THE DEMAND AND SUPPLY OF AUTOMOBILE INSURANCE: EVIDENCE FROM UNDERSERVED AREAS IN CALIFORNIA

by

MELVIN T. STITH, JR.

(Under the Direction of Robert E. Hoyt)

ABSTRACT

Automobile insurance availability is a serious issue for motorists, regulators and the insurance industry. The costs imposed on the system by uninsured motorists are not trivial. In order to minimize these costs it is necessary to understand the factors that lead motorists to drive without insurance. This paper uses data reported to the California Department of Insurance as well as demographic data collected at the ZIP code level to analyze the demand for auto insurance in areas that the California Department of Insurance has designated as underserved. The results show that areas – as measured by ZIP codes – that are saddled with high poverty and areas that are predominately urban are more likely to have lower demand for automobile insurance. However, the fact that a certain area is predominately minority does not make it more likely to exhibit lower demand for automobile insurance.

INDEX WORDS: Underserved areas; Automobile insurance; Zip codes; Insurance access; Service offices and agents.

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DEDICATION

To Drs. Melvin and Patricia Stith. Without your love and support none of this would have been possible.

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CHAPTER 1

Introduction

It has long been recognized that having access to affordable insurance is critical to everyday life in American society. Insurance is even more important in the automobile context because many states have mandated that motorists purchase insurance. As important as insurance is to the average American citizen, it is even more essential for urban communities and has been for some time. In 1968, a federal advisory committee observed:

> Insurance is essential to revitalize our cities. It is a cornerstone of credit. Without insurance, banks and other financial institutions will not – and cannot make loans. New housing cannot be constructed, and existing housing cannot be repaired. New businesses cannot expand, or even survive.
>
> Without insurance, buildings are left to deteriorate; services, goods and jobs diminish. Efforts to rebuild our nation's inner cities cannot move forward. Communities without insurance are communities without hope. (President's National Advisory Panel, 1968).

As the preceding paragraphs illustrate, a better understanding of both the demand and availability of insurance could have profound public policy implications; particularly if it led to a better understanding of the availability – or lack thereof – of insurance in urban areas where it is so badly needed.

The need to understand the availability of insurance is especially urgent in the context of automobile insurance. Because state law mandates automobile insurance in most states as a

necessary prerequisite to driving, not being able to secure insurance means that many otherwise qualified people do not have access to an automobile. This reality has severe implications for many minorities living in urban areas because they are often denied opportunities for employment in suburban areas simply because they lack the transportation to get to the job site (Raphael and Stoll, 2001). However, because car ownership rates for low skilled workers are sensitive to small changes in operating costs, even a small change in cost or availability of auto insurance can have a significant impact in opening opportunities for minorities everywhere, but especially in urban areas (Raphael and Rice, 2000).

Statistics show that this access problem is particularly acute in California because so many people rely on automobiles to get to work. According to the Census 2000 conducted by the U.S. Census Bureau, 10,432,462 workers over 16 years of age, which is 71.8% of all workers over 16, drive to work alone in a car, truck or van. According to the 2000 census another 2,113,313 workers over 16, or 14.5% of all workers over 16, carpool to work in a car, truck or van. That means 12,545,775 workers over 16 years of age or 86.3% of all workers over 16 rely on a car, truck or van to get to work. Only 1,979,547 workers over 16 or 13.7% of all workers over 16 walk to work, use public transportation or work at home. These statistics illustrate how important it is for people to have access to automobile insurance to allow them to get to work.

This problem of securing access to automobile insurance for those who perhaps need it the most was one of the major reasons that California found it necessary to enact the provisions creating the "underserved" designation. As the California Department of Insurance (CDI) says on its website, "The purpose of the regulations is to address the issue of availability and

affordability of insurance in "underserved" communities and to promote anti-discrimination so that all have equal access to insurance coverage in California." California is the only state of which I am aware that has put such a premium on trying to ameliorate this problem of inadequate access to automobile insurance. It is doing this not only through its creation of the underserved designation, but also through increasing the level of transparency in the insurance industry by requiring insurers to publicly disclose data from home, personal auto, commercial multiple peril and commercial fire policies in California, in all ZIP codes identified as "underserved". The California Commissioner of Insurance collects and reports earned exposures for the affected lines, as well as the number of agents and service offices in the underserved areas as a percentage of statewide totals for each insurance company.

California is an ideal state in which to conduct this study for several reasons. Not only does it provide a workable framework for studying these access issues through its creation of the underserved designation, it also provides the unprecedented level of transparency discussed above that allows us to study the impact of demographics on access to automobile insurance. Demographically, California also provides an excellent laboratory in which to study why certain areas have issues with automobile insurance access. Besides being the most heavily populated state in the United States with nearly 34 million residents, California provides a great deal of diversity because it contains large numbers of different ethnic groups and it has many different levels of income and education stratification. According to the most recent census taken in 2000, 26.2% of California residents were born in foreign countries and 39.5% of California residents belong to families that speak a language other than English in the home. For comparison

purposes, 11.1% of United States residents were born in foreign countries and 17.9% of all Americans belong to families that speak a language other than English in the home.

Table 1 provides selected California demographic characteristics that illustrate the rich diversity present in the state.

Table 1

State of California Selected Demographic Characteristics

Subject	**Number**	**Percent**
Total population	**33,871,648**	**100.0**
SEX AND AGE		
Male	16,874,892	49.8
Female	16,996,756	50.2
RACE		
One race	32,264,002	95.3
White	20,170,059	59.5
Black or African American	2,263,882	6.7
American Indian and Alaska Native	333,346	1.0
Asian	3,697,513	10.9
Asian Indian	314,819	0.9
Chinese	980,642	2.9
Filipino	918,678	2.7
Japanese	288,854	0.9
Korean	345,882	1.0
Vietnamese	447,032	1.3
Other Asian 1	401,606	1.2
Native Hawaiian and Other Pacific Islander	116,961	0.3
Native Hawaiian	20,571	0.1
Guamanian or Chamorro	20,918	0.1
Samoan	37,498	0.1
Other Pacific Islander 2	37,974	0.1
Some other race	5,682,241	16.8
Two or more races	1,607,646	4.7
Race alone or in combination with one or more other races 3		
White	21,490,973	63.4
Black or African American	2,513,041	7.4
American Indian and Alaska Native	627,562	1.9
Asian	4,155,685	12.3
Native Hawaiian and Other Pacific Islander	221,458	0.7
Some other race	6,575,625	19.4
HISPANIC OR LATINO AND RACE		

Subject	Number	Percent
Total population	33,871,648	100.0
Hispanic or Latino (of any race)	10,966,556	32.4
Mexican	8,455,926	25.0
Puerto Rican	140,570	0.4
Cuban	72,286	0.2
Other Hispanic or Latino	2,297,774	6.8
Not Hispanic or Latino	22,905,092	67.6
White alone	15,816,790	46.7
HOUSEHOLDS BY TYPE		
Total households	11,502,870	100.0
Family households (families)	7,920,049	68.9
With own children under 18 years	4,117,036	35.8
Married-couple family	5,877,084	51.1
With own children under 18 years	2,989,974	26.0
Female householder, no husband present	1,448,510	12.6
With own children under 18 years	834,716	7.3
Nonfamily households	3,582,821	31.1
Householder living alone	2,708,308	23.5
Householder 65 years and over	892,207	7.8
Households with individuals under 18 years	4,569,910	39.7
Households with individuals 65 years and over	2,570,170	22.3
Average household size	2.87	(X)
Average family size	3.43	(X)
EDUCATIONAL ATTAINMENT		
Population 25 years and over	21,298,900	100.0
Less than 9th grade	2,446,324	11.5
9th to 12th grade, no diploma	2,496,419	11.7
High school graduate (includes equivalency)	4,288,452	20.1
Some college, no degree	4,879,336	22.9
Associate degree	1,518,403	7.1
Bachelor's degree	3,640,157	17.1
Graduate or professional degree	2,029,809	9.5
Percent high school graduate or higher	76.8	(X)
Percent bachelor's degree or higher	26.6	(X)
NATIVITY AND PLACE OF BIRTH		
Total population	33,871,648	100.0
Native	25,007,393	73.8
Born in United States	24,633,720	72.7
State of residence	17,019,097	50.2
Different state	7,614,623	22.5
Born outside United States	373,673	1.1
Foreign born	8,864,255	26.2
Entered 1990 to March 2000	3,270,746	9.7
Naturalized citizen	3,473,266	10.3
Not a citizen	5,390,989	15.9
REGION OF BIRTH OF FOREIGN BORN		
Total (excluding born at sea)	8,864,188	100.0
Europe	696,578	7.9
Asia	2,918,642	32.9

Subject	Number	Percent
Africa	113,255	1.3
Oceania	67,131	0.8
Latin America	4,926,803	55.6
Northern America	141,779	1.6
LANGUAGE SPOKEN AT HOME		
Population 5 years and over	31,416,629	100.0
English only	19,014,873	60.5
Language other than English	12,401,756	39.5
Speak English less than 'very well	6,277,779	20.0
Spanish	8,105,505	25.8
Speak English less than "very well"	4,303,949	13.7
Other Indo-European languages	1,335,332	4.3
Speak English less than "very well"	453,589	1.4
Asian and Pacific Island languages	2,709,179	8.6
Speak English less than "very well"	1,438,588	4.6
ANCESTRY (single or multiple)		
Total population	33,871,648	100.0
Total ancestries reported	35,569,389	105.0
Arab	192,887	0.6
Czech1	118,889	0.4
Danish	207,030	0.6
Dutch	417,382	1.2
English	2,521,355	7.4
French (except Basque)1	783,576	2.3
French Canadian1	148,265	0.4
German	3,332,396	9.8
Greek	125,284	0.4
Hungarian	133,988	0.4
Irish1	2,622,089	7.7
Italian	1,450,884	4.3
Lithuanian	51,406	0.2
Norwegian	436,128	1.3
Polish	491,325	1.5
Portuguese	330,974	1.0
Russian	402,480	1.2
Scotch-Irish	410,310	1.2
Scottish	541,890	1.6
Slovak	24,535	0.1
Subsaharan African	184,921	0.5
Swedish	459,897	1.4
Swiss	115,485	0.3
Ukrainian	83,125	0.2
United States or American	1,140,830	3.4
Welsh	188,414	0.6
West Indian (excluding Hispanic groups)	63,639	0.2
Other ancestries	18,590,005	54.9

Source: U.S. Census Bureau, Census 2000

Table 2 is a profile of selected demographic and economic statistics compiled from the year 2000 United States Census.

