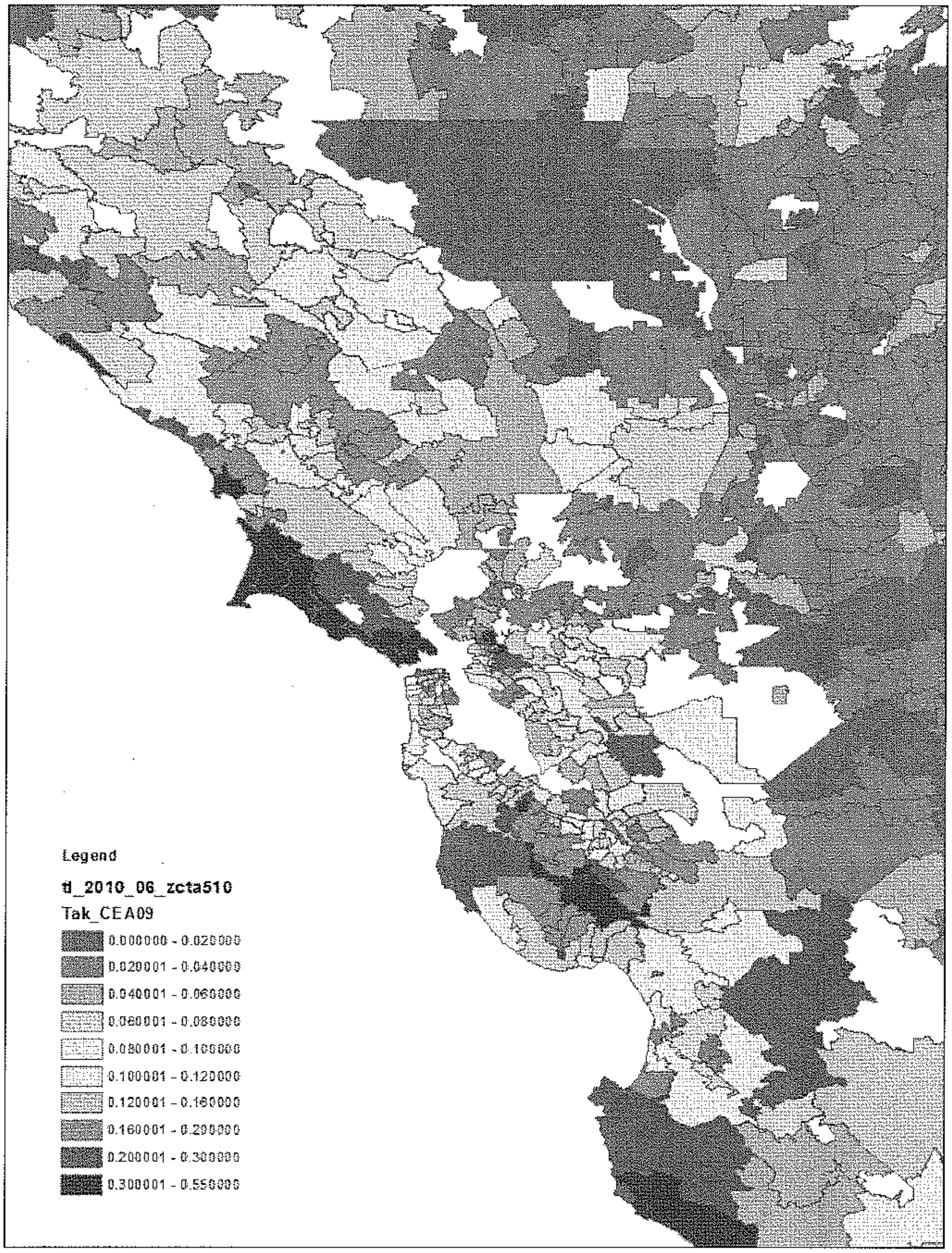

Figure 8: CEA take-up rate vs. PGA by Territory. Each plot represents one territory. Each dot represents a zip-code. The size of a zip-code is proportional to the total homeowners' policies in that zip-code. Y-axis is CEA take-up rate, x-axis is PGA. The scales for all the plots are the same. The fitted line is weighted by the size of each zip-code (weights are based on the number of total homeowners' policies.)