Table 2

State of California
Profile of Demographic and Economic Statistics

Subject	Number	Percent
EMPLOYMENT STATUS		
Population 16 years and over	**25,596,144**	**100.0**
In labor force	15,977,879	62.4
Civilian labor force	15,829,202	61.8
Employed	14,718,928	57.5
Unemployed	1,110,274	4.3
Percent of civilian labor force	7.0	(X)
Armed Forces	148,677	0.6
Not in labor force	9,618,265	37.6
Own children under 6 years	2,782,416	100.0
All parents in family in labor force	1,441,714	51.8
COMMUTING TO WORK		
Workers 16 years and over	14,525,322	100.0
Car, truck, or van -- drove alone	10,432,462	71.8
Car, truck, or van -- carpooled	2,113,313	14.5
Public transportation (including taxicab)	736,037	5.1
Walked	414,581	2.9
Other means	271,893	1.9
Worked at home	557,036	3.8
Mean travel time to work (minutes)	27.7	(X)
CLASS OF WORKER		
Private wage and salary workers	11,257,393	76.5
Government workers	2,158,071	14.7
Self-employed workers in own not incorporated business	1,249,530	8.5
Unpaid family workers	53,934	0.4
INCOME IN 1999		
Households	11,512,020	100.0
Less than $10,000	967,089	8.4
$10,000 to $14,999	648,780	5.6
$15,000 to $24,999	1,318,246	11.5
$25,000 to $34,999	1,315,085	11.4
$35,000 to $49,999	1,745,961	15.2
$50,000 to $74,999	2,202,873	19.1
$75,000 to $99,999	1,326,569	11.5
$100,000 to $149,999	1,192,618	10.4
$150,000 to $199,999	385,248	3.3
$200,000 or more	409,551	3.6
Median household income (dollars)	47,493	(X)

With earnings	9,502,776	82.5
Mean earnings (dollars)	64,725	(X)
With Social Security income	2,565,234	22.3
Mean Social Security income (dollars)	11,331	(X)
With Supplemental Security Income	607,106	5.3
Mean Supplemental Security Income (dollars)	6,990	(X)
With public assistance income	563,409	4.9
Mean public assistance income (dollars)	4,819	(X)
With retirement income	1,774,452	15.4
Mean retirement income (dollars)	18,826	(X)
Families	7,985,489	100.0
Less than $10,000	457,118	5.7
$10,000 to $14,999	365,527	4.6
$15,000 to $24,999	834,317	10.4
$25,000 to $34,999	873,396	10.9
$35,000 to $49,999	1,207,938	15.1
$50,000 to $74,999	1,615,410	20.2
$75,000 to $99,999	1,034,671	13.0
$100,000 to $149,999	955,377	12.0
$150,000 to $199,999	310,407	3.9
$200,000 or more	331,328	4.1
Median family income (dollars)	53,025	(X)
Per capita income (dollars)	22,711	(X)
Median earnings (dollars):		
Male full-time, year-round workers	40,627	(X)
Female full-time, year-round workers	31,722	(X)
POVERTY STATUS IN 1999 (below poverty level)		
Families	845,991	(X)
Percent below poverty level	(X)	10.6
With related children under 18 years	699,159	(X)
Percent below poverty level	(X)	15.3
With related children under 5 years	366,529	(X)
Percent below poverty level	(X)	19.0
Families with female householder, no husband present	350,138	(X)
Percent below poverty level	(X)	25.0
With related children under 18 years	310,533	(X)
Percent below poverty level	(X)	32.5
With related children under 5 years	147,900	(X)
Percent below poverty level	(X)	44.0
Individuals	4,706,130	(X)
Percent below poverty level	(X)	14.2
18 years and over	2,949,030	(X)
Percent below poverty level	(X)	12.3
65 years and over	280,411	(X)
Percent below poverty level	(X)	8.1
Related children under 18 years	1,705,797	(X)
Percent below poverty level	(X)	19.0
Related children 5 to 17 years	1,216,541	(X)

Percent below poverty level	(X)	18.5
Unrelated individuals 15 years and over	1,321,169	(X)
Percent below poverty level	(X)	23.1

Source: U.S. Census Bureau, Census 2000

This study will present and then estimate a model of the demand for insurance in areas deemed underserved by the California Department of Insurance, areas that are almost underserved and finally the state of California as a whole. These three areas are used to determine whether there are factors that are affecting demand in differently in different areas. Demographic data obtained from the 2000 United States Census is then used to regress the insurance demand variable on various factors such as poverty, income, minority status and whether the area is urban or rural.

The goal is to try to pinpoint factors that exist in these almost underserved areas that may be used to help lower the uninsured motorist rate in those areas that meet the full definition of underserved as defined by the California Department of Insurance. These factors will help us to better explain why people exhibit a demand for auto insurance. We will investigate potential barriers that need to be overcome so that access to insurance is improved for all potential motorists whether or not they happen to live in underserved or almost underserved areas.

Previous literature has focused on discrimination in insurance in the form of "redlining" that raises prices and restricts the availability of coverage (Squires, DeWolfe, and DeWolfe, 1979; Squires, Velez, and Taeuber, 1991). Harrington and Niehaus investigated whether racial discrimination affects market prices of auto insurance in Missouri (Harrington and Niehaus, 1998). This paper employs a framework established by a state government to examine factors that influence automobile insurance demand. This analysis will allow us to provide direct advice

to the state in order to improve the underserved framework so that California can better effectuate its goal of increased access to automobile insurance for all Californians. Because of the degree of specificity of the data that insurers are required to report in California we are able to directly observe the uninsured motorist rate in underserved communities and compare it to the uninsured motorist rate in California as a whole. Because automobile insurance is mandatory under California law in order to drive, employing the uninsured motorist rate allows us to use a very direct measure of auto insurance demand in order to investigate insurance access rather than concentrating on insurance pricing or firm profits. This study will analyze those factors that influence auto insurance demand at the ZIP code level while controlling for other factors that might influence the results.

CHAPTER 2

California Underserved Areas

California has promulgated regulations to "address the issue of availability and affordability of insurance in "underserved" communities and to promote anti-discrimination so that all have equal access to insurance coverage in California."

These regulations require the California Department of Insurance to collect and analyze data from home, personal auto, commercial multiple peril and commercial fire insurers in California, in all ZIP codes identified as "underserved". It is unclear whether California policy makers have taken action based on this information. The results reported in this paper could assist them when deciding what action to take to increase access to insurance in the state. Underserved ZIP codes are those in which:

1. The proportion of uninsured motorists is ten percentage points above the statewide average (statewide average was 25% in 2004);

2. The per capita income of the community (as measured in the most recent U.S. Census), is below the fiftieth (50th) percentile for California; and

3. The community (as measured in the most recent U.S. Census), is predominantly (2/3) minority (2004 Commissioner's Report on Underserved Communities).

The California Code of Regulations - §2646.6 provides that a predominately minority community can be quantified as any community that is composed of two-thirds or more

minorities. Minorities are those people that fall into one or more of the following groups: American Indian or Alaskan Native, Asian or Pacific Islander, African-American, or Latino.

The uninsured motorist rate is calculated by subtracting the number of insured vehicles in the ZIP code from the number of registered vehicles in the ZIP code and dividing that difference by the number of registered vehicles in the ZIP code. The estimated rate of uninsured motorists is based upon vehicle registration data maintained by the California Department of Motor Vehicles (DMV) and data for private passenger liability insurance reported to the California Department of Insurance (CDI) by insurers. Other methods of evaluating rates of uninsured vehicles, such as studies based upon accident claims, may result in different estimates (California Department of Insurance website).

These regulations have been in place since 1994. The regulations require insurers to file data annually about where they are and are not writing homeowners, automobile, and commercial policies. These statements, sometimes called "community service statements", disclose the numbers of policies and premiums in each ZIP code in California. The filings do not reveal individual policyholder information.

Pursuant to its authority under Proposition 103, the California Department of Insurance (CDI) promulgated a regulation requiring the public disclosure of the data described above. In 1999, the insurance industry led by State Farm sued claiming that the data constituted a trade secret. Consumers Union and the Southern Christian Leadership Conference of Greater Los Angeles, represented by Public Advocates, intervened in the case because they sought the data in order to track potential redlining abuses by insurers. The San Francisco Superior Court ruled for

the groups, finding that the public had a right to review the redlining data under Proposition 103. In a unanimous decision, the First District Court of Appeals affirmed the ruling. While the case was being decided, the CDI continued to collect the data from insurers, but did not make it public. On April 26, 2003 in State Farm v. Garamendi (Case # S102251) the California Supreme Court unanimously ruled that the state insurance commissioner did not exceed his statutory authority under Proposition 103 when he promulgated the public disclosure regulation. The Court noted that regardless of whether the filings contain trade secrets, the Commissioner's regulation and Proposition 103 make those filings available for public inspection.

ZIP codes are used as the relevant unit of analysis for several reasons. As discussed earlier, the CDI uses them in their analysis and determination of underserved areas. Also, United States census data are reported at the ZIP code level. Therefore, ZIP codes provide a comparable unit of measurement when analyzing the data collected from the census and the CDI. Finally, ZIP codes represent the smallest geographic breakdown there is for insurance data (Klein and Grace, 2001).

Table 3 contains summary data on the portion of drivers in underserved areas, as well as other relevant data. The CDI defines the word "earned" in the term "earned exposure" as a condition where the exposure is recognized by the insurance company after time has passed and the insurance company has delivered the services promised under the insurance policy. Furthermore, an "exposure" is defined as the risk or loss potential an insurance company assumes from its policyholder in exchange for premium (an automobile or home are examples of exposures). "Assigned Risk" is an automobile insurance plan that covers individuals who cannot

obtain conventional automobile liability insurance usually because of adverse driving records. These individuals are then placed in a residual insurance market. Insurance companies are assigned to write insurance for them, at higher prices, in proportion to the premiums written in a particular state. These plans protect motorists who suffer injury or property damage through the negligence of bad drivers who otherwise would not have insurance.

California maintains a Low Cost Automobile Insurance Program. The primary goal of this program is to provide affordable liability only auto insurance so that drivers may meet the state's automobile insurance requirements. The state is concerned that too many low income drivers may remain uninsured without this program because the standard insurance premiums are too expensive.

The Low Cost Automobile Insurance Program provides for the following maximum limits on the offered policies:

Bodily Injury liability per person - $10,000;

Bodily Injury liability per accident - $20,000;

Property Damage liability per accident - $3,000.

In order to be eligible for the Low Cost Automobile Insurance Program the following conditions must be met by all applicants:

1. Applicant must be 19 years of age or older and a continuously licensed driver for the past three years;
2. Applicant must qualify as a good driver;
3. Applicant must have a vehicle currently valued at $20,000 or less;

4. Applicant must meet income eligibility requirements determined by household size.

Table 3

Summary Statistics for
Underserved Communities

Coverage	Total Earned Exposures for California	Total Earned Exposures for Underserved Communities	Percentage of Total Earned Exposures in Underserved Communities	Percentage of Total Earned Exposures in Non Underserved Communities
Private Passenger Automobile	19,863,126	1,719,621	8.7%	91.3%
Assigned Risk	66,102	25,167	38.1%	61.9%
Low Cost Auto	4,395	2,511	57.1%	42.9%
Total	19,933,623	1,747,299		

	In California	In Underserved Communities	Percentage in Underserved
Registered Vehicles	23,987,027	2,941,920	12.3%
Population	35,072,540	5,603,855	16.0%
Uninsured Motorist Rate	14.3%	37.9%	
Minority Percentage	55.0%	89.7%	
Per Capita Income (Median)	20,286	11,021	

California Department of Insurance,
Statistical Analysis Division

CHAPTER 3

Motivation

It is especially instructive to examine those areas that meet the last two requirements of the underserved criteria, but not the first. That is, those ZIP codes in which the per capita income of the community is below the fiftieth (50th) percentile for California, and the community is predominantly minority, but the proportion of uninsured motorists is *not* ten percentage points above the statewide average. We will investigate these areas to determine whether there are characteristics in these ZIP codes that suggest potential solutions to improving access to automobile insurance in underserved areas.