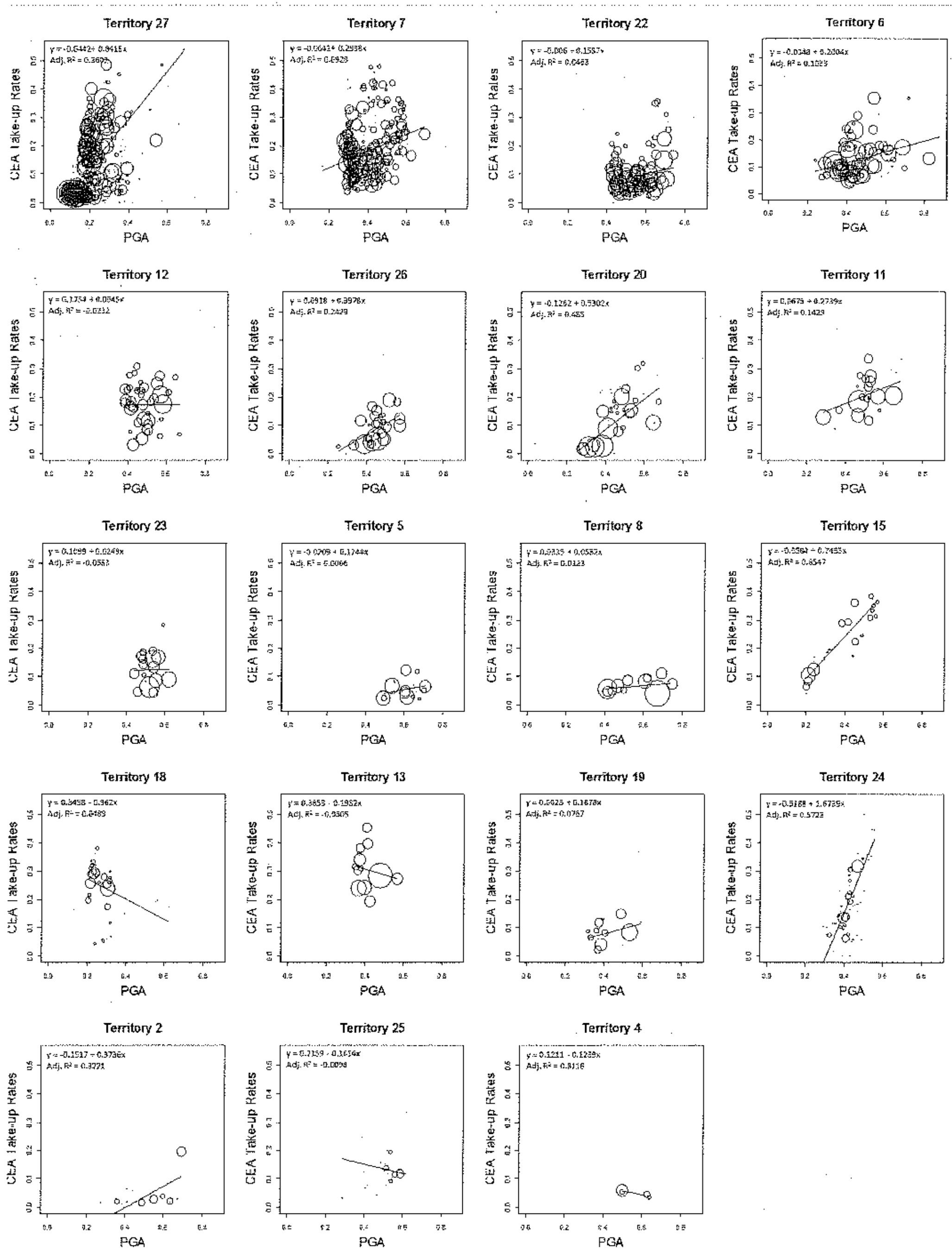

Figure 9: CEA take-up rate vs. PGA correlation maps. Hatched areas represent above median take-up rate in that territory. PGA (the risk level) is defined by color ramp from green (lowest risk) to red (higher risk). Territory 27 occupies a entire map since it's the largest territory. Other territories are grouped into 5 remaining maps by their geographical vicinity.

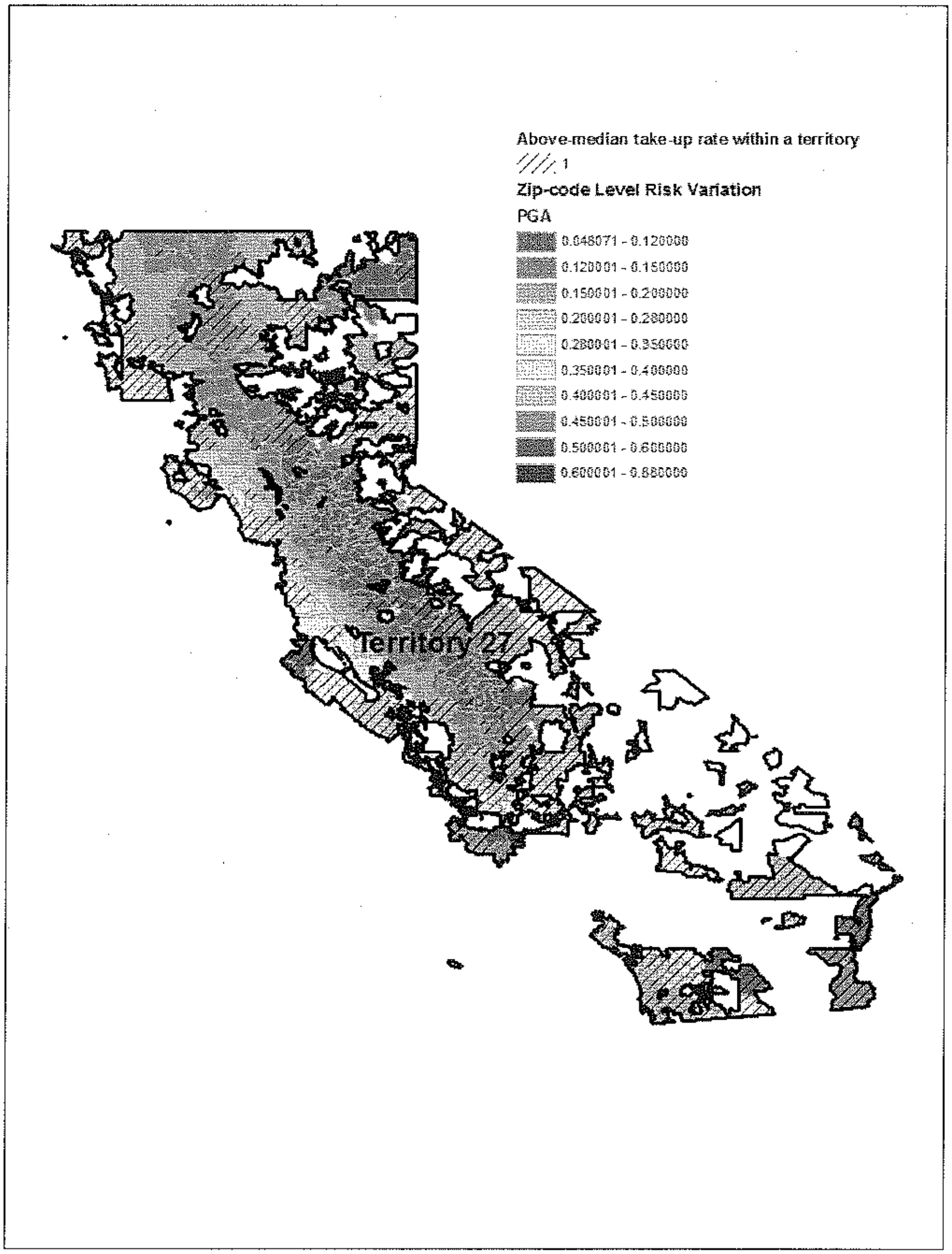

Figure 10: Comparison of demand for CEA and non-CEA by Territory. Y-axis is take-up rate, x-axis is PGA. The solid line is the best fitted line for the risk-demand relationship of the CEA. The dashed line is the best fitted line for the risk-demand relationship of the non-CEA insurers. The fitted line is weighted by the size of each zip-code (weights are based on the number of total homeowners' policies.)