This is important because while previous studies have established that certain demographic groups have a larger percentage of uninsured drivers (Hunstad, 1999), these studies have not examined the issue in the context of underserved markets.

In particular we can assess whether consumers in underserved markets have lower demand for insurance. We will construct a demand model to test various hypotheses related to the demand for insurance in underserved areas. Combining this data with currently available census data may shed light on the reasons that citizens are not purchasing automobile insurance even when they are mandated to do so by law.

By examining this equation we should be able to gain a better understanding of the unique challenges encountered when attempting to provide affordable insurance to the

underserved community so that there are fewer ZIP codes on the underserved list when the commissioner delivers the next report. This is important because costs imposed on society by uninsured motorists can be significant (Cole and McCullough, 2007). An Insurance Research Council study found that approximately $2.4 billion, or 6.45% of all paid losses from injury claims, were paid under uninsured motorist coverage in 1997 (Insurance Research Council, 1999). The costs to individuals can be just as severe as the costs to society. In most states, including California, not having access to auto insurance means not being able to drive. This has important ramifications in the context of employment because there is a significant difference in employment rates between car owners and non car owners, particularly in the African-American community (Raphael and Stoll, 2001).

CHAPTER 4

Historical Motivation

The California Department of Insurance promulgated these regulations in part "to promote anti-discrimination so that all have equal access to insurance coverage in California." The CDI felt the need to promulgate these regulations because there is an unfortunate legacy of racial and ethnic discrimination in the United States that we are still grappling with today.

The legal history of these discrimination cases is a long one. Appendix A details some of the most important cases in civil rights jurisprudence. This survey of legal precedent is not meant to be completely exhaustive. Rather, this is meant to highlight some important cases in United States history that illuminate why the CDI feels that it is important to promote anti-discrimination. It is important to highlight some of the seminal cases in the jurisprudence of racial discrimination in the United States because from 1938, when the National Association for the Advancement of Colored People (NAACP) won its first Supreme Court victory in a school desegregation case, until the 1960's when we again experienced a political consensus favoring civil rights, the courts were virtually alone in articulating the importance of race discrimination laws, as well as insisting on their enforcement.

As the cases detailed in Appendix A make clear, equal access for all to all opportunities is not only desirable it is a minimum requirement if all citizens are to be expected to participate and fully contribute to the well being of society. This holds true whether the issue is access to a public conveyance, access to equal education or access to affordable automobile insurance. The

problem of race in general and access in particular has long been a thorny one and difficult to resolve. In creating the underserved designation and requiring the disclosure of the community service statements, the CDI is attempting to provide some measure of relief to those who have been affected by discrimination, whether intentional or not.

CHAPTER 5

California Automobile Insurance Regulation

The question of whether or not all citizens in California have adequate access to automobile insurance is an important one because in California proof of "financial responsibility" is required to drive lawfully in the state. Motorists are limited in the manner that they can prove their financial responsibility. The four types of financial responsibility that will be accepted by the California Department of Motor Vehicles (DMV) are provided below:

- A motor vehicle liability insurance policy;
- A cash deposit of $35,000 with DMV;
- A DMV issued self-insurance certificate; or
- A surety bond for $35,000 from a company licensed to do business in California.

Obviously, the vast majority of California motorists will choose to purchase a motor vehicle liability insurance policy to satisfy the financial responsibility requirement.

In 2006, the California Vehicle Financial Responsibility Law changed the way the Department of Motor Vehicles verifies insurance for privately owned vehicles. Changes were made to ensure that vehicles driven on California roads have liability insurance that provides financial responsibility for any damage or injury caused by a traffic accident, regardless of fault, and to remove uninsured vehicles from the highways. Insurance companies in California are required by law (*California Vehicle Code* (CVC) §6058) to electronically report private-use vehicle insurance information to the DMV. Insurance companies are not required to electronically report information for vehicles covered by "commercial" or "business" insurance policies. Customers whose vehicles are covered by this

type of policy will be required to submit paper proof of insurance when required for registration renewal and when a vehicle is registered in their name for the first time in California.

Law enforcement and court personnel have electronic access to insurance status on DMV records.

Motorists in California must meet mandatory vehicle registration financial responsibility requirements. Financial responsibility must be obtained and maintained on any vehicle operated or parked on California roadways and must be provided as specified below:

- When requested by law enforcement;
- When renewing vehicle registration (if requested);
- Within 30 days of issuance of a registration card for a vehicle being registered in California for the first time, or transfer of ownership;
- Within 45 days of the cancellation of a policy for a currently registered vehicle;
- When the vehicle is involved in a traffic accident.

Motorists must carry evidence of financial responsibility (proof of insurance) in their vehicles at all times.

California has set minimum liability insurance requirements for private passenger vehicles. The requirements are as follows:

- $15,000 for injury/death to one person;
- $30,000 for injury/death to more than one person;
- $5,000 for damage to property.

Liability insurance compensates a person other than the policy holder for personal injury or property damage (*California Insurance Code §11580.1b*).

When the DMV does not have insurance information for a vehicle it is empowered to issue a suspension of a motorist's vehicle registration.

Vehicle registrations are subject to suspension (*California Vehicle Code §4000.38*) when:

- DMV is notified that a policy has been cancelled and a replacement policy has not been submitted within 45 days;
- Insurance information is not submitted to DMV within 30 days of the issuance of a registration card upon initial registration or transfer of ownership;
- The registration is obtained by providing false evidence of insurance.

California law has set forth a range of penalties in the event that any motorist fails to maintain financial responsibility on a vehicle. If financial responsibility is not maintained the possible penalties are as follows:

- Registration of the vehicle will be subject to suspension. DMV will begin the process to suspend any motorist's registration if:
  — Liability insurance is cancelled and a replacement policy is not submitted within 45 days;
  or
  — The motorist's insurance company has not electronically provided evidence of insurance within 30 days of a registration card being issued on a vehicle being registered in California for the first time;
  or
  — The motorist provides false evidence of insurance.
- The motorist may be cited**.** Failure to provide evidence of financial responsibility when requested by a peace officer may result in a citation with fines that could reach $1,000 or more. (DMV cannot clear or sign citations relating to financial responsibility. Only a court can clear or sign these citations.);
- The vehicle may be impounded**.** Failure to provide evidence of financial responsibility may result in the vehicle being impounded, in addition to any fines;
- The motorist may be personally liable for damages**.** If a motorist contributes to the cause of an accident and cannot provide evidence of financial responsibility, that motorist may be forced to compensate the other party for any injuries and damages.

As the foregoing discussion makes clear, the state of California is serious in insisting that motorists in the state comply with the applicable financial responsibility laws. However, it remains true that many motorists drive without meeting these financial responsibility laws. A California survey found that 10% of vehicle owners in California owned an uninsured vehicle

(Hunstad, 1999). Although there are a wide variety of reasons cited by motorists for non-compliance, 80% of uninsured drivers in the survey cited non-use of the vehicle or the cost of insurance as the main reason that they did not insure (Hunstad, 1999). Because insurance is the only practical way for the vast majority of drivers to comply with the financial responsibility law, it is essential that they have affordable access to auto insurance in their area.

CHAPTER 6

Prior Literature

Prior literature has focused on the question of insurance demand. Browne and Hoyt (2000) estimate a flood insurance demand model. They test whether different determinants factor into the decision to purchase flood insurance. These determinants include price, income and price elasticities, recent flood experience, federal government mitigation efforts, and increased federal disaster relief payments. Because they have both time series and cross sectional data, they estimate their model as a fixed effects model. They estimate their model twice in order to account for different definitions of insurance demand. The two definitions are the number of flood insurance policies purchased per 1,000 population in a state during a year and the face amount of flood insurance in force per capita in a state during a year. The number of flood insurance policies in force is a proxy for the number of individuals and businesses that have bought flood insurance coverage. Therefore, it measures what portion of the population has purchased at least some amount of flood insurance. The face amount of flood insurance in force reveals the total value insured in a state during a year.

For their price variable, they use the dollar value of premiums paid for flood insurance in the state during the year divided by the dollar value of insurance in force (in thousands) in the state during the year. The proxy they use for income is disposable personal income per 1,000 population. They also include a variable to control for the effect that a recent flood might have on a person's feeling about the likelihood of another flood. They include this variable to account for the likelihood that an individual's perception about the risk of loss may influence the decision

to buy insurance. This variable is defined as the dollar value of total flood damage (not just insured losses) in the state during the preceding year.

They ultimately find that flood insurance purchases are positively related to income and negatively related to price. Specifically they find that demand for flood insurance is relatively insensitive to changes in price, but when demand is measured by the amount of insurance in force it becomes sensitive to changes in price. They also find that those with higher income are more likely to purchase insurance and purchase greater amounts of insurance than those with lower incomes. Therefore, this study reinforces the notion that as the level of an individual's income increases, the amount of insurance purchased by that individual is likely to increase. Given the fact that auto insurance is mandatory in many states and flood insurance is not, it will be interesting to expand this notion from the area of flood insurance to the area of auto insurance to determine if this relation still holds true.

The theory of insurance demand has been investigated in other contexts as well. For example, Kunreuther and Pauly (2004) construct an insurance demand model for low probability high loss events. They seek to explain why people often don't buy insurance against low probability high loss events even when it is offered at favorable premiums. They model factors that an individual should consider in deciding whether to seriously consider the purchase of insurance. They show that there are search costs involved with collecting insurance information. These search costs can discourage people from undertaking the type of analysis often necessary to discover that buying insurance against low probability high loss events would often be in their best interest. We can investigate this conclusion in the context of auto insurance by including

the language isolated variable. Families that are language isolated face greater search costs than those who aren't because in America most insurance information is written in English. Because these families face greater search costs they should buy less insurance. Kunreuther and Pauly construct two models. In the first model insurers are sure about the probability of loss while consumers are not. In the second model, both insurers and consumers are unsure about the probability of loss.

There have also been several papers focused on the question of access, discrimination and potential redlining in insurance markets. Regarding discrimination, Dane (2006) analyzes the potential racial implications of using geographic rating territories in the homeowners insurance rating process. He notes that insurance ratemaking has historically been premised on actuarial analysis of loss and claims data that are not known to have racial implications. However, the one area where traditional insurance pricing procedures might have racial consequences is the use of geography. Because many cities in the United States remain racially segregated, there is the potential for racially identifiable neighborhoods in the same city to be charged different rates. Pricing differentials at the small geographic level of the ZIP code have potentially significant racial consequences because if two rating territories that have been created based on ZIP code have different base rates, the chances that two different racial groups will be charged different base rates increases dramatically. Because ZIP codes are so small geographically, generally there is not enough loss data at the ZIP code level to justify the calculation of an actuarially sound base rate. Loss data at the ZIP code level is not credible enough to be the sole basis for

generating a base rate. We use the minority variable to try to investigate whether there are any measurable differences in auto insurance demand between different ethnic groups.