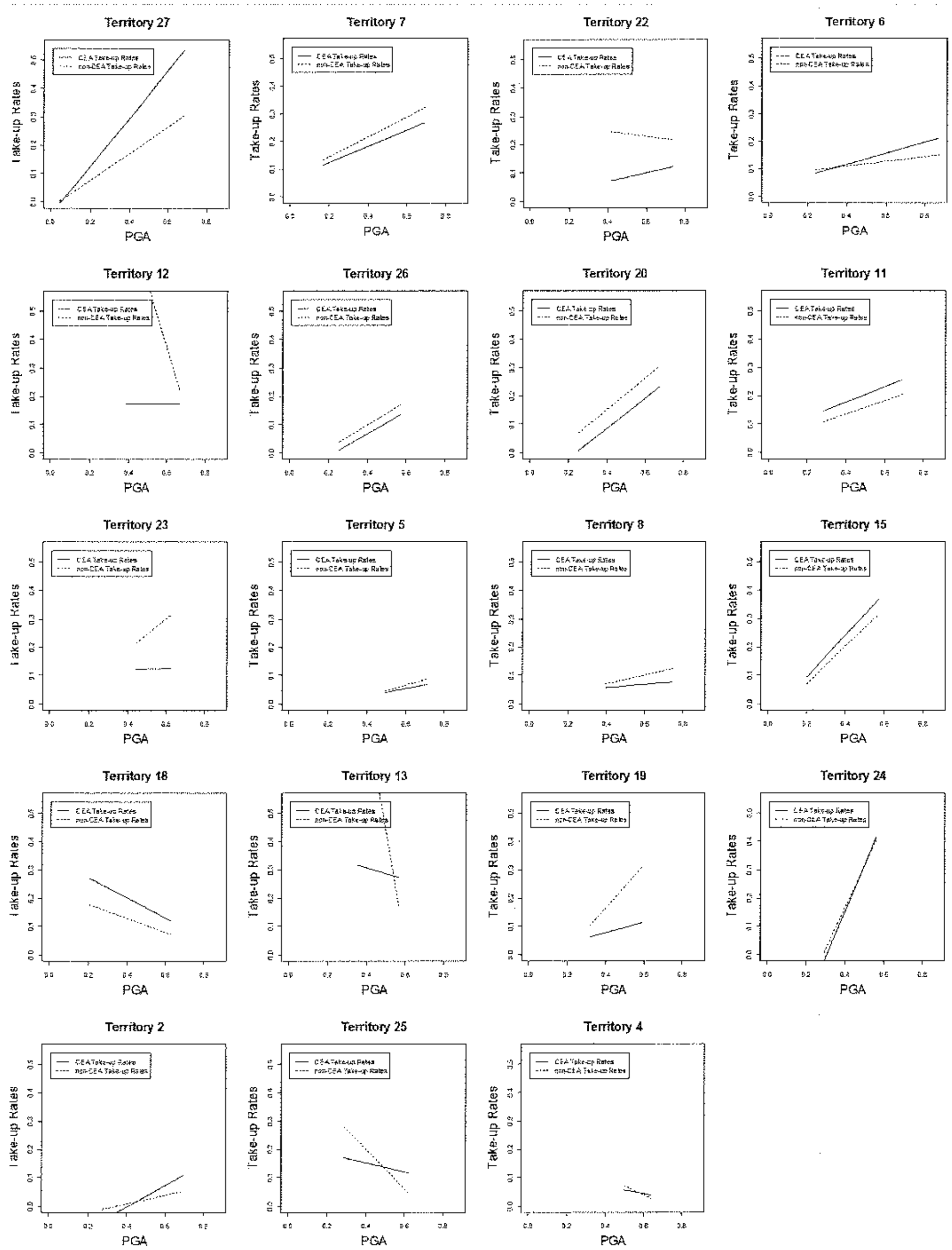

Figure 11: CEA EQ share vs. PGA by Territory. Each plot represents one territory. Each dot represents a zip-code. The size of a zip-code is proportional to the total homeowners' policies in that zip-code. Y-axis is CEA EQ share, x-axis is PGA. The scales for all the plots are the same. The fitted line is weighted by the size of each zip-code (weights also based on the number of total homeowners' policies.)