Harrington and Niehaus (1998) investigate whether racial discrimination affects the pricing of auto insurance at the market level. They contend that if insurers discriminate then the expected loss ratio will be lower in areas with a higher percentage of minorities. This would be consistent with higher expected profit margins in these areas. They use ZIP code level data from Missouri.

They define the loss ratio as the average claim costs in a particular ZIP code divided by the average premium per exposure in a particular ZIP code. They use a model that has the log of the loss ratio as the dependent variable and has the percentage of the total population in the ZIP code that is black as an independent variable. The other independent variable is a vector of demographic and other factors. They find that loss ratios are not significantly lower in ZIP codes with larger minority populations. They reason that this finding implies that higher auto insurance premiums in urban areas are attributable to high claim costs in these areas and not to discrimination.

Squires and Kubrin (2006) reach a different conclusion by examining the historical and ongoing practices of racial profiling and other discriminatory actions in the property insurance industry. They detail how important insurance is to people in their everyday life. They assert that households that confront the problem of insurance availability tend to be located in inner city neighborhoods where there are high concentrations of non-white residents.

They contend that inner city residents must deal with a host of factors not relating to risk that causes them to have insurance availability problems. They point out that insurers don't know the cost of their product when it is sold to the consumer because they can't know whether or not any particular consumer will ever file a claim. Therefore, the authors contend that as part of their underwriting practices, insurers use race as a way to classify and price risks. Their contention is that many residents of urban areas are offered less attractive insurance products for reasons unrelated to the actual risk that they pose to the insurance company. They detail many factors that could have an adverse effect on the ability of urban residents to procure insurance. These factors include agent location, underwriting guidelines, and the claims process.

The authors advocate state programs that would establish an affirmative obligation for insurers to provide insurance products and investment activity in low and moderate income neighborhoods. They also urge the adoption of a federal insurance disclosure requirement to force insurers to reveal the areas where they are writing their insurance policies.

Klein and Grace (2001) analyze the urban homeowners insurance market in Texas to determine whether insurance firms are redlining. They assess whether there is significant statistical evidence to prove the existence of redlining. Their paper controls for other factors that affect market outcomes thereby avoiding the omitted variable bias that occurs in prior literature because the effects of race are confounded with other factors correlated with race.

They begin by discussing the general conditions in urban insurance markets focusing on the differences between metropolitan and nonmetropolitan areas. They compare data on insurance prices and claim costs in the three largest Texas metropolitan areas with

nonmetropolitan areas in the state. They find that metropolitan homeowners pay higher average premiums for insurance than homeowners in nonmetropolitan areas for both fire and multi-peril coverage. However, they do not conclude that metropolitan homeowners are being overcharged because the loss costs in metropolitan areas are greater than the loss costs in nonmetropolitan areas. Therefore, it seems that homeowners in metropolitan areas are receiving a bargain when what they pay in premiums is compared to what they pay in claims.

They examine claim costs because this is a prime way to determine the pricing efficiency in urban areas. They assert that if claim costs are higher in areas with a higher concentration of minorities then it is reasonable to expect that these areas will have to pay higher prices for insurance. They ask whether the difference in claim costs and other economic/demographic factors account for all of the difference in premiums or whether the racial composition of an area has an additional effect that may be accounted for by recognizing the existence of unfair discrimination. To investigate this question they use a model that has a dependent variable of average claim costs. For independent variables it has a variable to proxy for the sensitivity of claims costs to the percentage of Blacks and Hispanics in a ZIP code. The other independent variable in the model is a vector of several economic, demographic, and housing variables. They use variables to proxy for risk of loss, volatility in homeowners' claims, and supply of and demand for insurance.

They find no significant relation between claim costs and the percentage of minorities in a ZIP code. They find that as owner occupancy increases, claim costs decrease. They also find that as the total wealth of the ZIP code increases, average claim costs decrease. Furthermore,

they find that the percentage of minorities in a ZIP code is not statistically related to the loss ratio. These findings lead them to conclude that no statistical evidence of redlining exists and that the risk of loss and the demand for insurance appear to primarily drive the terms of insurance transactions.

Harrington and Niehaus (1992) analyze a California program that seeks to deal with insurance unavailability and affordability problems in urban areas. The California program gives the insurance commissioner discretion to adjust the allowable rate of return depending on the amount of business that an insurer writes in inner city areas. After discussing possible sources of availability and affordability problems and describing the California proposal, the authors conclude that the program suffers from severe defects. These regulations would provide an incentive for some insurers to reduce quality or exit from the California market. The authors contend that the regulations would also promote cross-subsidies that would make consumers in other areas pay more to finance the urban areas.

Cole and McCullough (2007) investigate the uninsured motorist problem and provide a survey of some possible solutions. They explain the gravity of this problem by noting how the uninsured motorist rate has been increasing in recent years. They go on to detail the many different approaches that have been tried to deal with the problem. The approaches include improving tracking techniques designed to enforce compulsory insurance and financial responsibility laws, the availability of low-cost automobile insurance policies, the creation of uninsured and underinsured motorist coverage, the implementation of no pay, no play laws, and proposals for pay at the pump laws. The authors point out that increased understanding of the

uninsured motorist problem through future studies will help identify the most cost effective solutions.

This study follows in that tradition by examining the uninsured motorist problem through the prism of access. California is attempting to help alleviate the uninsured motorist problem by providing its more underserved citizens with increased access to much needed insurance. This study will help that strategy be more effective by focusing on identifying what factors lead to greater auto insurance demand. The results of this study will help policymakers in the future as they design their own strategies to deal with the problem of the uninsured motorist.

CHAPTER 7

Econometric Model and Data

The data used in this study is cross-sectional in nature and we are interested in its impact in determining whether these areas will be categorized as underserved or almost underserved. The models are estimated using the method of ordinary least squares. We combine data from the US Census Bureau's 2000 census and insurance data for 2004 collected by the California Department of Insurance. Following Butler (1994), we log the explanatory variable insurance demand to reduce the positive skewness in the regression's error term. Insurance demand is defined as 1- uninsured motorist rate. The uninsured motorist rate is calculated by subtracting the number of insured vehicles from the number of registered vehicles and dividing this difference by the number of registered vehicles.

In order to investigate auto insurance demand it is necessary to examine certain factors that are likely to have an affect on a typical consumer's demand for auto insurance. In particular we can focus on the question of which factors have a greater influence in determining whether a particular area in California will end up meeting the entire definition set forth by the California Department of Insurance and thereby be deemed underserved.

We follow Browne and Hoyt (2000) for the structure of the model and Klein and Grace (2001) for many of the variables included in the final equation. The variables in the model were chosen based on demographic relevance and previous literature. All of the demographic factors used in previous literature like Klein and Grace (2001) that are relevant to the automobile insurance market have been included in the model used in this study.

Other variables such as the theft and Asian variables are discussed in fuller detail in the Appendix. The theft variable is not included in the main model because several counties did not report motor vehicle theft data to the California Department of Justice. Therefore, including this variable in the main model would have necessitated the omission of nearly 200 ZIP codes. The theft variable is discussed in greater detail in Appendix C. The Asian variable is not included in the main model because its inclusion would have introduced a significant level of multicollinearity into the model. The Asian variable is discussed in greater detail in Appendix B.

The model is specified as follows:

$$\text{Log(Insurance Demand)} = \beta_0 + \beta_1 \text{ (Urban)} + \beta_2 \text{ (Minority)} + \beta_3 \text{ (Per Capita Income)} + \beta_4 \text{ (Poverty)} + \beta_5 \text{ (Language Isolated)} + \beta_6 \text{ (High School)} + \beta_7 \text{ (Hispanic)}$$

Urbanization

We include a binary variable to capture the effect that an urban ZIP code would have on the demand for automobile insurance. Demand for automobile insurance in urban areas is different than the demand in rural areas (Cummins and Tennyson, 1992). Using a binary variable is admittedly a crude measure of urbanization but it is the best possible measure that can be used. The difficulty is due to the nature of ZIP codes. ZIP codes are a convenience for the United States Postal Service. They were invented for the sole purpose of allowing the mail to be delivered more accurately and efficiently. They don't necessarily have defined boundaries. ZIP codes do not represent geographic regions; they generally correspond to address groups or delivery routes. Consequently, ZIP code "areas" can overlap, be subsets of each other, or be artificial constructs with no geographic area. Therefore, it is very difficult to calculate even

basic statistics like square footage for many ZIP codes. The difficulty this creates for our purposes is that we can't calculate a reliable area for these ZIP codes to compare against the population measure that we have from the census data. Therefore we are reduced to using the binary variable so that we have at least an approximation of urbanization in the model. The US Census Bureau defines an urban area as: "Core census block groups or blocks that have a population density of at least 1,000 people per square mile (386 per square kilometer) and surrounding census blocks that have an overall density of at least 500 people per square mile (193 per square kilometer)." Using this metric, ZIP codes in the counties of San Francisco, Orange, Los Angeles, Alameda, San Mateo, Sacramento, Santa Clara, Contra Costa, San Diego, and Santa Cruz all qualify as urban.

The expectation is that urbanization will have a negative impact on demand for automobile insurance perhaps due to the fact that more people per capita live in these areas so accidents are more likely. It has also been observed that automobile insurance claiming behavior is different in large metropolitan areas than in more rural areas (Cummins and Tennyson, 1996). Also, the ratio of bodily injury claim frequency to property damage claim frequency is usually much higher in urban areas. The ratio is more than twice as high in Los Angeles and New York than their individual state averages and in Philadelphia the ratio is more than three times higher than the state average (Hoyt, Mustard and Powell, 2006). This leads to higher premiums in urban areas because claim costs are higher and higher premiums lead to lower demand for insurance (Harrington and Niehaus, 1992).

Minority

The variable Minority refers to the percentage of Blacks and non-Black Hispanics in a ZIP code. We expect that a higher concentration of minorities in a ZIP code will have a negative effect on demand for automobile insurance due perhaps to a lack of income and a lack of awareness about mandatory insurance laws. Also, minorities tend to be more concentrated in urban areas. Therefore the level of minorities in a ZIP code may reflect the level of urbanization in the ZIP code. *Ceteris paribus*, urban ZIP codes will have higher premiums than non urban ZIP codes due to higher claim costs (Harrington and Niehaus, 1998).

In other contexts it has been shown that there are disparities in access to insurance among different racial groups. Weinick, Zuvekas, and Cohen studied trends in disparities and access to health care services. In each of the years that they studied (1977-1996) they found that Hispanic and African Americans were considerably more likely to lack a usual source of care than white Americans (Weinick, Zuvekas, and Cohen, 2000).

This variable will also be instructive in determining if the business practices of insurers in California are resulting in a "disparate impact" against minorities. If a business practice has a disparate impact on minorities it can be legally impermissible even if it is racially neutral on its face. If a policy or practice is shown to have such an effect, even if it is unintended, then the policy or practice is illegal unless the insurer can show that there is a compelling business justification for the policy or practice, and that no less discriminatory alternative exists to achieve the same business purpose (Dane, 2006; *Metropolitan Housing Development Corp. v. Village of Arlington Heights*, 558 F.2d 1283, 1977).

Income

From the 2000 census conducted by the United States Census Bureau we have data on per capita income for each ZIP code. There is evidence in prior literature that supports the proposition that per capita income will be positively correlated with insurance demand (Klein and Grace, 2001). Those households with more discretionary income will likely have more willingness and certainly have more ability to purchase insurance. Consumers with higher income are also more likely to have an understanding of the importance of purchasing insurance and how such a purchase can protect them and their property. Higher income consumers will also be more likely to have more wealth at risk from lawsuits and will therefore perceive the value of having liability insurance (Harrington and Niehaus, 1992). In other contexts income has been found to play a role in access to insurance. Income has been found to be a factor in explaining disparities in access to health care and health insurance between ethnic minorities and whites. Income was found to be important in explaining disparities in two main areas: having a usual source of care and family perceptions of access to health care (Zuvekas and Taliaferro, 2003).

The income variable can also be used to investigate the question of whether automobile insurance in the California market exhibits the characteristics of an inferior good. An inferior good is a good in which demand decreases as a consumer's income rises. With a normal good, the reverse is true. There is support in prior literature for the proposition that insurance is an inferior good (Mossin, 1968). If insurance is in fact an inferior good we will observe a negative correlation between insurance demand and the income variable. Because of this conflict in the

theory I am unsure whether the income variable will be positively or negatively correlated with insurance demand.

Poverty

From the 2000 census conducted by the United States Census Bureau we have data on the percentage of families living below the poverty level in each ZIP code. The rationale here is the reverse of the one made above when dealing with those with high incomes. The percentage of families living in poverty should be negatively correlated with insurance demand likely due to the fact that these families will have fewer funds to spend on insurance (Klein & Grace, 2001). These families will also have little if any discretionary income and probably will have a hard time affording insurance when they have to worry about having money to pay for basic needs like food, clothing and shelter (Harrington and Niehaus, 1992).

This variable will also help us determine whether certain areas are underserved because they have a high concentration of minorities or because the people in these areas don't have enough money to pay for adequate insurance (Squires, 2003). In essence, this variable will help us determine how much of the decreased demand in underserved areas is due to uninsured, working poor drivers.

Language Isolated

From the 2000 census conducted by the United States Census Bureau we have data on the percentage of households that are language isolated. Households are considered to be language isolated if English is not the primary language spoken inside the home. This variable will allow us to identify the effect of language in purchasing auto insurance. This is important because in

California, uninsured motorists are more likely to be Hispanic or African-American (Hunstad, 1999).

The percentage of families that are language isolated should also be negatively correlated with insurance demand because these families are probably less likely to be aware of the necessity of purchasing auto insurance. Language isolated families also may have a more difficult time shopping around and purchasing insurance (Klein & Grace, 2001). For example, the internet is a vehicle that many people use to purchase insurance. If the ultimate purchase is not done on the internet many consumers still use the internet as a tool for researching their insurance needs and for comparison shopping. Since most – if not all – of the relevant insurance websites are in English, being language isolated represents a significant barrier to properly using the internet as a mechanism for purchasing insurance.

Language has been found to be an important factor in determining health care use. Previous studies have shown that the use of heath care for English speaking Hispanic patients was not significantly different than for non-Hispanic patients. However, Spanish speaking Hispanic patients were shown to be significantly less likely to have had an array of health services than non-Hispanic white patients. These services included physician visits, mental health visits, and influenza vaccinations (Fiscella, et al, 2002).

Language is also subjectively seen as a problem by many Latinos. One study that investigated access barriers to health care found that 26% of Latino parents thought that language problems were the single greatest barrier to obtaining heath care for their children. Another 15%

said that the greatest obstacle was doctors and nurses who don't speak Spanish. Additionally, another 11% mentioned lack of interpreters as the biggest problem (Flores et al, 1998).

High School Education

The percentage of adults with at least a high school education should be positively correlated with insurance demand. This metric reveals which consumers are more educated. Those consumers with higher education should better understand the necessity of buying insurance. Those consumers with less education may also feel less comfortable buying insurance because purchasing insurance requires consumers to pay premiums for a benefit that they may only realize in the future if at all. Consumers with less education may be less willing to see this type of purchase as valuable (Klein & Grace, 2001). Previous studies have found that uninsured drivers are more likely to have less than a high school education (Hunstad, 1999). This variable will allow us to test that finding with our new data.

In other contexts education has been found to be a factor in explaining racial and ethnic disparities in ambulatory care use (Zuvekas and Taliaferro, 2003). The education level of parents has also been found to have an impact in explaining the likelihood of children having health insurance. Children were more likely to be privately insured and less likely to be publicly insured or uninsured if their parents had a higher level of education. Specifically, children who had parents with more than twelve years of education were most likely to have private insurance and least likely to be uninsured (Weinick, Weigers, and Cohen, 1998).

Hispanic

The Hispanic variable reports the percentage of people in each ZIP code who claimed that they were of Hispanic descent. On the 2000 United States Census form the Hispanic question is distinct from the race question. Specifically, the Hispanic question asks respondents if they are Spanish, Hispanic, or Latino. A separate question on race asks respondents what race they consider themselves. Both questions rely on self-identification. Therefore, for purposes of the Census a person can be both Hispanic and black or Hispanic and white or Hispanic and Asian or Hispanic and some other race (US Census Bureau, Census 2000). The Census uses the terms "Hispanic" and "Latino" interchangeably. This study will only use the term "Hispanic" to avoid any confusion.

California as a whole is home to 13,160,978 people who identify themselves as Hispanic, or 36.1% of California's total population (U.S. Census Bureau, 2006-2008 American Community Survey). This is more than double the percentage of Hispanics found in the United States as a whole (15.1%). Because of the more pronounced presence that the Hispanic community exerts on the state of California it is important to account for it separately in our analysis. It will also be interesting to explore whether the Hispanic variable will be demonstrably different from the language isolated variable in our analysis. I don't believe that there is any reason to believe that it will be much different so I predict that the Hispanic variable will be negatively correlated with insurance demand.

Table 4

Summary of the Predicted Signs
of the Regression Coefficients

Variable	Definition	Hypothesized Sign
Minority	% of minority population in each ZIP code	-
Per Capita Income	Per Capita Income in each ZIP code	+/-
Poverty	% of families below poverty level in each ZIP code	-
Language Isolated	% of families that don't speak English as a first language in each ZIP code	-
High School	% of adults with at least a high school education in each ZIP code	+
Urban	Binary variable with a value of 1 if the ZIP code is urban and 0 if not	-
Hispanic	% of people in each ZIP code who claimed Hispanic descent	-

Table 5 reports the results of a difference in means test performed on the underserved and almost underserved datasets. The difference in all cases is the underserved dataset minus the almost underserved dataset.

Table 5

Difference in Means Test

	Under	Almost	Difference	P-value
Minority	.8897794	.7977587	.0920208	0.0000
	(.007858)	(.0065708)	(.0099074)	
Poverty	.2507647	.1698603	.0809044	0.0000
	(.0075849)	(.0069124)	(.0107097)	
Language	.6735735	.5803456	.0932279	0.0000
	(.0138825)	(.0117178)	(.0183213)	
High School	.48	.5998897	-.1198897	0.0000
	(.011413)	(.0112255)	(.0154407)	
Income	11334.55	13687.29	-2352.735	0.0000
	(253.4618)	(292.18)	(394.9049)	
Demand	1.843855	2.28649	-.4426348	0.0000
	(.0201589)	(.0210633)	(.2456379)	
Hispanic	.6435662	.5567353	.0868309	0.0002
	(.0179308)	(.0165424)	(.0223528)	

CHAPTER 8

Results

Table 6 reports the correlation matrix and the variance inflation factors for each of the variables in the model for the underserved ZIP codes. The matrix supports the predictions made in Table 4 regarding the relationship between demand and the other variables in the model.

Table 6

Correlation Matrix of Model Variables in Underserved ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	High School
Demand	1.0000							
Urban	-0.2365	1.0000						
Hispanic	0.0526	-0.2211	1.0000					
Minority	-0.3019	0.2507	0.4043	1.0000				
Income	0.3252	0.3627	-0.5544	-0.3927	1.0000			
Poverty	-0.5420	-0.2084	0.1622	0.2911	-0.7159	1.0000		
Language	0.0466	0.0489	0.8047	0.3688	-0.3498	0.0992	1.0000	
High School	0.2164	0.2812	-0.8108	-0.5021	0.7810	-0.5074	-0.6685	1.0000

Table 7 reports the results from the underserved ZIP codes. The underserved ZIP codes are those ZIP codes in which the proportion of uninsured motorists is ten percentage points above the statewide average, the per capita income of the community (as measured in the most recent U.S. Census), is below the fiftieth (50th) percentile for California, and the community (as measured in the most recent U.S. Census), is predominantly minority.

Table 7

Results from Insurance Demand Model on Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	1.763572	.4300764	4.10	0.000		
Urban	-.2127642	.0467522	-4.55	0.000	-	1.76
Hispanic	.1382657	.1965803	0.70	0.483	-	5.98
Minority	-.0712257	.201547	-0.35	0.724	-	1.78
Income	1.34e-06	.0000155	0.09	0.931	+/-	4.51
Poverty	-1.251045	.3295442	-3.80	0.000	-	2.69
Language	.3538241	.1669982	2.12	0.036	-	3.69
High School	.5706342	.3521216	1.62	0.107	+	6.69

n = 145

R^2 = .4645

The results reported in Table 7 provide some support for the previously stated hypotheses. The result for the poverty variable is statistically significant and consistent with our hypotheses. Therefore, these results provide some support for the proposition that ZIP codes with lower income experience lower demand for auto insurance even though the income variable is inconclusive. The urbanization variable also conforms to our expectations and is statistically significant. This may be due to the fact that urban areas tend to have an increased number of lower income people who have trouble affording insurance. The language variable is significant and contrary to our expectations. The coefficient estimates for the high school variable, the income variable, the minority variable, and the Hispanic variable are not statistically different from zero.

Table 8 reports the correlation matrix and the variance inflation factors for each of the variables in the model for the almost underserved ZIP codes. Table 9 reports the results from those ZIP codes in which the per capita income of the community (as measured in the most recent U.S. Census) is below the fiftieth (50th) percentile for California and the community (as measured in the most recent U.S. Census) is predominantly minority and yet the ZIP code is not underserved because the proportion of uninsured motorists is not ten percentage points above the statewide average.

Table 8

Correlation Matrix of Model Variables in Almost Underserved ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	High School
Demand	1.0000							
Urban	-0.0925	1.0000						
Hispanic	-0.0869	-0.4814	1.0000					
Minority	-0.0218	0.0024	0.3373	1.0000				
Income	0.0040	0.6281	-0.5367	-0.3299	1.0000			
Poverty	-0.1453	-0.3187	0.2008	0.1920	-0.5223	1.0000		
Language	-0.0963	-0.0476	0.6371	0.6663	-0.3296	0.0703	1.0000	
High School	0.0883	0.5355	-0.7824	-0.4596	0.7601	-0.4833	-0.6485	1.0000

Table 9

Results from Insurance Demand Model on Almost Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	2.341725	.3455357	6.78	0.000		
Urban	-.1047831	.0334258	-3.13	0.002	-	2.23
Hispanic	-.1766486	.2006216	-0.88	0.380	-	3.34
Minority	.353107	.4530652	0.78	0.437	-	1.69
Income	-5.57e-06	.0000106	-0.52	0.602	+/-	3.20
Poverty	-.6533843	.3690001	-1.77	0.079	-	2.69
Language	-.1158647	.2557377	-0.45	0.651	-	3.90
High School	.1100983	.3152558	0.35	0.727	+	6.64

n = 136
R^2 = .0717

The results reported in Table 9 provide some confirmation for our previously stated hypotheses. The coefficient for the urban variable is negative and significant. This result supports our expectation that urbanization will have a negative impact on demand for automobile insurance. The coefficient for the poverty variable is also negative and significant which is in line with our previously stated hypothesis. The other variables are not significant.

It is interesting to consider the underserved and almost underserved ZIP codes in conjunction with one another. In both of the underserved and almost underserved datasets, the urban variable and the poverty variables are negative and significant. In both cases this is consistent with our expectations and our previously stated hypotheses.

The language variable for the underserved ZIP codes is positive and significant which is contrary to our expectations. Perhaps this is due to an increased number of families with

bilingual family members or an effort by insurance firms in heavily Hispanic areas of California to advertise in Spanish in order to reach this segment of the market.

The minority, high school, income, and Hispanic variables are not significant in either sample. Because the minority variable is inconclusive we are unable to find support for Dane's concern that racially identifiable neighborhoods in the same city may be charged different rates.

Table 10

Correlation Matrix of Model Variables in Underserved and Almost Underserved ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	High School
Demand	1.0000							
Urban	-0.2847	1.0000						
Hispanic	-0.1394	-0.2822	1.0000					
Minority	-0.4187	0.2291	0.4153	1.0000				
Income	0.3341	0.3781	-0.5655	-0.4525	1.0000			
Poverty	-0.5231	-0.1211	0.2402	0.3933	-0.6679	1.0000		
Language	-0.2055	0.0750	0.7443	0.5441	-0.3991	0.1965	1.0000	
High School	0.3766	0.2614	-0.7927	-0.5752	0.7976	-0.5822	-0.6915	1.0000

Table 11

Results from Insurance Demand Model on Underserved and Almost Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	1.999073	.4657944	4.29	0.000		
Urban	-.274689	.0364519	-7.54	0.000	-	1.82
Hispanic	.0376104	.2031006	0.19	0.853	-	4.22
Minority	-.2335388	.1998632	-1.17	0.244	-	2.04
Income	3.81e-07	.0000145	0.03	0.979	+/-	3.89
Poverty	-1.269234	.4691928	-2.71	0.007	-	2.29
Language	.3549792	.1448801	2.45	0.015	-	3.35
High School	.8211676	.3068362	2.68	0.008	+	7.47

n = 281

R^2 = .4416

Table 10 reports the correlation matrix and the variance inflation factors for each of the variables in the model for the underserved and almost underserved ZIP codes. Table 11 reports the results obtained when the underserved ZIP codes and the almost underserved ZIP codes are combined together into one sample. The urban variable continues to be negative and significant indicating that people in urban areas are less likely to demand auto insurance. The poverty variable is negative and significant. This result is consistent with what was observed previously and it is also consistent with our expectations. The language variable continues to be positive and consistent which is contrary to our expectations. The high school variable is positive and consistent which is what we expected. It is interesting that the high school variable is significant in the combined dataset but it is not significant in either the underserved or almost underserved datasets when they are considered separately. An examination of the minority, income, and

Hispanic variables reveals that they are insignificant here like they were in the previous specifications.

In order to provide further context it is important to investigate the entire universe of California ZIP codes. The remaining analysis will concentrate on all of the ZIP codes in California on which the California Department of Insurance collected data and which had more than 200 residents as reported by the 2000 United States Census. The hypotheses discussed above remain the same for the data containing all of the California ZIP codes.

Appendix B contains the results and discussion of the models performed on all of the ZIP codes in California with the asian variable added.

Table 12 reports the correlation matrix for all of the included ZIP codes in California. The matrix supports the predictions made regarding the relationship between demand and the other variables in the model. We can make some other observations based on the correlation matrix in Table 12. The Hispanic variable is positively correlated with the minority and language isolated variable but negatively correlated with the high school variable. The minority and language isolated variables are also positively correlated.

Table 12

Correlation Matrix of Model Variables for all California ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	High School
Demand	1.0000							
Urban	-0.1792	1.0000						
Hispanic	-0.4929	0.0341	1.0000					
Minority	-0.5265	0.3087	0.8253	1.0000				
Income	0.2324	0.3203	-0.5265	-0.4600	1.0000			
Poverty	-0.4299	-0.1239	0.5667	0.5328	-0.5700	1.0000		
Language	-0.5115	0.3242	0.8510	0.8900	-0.3341	0.4671	1.0000	
High School	0.5414	0.1036	-0.8825	-0.7470	0.6444	-0.7350	-0.7547	1.0000

Table 13 reports the results for the full universe of ZIP codes with all of the variables included in the model.

Table 13

Results from Insurance Demand Model on all California ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	1.59356	.2356907	6.76	0.000		
Urban	-.1223736	.0249196	-4.91	0.000	–	1.96
Hispanic	.2601951	.1117203	2.33	0.020	-	7.89
Minority	-.3910937	.1098155	-3.56	0.000	-	6.63
Income	-4.88e-06	1.82e-06	-2.69	0.007	+/-	2.26
Poverty	-.4141546	.215578	-1.92	0.055	-	2.46
Language	.112872	.1386286	0.81	0.416	-	7.87
High School	1.472561	.2967999	4.96	0.000	+	8.50

n = 1553

R^2 = .3714

The results presented in Table 13 reveal that the urban and minority variables remain negative and significant which is as expected. The high school variable is positive and significant which is also in line with expectations. The Hispanic variable is positive and significant which is contrary to expectations. This may be due to the fact that California has such a high Hispanic population that there is plenty of insurance advertising in both Spanish and English so everyone is more aware of the importance of purchasing automobile insurance. The language isolated variable is not significant. It is interesting that the Hispanic variable is positive and significant and the language isolated variable is not significant. This may be due to the fact that there are many people in the Hispanic community who are bilingual. Also, as noted above California is 36.1% Hispanic which means that there is strong incentive for insurers to court the Hispanic market in order to convince them of the need to purchase insurance. This outreach includes Spanish language advertising so the fact that a family may be language isolated would be rendered much less important.

With regard to the two explicitly economic variables we get interesting results. The poverty variable is negative and significant which matches our expectations. However, the income variable is negative and significant. This result seems to confirm Mossin's contention that insurance is an inferior good.

Table 14 presents the results of several models. All of the models have insurance demand as the dependent variable. The models have different independent variables in order to explore the interactions between the variables. Specifically, there are some variables in the complete model that have relatively high correlations. For example, in model 2, the High School

variable was deleted because of its high correlation with the Hispanic variable. In model 3, the Language variable was deleted because of its high correlation with both the minority and the Hispanic variable. In model 4, the Language and High School variables were deleted because of their high correlations with the Hispanic and Minority variables. In model 5, the Minority variable was deleted because of its high correlation with the Hispanic, Language, and High School variables. All of the following regressions were performed on the dataset containing all of the California ZIP codes.

The models were specified as follows:

Model 1

$$\text{Log(Insurance Demand)} = \beta_0 + \delta_0 \text{ (Urban)} + \beta_1 \text{ (Hispanic)} + \beta_2 \text{ (Minority)} + \beta_3 \text{ (Median Income)} + \beta_4 \text{ (Poverty)} + \beta_5 \text{ (Language Isolated)} + \beta_6 \text{ (High School)}$$

N=1553
R^2=.3601

Model 2

$$\text{Log(Insurance Demand)} = \beta_0 + \delta_0 \text{ (Urban)} + \beta_1 \text{ (Hispanic)} + \beta_2 \text{ (Minority)} + \beta_3 \text{ (Median Income)} + \beta_4 \text{ (Poverty)} + \beta_5 \text{ (Language Isolated)}$$

N=1553
R^2=.3338

Model 3

$\text{Log(Insurance Demand)} = \beta_0 + \delta_0\,(\text{Urban}) + \beta_1\,(\text{Hispanic}) + \beta_2\,(\text{Minority}) + \beta_3\,(\text{Median Income}) + \beta_4\,(\text{Poverty}) + \beta_5\,(\text{High School})$

N=1553
R^2=.3599

Model 4

$\text{Log(Insurance Demand)} = \beta_0 + \delta_0\,(\text{Urban}) + \beta_1\,(\text{Hispanic}) + \beta_2\,(\text{Minority}) + \beta_3\,(\text{Median Income}) + \beta_4\,(\text{Poverty})$

N=1553
R^2=.3309

Model 5

$\text{Log(Insurance Demand)} = \beta_0 + \delta_0\,(\text{Urban}) + \beta_1\,(\text{Hispanic}) + \beta_2\,(\text{Median Income}) + \beta_3\,(\text{Poverty}) + \beta_4\,(\text{Language Isolated}) + \beta_5\,(\text{High School})$

N=1553
R^2=.3568

Model 6

$\text{Log(Insurance Demand)} = \beta_0 + \delta_0\,(\text{Urban}) + \beta_1\,(\text{Hispanic}) + \beta_2\,(\text{Minority}) + \beta_3\,(\text{Median Income}) + \beta_4\,(\text{Language Isolated}) + \beta_5\,(\text{High School})$

N=1553
R^2=.3680

Table 14

Results from Selected Insurance Demand Models on all California ZIP codes

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Urban	-.1223736	-.0736853	-.1156684	-.0808134	-.1582557	-.1231787
	[.0249196]***	[.0319434]**	[.0288837]***	[.0340751]**	[.0207523]***	[.0251033]***
Hispanic	.2601951	-.2808984	.2982317	-.348806	.1551071	.3214595
	[.1117203]**	[.092757]***	[.1307203]**	[.0718988]***	[.1021099]	[.1003049]***
Minority	-.3910937	-.3359965	-.3433327	-.3965755		-.4290201
	[.1098155]***	[.1078165]***	[.0711541]***	[.0802178]***		[.1000923]***
Income	-4.88e-06	-2.57e-06	-4.62e-06	-2.84e-06	-3.53e-06	-4.63e-06
	[1.82e-06]***	[5.79e-07]*	[1.59e-06]***	[1.39e-06]**	[1.56e-06]**	[1.88e-06]***
Poverty	-.4141546	-1.169928	-.4327324	-1.171048	-.5183771	
	[.215578]*	[.1915749]***	[.2034048]**	[.1949671]***	[.2033243]***	
Lang Iso	.112872	-.1390726			-.1426441	.1490397
	[.1386286]	[.1180199]			[.0910867]	[.1291406]
High School	1.472561		1.434694		1.428258	1.693702
	[.2967999]***		[.2658697]***		[.2921763]***	[.2200346]***
Intercept	1.59356	2.934575	1.619121	2.946239	1.553625	1.36007
Observations	1553	1553	1553	1553	1553	1553
R^2	.3714	.3303	.3709	.3296	.3626	.3680

Note: The dependent variable is insurance demand. Standard errors appear in brackets below each coefficient estimate. ***,**, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

When examining the variables contained in the various models a few things are revealed. The first thing that stands out is the Hispanic variable. Throughout all of the models the Hispanic variable displays a lack of consistency. In three of the models it is positive and in two it is negative and in one it is insignificant. The Hispanic variable is not only the sole one that demonstrates this level of inconsistency, it is the only one that demonstrates any inconsistency at all. Every other variable is always positive or always negative.

The urban and minority variables are negative and consistent at the 1% level in every specification in which they appear (except for the urban variable in model 2). The high school variable is positive and consistent at the 1% level in every specification in which it appears. The

poverty and language isolated variables never change their sign but are insignificant in some specifications.

The income variable is negative and consistent in every specification. These results continue to indicate that income has a negative correlation with automobile insurance demand when all ZIP codes in California are considered. Therefore, the result found when considering the entire California market provides evidence in agreement with previous literature that concluded that insurance is an inferior good.

When these results are examined in conjunction with the results of the income variable that we saw in the underserved and almost underserved ZIP codes they suggest that there is some dynamic occurring in the other California ZIP codes that is not present in the underserved and almost underserved ZIP codes. At the present time I am unable to precisely identify this dynamic.

Overall, with the previously noted exception of the Hispanic variable all of the other variables in the different specifications demonstrated remarkable consistency. Table 14 suggests that even in the face of some rather high correlation reported in Table 12 the results can be regarded with some degree of trust. This should bolster our confidence when interpreting the effect of the various variables on automobile insurance demand. With the exception of the Hispanic and the income variable, all of the remaining variables are in line with our hypotheses.

Table 15 presents the results when all of the variables in the main model are regressed against insurance demand separately.

Table 15

Results from Single Variable Insurance Demand Models on all California ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	N	R^2
Urban	-.146621	.0212883	-6.89	0.000	–	1562	0.0311
Intercept	2.512509	.012028	208.89	0.000			
Hispanic	.2601951	.1117203	2.33	0.000	-	1553	0.2429
Intercept	2.673335	.0139745	191.30	0.000			
Minority	-.3910937	.1098155	-3.56	0.000	+/-	1562	0.2756
Intercept	2.829218	.0171208	165.25	0.000			
Income	-4.88e-06	1.82e-06	-2.69	0.000	+	1562	0.0547
Intercept	2.278578	.0254562	89.51	0.000			
Poverty	-.4141546	.215578	-1.92	0.000	-	1562	0.1794
Intercept	2.660896	.0192021	138.57	0.000			
Language	.112872	.1386286	0.81	0.000	-	1561	0.2572
Intercept	2.736481	.0142284	192.32	0.000			
High School	1.472561	.2967999	4.96	0.000	+	1561	0.2893
Intercept	1.397044	.0428268	32.62	0.000			

The results reported in Table 15 are largely in agreement with the previously reported results. The coefficients for the urban, minority, income, and poverty variables remain negative while the coefficients for the Hispanic, language, and high school variables remain positive.

Table 16 summarizes the results found in the various models that contained all of the independent variables. The underserved column presents the results from the underserved ZIP

codes only. The almost column presents the results from only the almost underserved ZIP codes. The combined column presents the results from the dataset that combines the underserved and the almost underserved ZIP codes. The California column presents the results from all of the ZIP codes in California that had a population of 200 or more people according to the 2000 United States Census.

Table 16

Summary of Results from Complete Insurance Demand Model on All Samples

	Underserved	Almost	Combined	California	Expected Sign
Urban	-.2127642 [.0467522]***	-.1047831 [.0334258]***	-.274689 [.0364519]***	-.1223736 [.0249196]***	-
Hispanic	.1382657 [.1965803]	-.1766486 [.2006216]	.0376104 [.2031006]	.2601951 [.1117203]**	-
Minority	-.0712257 [.201547]	.353107 [.4530652]	-.2335388 [.1998632]	-.3910937 [.1098155]***	-
Income	1.34e-06 [0000155]	-5.57e-06 [.0000106]	3.81e-07 [.0000145]	-4.88e-06 [1.82e-06]***	+
Poverty	-1.251045 [.3295442]***	-.6533843 [.3690001]*	-1.269234 [.4691928]***	-.4141546 [.215578]*	-
Language Isolated	.3538241 [.1669982]**	-.1158647 [.2557377]	.3549792 [.1448801]**	.112872 [.1386286]	-
High School	.5706342 [.3521216]	.1100983 [.3152558]	.8211676 [.3068362]***	1.472561 [.2967999]***	+
Intercept	1.763572	2.341725	1.999073	1.59356	
Observations	145	136	281	1553	
R^2	.4645	.0717	. 4416	. 3714	

Note: The dependent variable is insurance demand. Standard errors appear in brackets below each coefficient estimate. ***,**, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

CHAPTER 9

Conclusion

In California a significant portion of the automobile insurance market remains underserved. California has tried to remedy this problem by promulgating regulations to improve the availability and affordability of insurance in these underserved areas. This analysis of automobile insurance demand in these underserved areas and in nearly underserved areas provides some support for several hypotheses that attempt to explain why some areas remain underserved.

The analysis consistently suggests that both poverty and urbanization have negative impacts on the demand for automobile insurance. People living in poor urban areas are less likely to have a demand for auto insurance. This may be due to the fact that individuals in these areas can't afford to buy insurance or don't appreciate the value of insurance. Insurance may not have enough value to them to justify the premiums because they may feel that the vehicle that they own is not worth enough to insure (Hunstad, 1999). We may also be observing less demand in urban areas because people in these areas are more likely to have access to public transportation and therefore feel that they don't need automobile insurance because they don't drive as much.

These findings provide evidence consistent with Harrington and Niehaus (1998). In underserved and almost underserved areas the results suggest that the percentage of minorities present in a ZIP code has no statistical effect on automobile insurance demand. Even though

there is evidence that the minority status of a ZIP code matters in assessing insurance demand for California as a whole; it is still consistent with the data to assert that it is the economic condition of a particular ZIP code which has more impact on automobile insurance demand.

The income level of a particular ZIP code was found to be inconclusive in helping to predict the level of automobile demand except when considering California as a whole. When examining the entire state the level of income of a ZIP code was found to be inversely related to insurance demand. In California as a whole, the results suggest that the higher the income level in a particular ZIP code the lower the insurance demand. This result confirms prior literature that contended that insurance is an inferior good. However, it is inconsistent with Browne and Hoyt (2000).

The high school variable was found to be positively correlated with insurance demand in California as a whole and in the combined sample. This result is consistent with expectations and with Klein & Grace (2001) and Hunstad (1999).

Another factor that was observed to have an impact on insurance demand in underserved communities was whether or not the household was language isolated. In the almost underserved ZIP codes and in California as a whole this variable was inconclusive. However, in the underserved ZIP codes this variable was positive and significant. It is useful to consider the language isolated variable in conjunction with the Hispanic variable. These two factors should be somewhat related because after English the next most popular language spoken in the home is Spanish. Like the language isolated variable, the Hispanic variable was contrary to expectations.

The Hispanic variable was positive for California as a whole. It was inconclusive in the other samples.

While this result was contrary to expectations, and previous research (Kunreuther and Pauly, 2004) these findings may have important implications for California policymakers. The results of this study indicate that being language isolated in underserved ZIP codes and Hispanic in California tends to make a household have more demand for automobile insurance. Perhaps these language isolated households are still in underserved ZIP codes despite their greater demand because they have more trouble than English speaking households in understanding the details related to purchasing insurance. These details could involve not being able to communicate with anyone at an insurance company, not knowing which of the many insurance companies to choose from, and not understanding what types or amounts of insurance to purchase (Hunstad, 1999).

The goal of the California Department of Insurance in promulgating these regulations is to address the issue of availability and affordability of automobile insurance in underserved communities. The strongest most consistent results found in this study are most relevant for poverty stricken urban areas. The results suggest that both poverty and urbanization are factors that lead to a lower demand for automobile insurance. Perhaps the problem of low insurance demand in these areas could be partially remedied by outreach programs to better educate people about the importance of automobile insurance. These programs could also help the public find affordable insurance that would meet their needs. Vouchers or targeted subsidies could also be used to remedy the problem of low automobile insurance demand in some urban areas.

Another idea would be to expand the Assigned Risk program in California. As currently constituted the program only covers those who cannot obtain conventional automobile liability insurance. The usual reason that they find it hard to get insurance is because of poor driving records. Insurance companies are then assigned to write insurance for them usually at higher prices. It could be modified so that the insurance companies would not charge unwarranted higher prices. If this program were expanded to cover those in urban areas that find it hard to obtain insurance it could increase access to automobile insurance.

Another way to increase access to automobile insurance would be to increase the number of agents and service offices in underserved areas. Because automobile insurance is still a localized market, having a greater number of agents in underserved areas would likely increase demand in these areas. Potential customers in these areas would have agents that were familiar with their communities and better able to help them find insurance products that would fit their needs.

This research highlights some interesting results for Hispanics and language isolated families. Future research could be devoted to determining why Hispanics and language isolated families actually have greater demand for automobile insurance. Perhaps by studying this surprising result new ideas could be found to help others increase their access to automobile insurance.

CHAPTER 10

Introduction

California has promulgated regulations to "address the issue of availability and affordability of insurance in "underserved" communities and to promote anti-discrimination so that all have equal access to insurance coverage in California." These regulations require the California Department of Insurance (CDI) to collect and analyze data from home, personal auto, commercial multiple peril and commercial fire insurers in California, in all zip codes identified as "underserved".

Combining this data with data currently available on the NAIC tapes will shed light on the incentives that insurers have – or don't have – to operate in underserved communities. If we can better understand some reasons why insurers avoid underserved areas perhaps appropriate policy recommendations can be identified to address this imbalance. Studying the supply component of the underserved equation is important because if automobile insurance isn't offered in underserved areas the residents of these areas have diminished access to insurance.

Studying the placements of agencies and the availability of agents in a particular area has the potential to provide answers to the question of whether or not certain areas have adequate access to insurance. Previous studies have found that uninsured motorists experience greater difficulty even locating a place to purchase auto insurance (Hunstad, 1999). Even with the advent of the internet, it is still accepted that auto insurance is a very localized market. The importance of the presence of agents or agencies in an area is even more magnified by the fact that consumers usually do not comparison shop for insurance (Cummins, 1974). That fact

combined with the localized insurance market means that consumers are even more dependent on the presence of a variety of agents and agencies in order to have choice and competition and true and adequate access to insurance in their community.

The data collected by the CDI on insurers that operate in California can be organized into three categories:

1. Earned exposures in California and earned exposures in underserved areas in the following segments:
   Private Passenger Auto
   Assigned Risk
   Low Cost Auto;

2. Service office data per company in California and in underserved areas;

3. Number of agents or agencies per company in California and in underserved areas.

The CDI asked the insurers to respond to the following instructions.

"Provide the total number of offices located in each ZIP code for each line of business that perform claim services and/or sales/marketing services. Count the office only once if an office performs both functions. Do not double count the offices.

Provide the total number of agents or agencies maintaining offices in each ZIP code for each line of business. This includes independent as well as employed or captive types. Report only one type - either the number of agents or the number of agencies."

It is important to note that the number of agents or agencies will differ somewhat between companies due to the different marketing techniques that each company utilizes. The three major marketing techniques are: captive agent, independent agent, and direct. Also, some companies provided the number of agents, whereas, others provided the number of agencies. Those that write using the direct approach are not included.

CHAPTER 11

Motivation

This paper will investigate whether the problem of underserved areas in California can be attributed in whole or in part to a lack of access to automobile insurance. In order to study this access issue I will concentrate on the insurance firms that operate in California. Particular attention will be paid to determine if there are characteristics that can be identified that are more common to firms that operate successfully in underserved areas.

I will construct a model that is designed to discover whether there are factors that we can identify that will have a positive impact on access to automobile insurance by increasing supply to potential consumers. Because this essay is principally concerned with the question of insurance supply I will concentrate on firm specific factors including size, structure and business mix to investigate this access issue.

This study is focused on the issue of automobile insurance supply in general but it is also concerned with identifying ways to increase supply of insurance to traditionally disadvantaged or underserved areas. Therefore, it is important to discover if these factors operate differently in underserved areas compared with other areas of California. I will investigate this issue by applying the model in three different settings; underserved areas, non-underserved areas, and California as a whole. I will also study whether a firm's actual presence in a certain area impacts

the supply of insurance in that area by including the number of service offices and agents each firm has in underserved and non-underserved areas in California. I will assess what impact these factors have on automobile insurance supply by determining the effect that they have on the number of earned exposures realized by each firm. Perhaps learning what works for these firms will enable policymakers and other stakeholders to better understand the market and eventually increase access to insurance in underserved areas.

CHAPTER 12

Prior Literature

Previous literature has been devoted to investigating the role of ownership structure in the insurance industry. This paper will continue in that tradition by examining whether stock or mutual automobile insurance companies are more likely to write insurance in underserved areas. Mayers and Smith (1988) scrutinize ownership structure to try to determine whether "there are significant differences in activity choices associated with the alternative ownership structures." They don't study the efficiency of different ownership structures. They treat that as a given. Instead, Mayers and Smith are interested in why different ownership structures are most efficient in different lines of business. They characterize this as an equilibrium approach.

The authors focus on geographic and line of business concentration while controlling for firm size. The goal is to determine whether there are differences in activity choice that might depend on ownership structure. They examine stock companies, mutual companies, reciprocals, and Lloyds associations. For stocks, mutuals, and reciprocals they find a strong inverse relation between size and geographic concentration. Moreover, they find that large firms are less geographically concentrated than small firms. This finding persists in all ownership structures.

When they examine how ownership structure relates to line of business concentration the authors find that mutuals and stocks are virtually indistinguishable. However, other researchers have found significant differences (Berry-Stölzle, Liebenberg, Ruhland, and Sommer, 2011). On the matter of line of business specialization Mayers and Smith report that mutual and stock companies appear to concentrate their business in different lines of insurance.

Lamm-Tennant and Starks (1993) follow this research by focusing on the question of whether there is a relationship between ownership structure and firm environment in the property-liability insurance industry. Their inquiry is focused specifically in the risk characteristics of stock versus mutual companies.

Lamm-Tennant and Starks use a logistic regression model with maximum-likelihood estimation to test whether risk is related to organizational type. Even after controlling for size they find that stock insurers still have more total risk than mutual insurers. Next they investigate the effect of line of business and geographic area. They find that stock companies tend to do more business in lines that have greater total risk. Further analysis reveals that stocks operate in more lines of business than mutuals. With regard to geography, Lamm-Tennant and Starks find that stock firms have greater concentration in areas with the greatest risk.

It will be interesting to see if ownership structure has such an effect in the context of this study. We can observe the structure variable to investigate whether stocks or mutuals are more prone to operate in underserved areas. If the findings of Lamm-Tennant and Starks hold we should find that stock firms are more prevalent in underserved areas because writing business in underserved areas is perceived to entail greater risk.

The size of a firm may have an impact on its ability to garner sales and deliver service to underserved areas. The larger the firm the more likely it is to be able to afford to pay for the resources necessary to operate in underserved areas where the insurance industry does not have a history of being able to generate large profits. Because of this history, operating in these areas

often requires a firm to have a greater than normal tolerance for risk. Larger firms generally have the ability to absorb more risk than smaller firms.

Ranger-Moore (1997) studies how failure rates in life insurance companies are affected by organizational age and size. He focuses on New York life insurers that operated in the time frame of 1813 to 1985. This study also concentrates on two particular ways that aging may be affecting failure rates. The first is senescence which means the various internal processes cause organizations to decline in quality over time, similar to what we see in biological organisms. The second is obsolescence where internal processes increase organizational inertia so that organizations are less responsive to environmental change.

He tests four hypotheses. Hypothesis 1: "There exists a liability of smallness, in which failure rates decline monotonically as a function of size." Hypothesis2: "Organizations experience a monotonic liability of aging that is reflected in a failure rate that increases at a decreasing rate with age." Hypothesis3a: "In stable environments, there will be positive age-dependence in failure rates reflecting the liability of senescence." Hypothesis3b: "In turbulent environments, there will be positive age-dependence in failure rates higher than that seen in stable environments, reflecting the combined liabilities of senescence and obsolescence."

Ranger-Moore uses several variables to test his hypotheses. He uses total assets to proxy for organizational size. For organizational density he uses the number of companies existing at founding. He also uses variables to capture the current performance of the firms as well as net income of the firms. For environmental variables, the author uses the number of life insurance company failures in the previous year as well as a dummy variable for war years. Another

dummy variable was used for capturing the effect of the depression. He also uses two sets of period effects. The first is regulatory or legislative periods which is meant to capture changes in government regulation. The second set is environmental periods. This set is meant to capture a severe economic challenge to the entire life insurance industry.

Ranger-Moore's results show that size does indeed reduce the failure rate. This finding ratifies the first hypothesis. He also finds support for his second hypothesis. However, he finds that no significant age effect occurs outside the 1870s. This result contradicts hypothesis 3a because no evidence of senescence is found. Hypothesis 3b fares much better. He finds a strong evidence of the effect that age has on failure rates especially during the 1870s. Ranger-Moore interprets this finding to mean that harmful inertia grows with age during times of environmental upheaval which results in obsolescence.

We can use the size variable to try to analyze the effect of size in the context of underserved areas. If larger firms do better in these areas it would lend credence to Ranger-Moore's finding that size reduces failure rates.

This study uses the inverse of the loss ratio to proxy for price. It will be interesting to observe this variable to determine its relationship to supply. I expect to observe an inverse relationship between price and supply.

Witt (1979) investigates how automobile insurance rates are developed for different territories. He begins by describing how there are both actuarial equity and social equity issues involved when a large existing territory is split into two smaller rating territories. He points out that when a territory is split some insureds will have to pay more and some will pay less. Witt

contends that as long as the new rates are based on differences in average loss and expense costs they are considered to be fair discrimination under most regulatory laws. He explains that insurers have determined that the rate of underwriting profit should be equal for all territorial classes. They have made this determination because insurance regulation has mandated that insurance rates cannot be unfairly discriminatory. However, because loss costs are random actual profit ratios will vary among territories despite efforts by insurers to maintain equality when setting their territorial rates.

After explaining the ratemaking process, Witt lays out his method of analysis. He computes a weighted average loss ratio, a weighted standard deviation, a coefficient of variation, and an expected loss and allocated loss adjustment expense ratio. He compares these ratios to the actual statewide loss ratio to determine whether in retrospect rates turned out to be too high or too low.

Witt finds that seventeen of the thirty territories in Illinois had loss ratios greater than the statewide loss ratio and the remaining territories had loss ratios less than the statewide loss ratio. He reasons that from this evidence rates were probably too low in the first seventeen territories and too high in the remaining thirteen territories. Witt concludes that "complete actuarial equity was not achieved for automobile insurance rates in Illinois during 1970 through 1974." He explains that loss costs are random so this result should not be taken as surprising.

Finally, he contends that automobile insurance prices are not economically correct because the mean loss ratios and standard deviations for each territory do not vary inversely with one another. In fact he finds that they are directly correlated with each other. Witt interprets this

to mean that insurers do not properly price underwriting risk when determining their territorial rate structures.

Previous literature has analyzed the effect of the locations of agents and agencies to determine what impact this has on the availability of insurance in a specific geographical area. This paper extends that literature by focusing on the effect that the presence of agents and agencies have on the amount of automobile insurance supply delivered to underserved areas.

Schultz (1995) observed that "agencies or agents in an area represent a physical presence that increases the likelihood of sales to prospective customers in that area". In his study Schultz investigates whether the racial composition and the income of an area have an effect on location of agents regardless of fundamental insurance or economic factors. He finds evidence consistent with the proposition that the location of agents or agencies is correlated with the racial composition and income of a certain area.

The principal issue studied by Schultz is whether higher income and/or predominately white neighborhoods enjoy higher accessibility to homeowners insurance than their counterparts in high minority areas. He examines the St. Louis, Missouri area. He observes that in higher income areas there are a higher concentration of agents and a higher profitability but a similar loss experience when compared to low income areas. In predominately white areas he also observes a higher concentration of agents and a higher profitability while having a similar loss experience when compared to high minority areas. In order to determine whether or not these effects are of a causal nature he applies a regression analysis that has the number of agent combinations for each company in each ZIP code as the dependent variable. For independent

variables he uses the number of owner-occupied houses in a ZIP code, the percent of houses built before 1950 in a ZIP code, the average income of each ZIP code, the cash flow loss ratio in each ZIP code, the minority population of each ZIP code, and the percent of houses less than $35,000 in each ZIP code.

Schultz finds that the number of agents in an area is highly correlated with the number of exposures in that area. He also reveals that the number of agents in an area decreases as the percent of minority residents rises and income falls. Even after controlling for a number of economic and demographic variables he finds a negative relation between the size of a minority population and the number of agents in an area. He finds a similar relation between income and the number of agents. He ultimately concludes that the hypothesis that racial composition and income of a community affect the location of agents independently of normal insurance and economic factors cannot be rejected.

One way to determine whether insurance firms are providing access or availability of insurance for a particular area is to simply count the number of policies written per company in the area. However, as Schultz points out, this approach may indict a firm that is trying to operate in the market in question but cannot get the requisite market penetration to sell more than a token number of policies in the area. If a firm can point to the presence of agencies or agents in the area then it can credibly claim that it is trying to service the area but other factors outside its control are conspiring to keep it from writing a large number of policies in the area. While Schultz focused on the homeowners insurance market and this study examines the automobile insurance market, there is no reason to expect that the underlying theories will not apply because

the markets being studied are slightly different. Examining the number of agents or agencies maintained by a firm in an area doesn't completely exonerate a firm from charges of ignoring an area or from the worse charge of redlining but it does provide a firmer basis for analysis than simply counting the number of policies written by a firm in a particular area.

CHAPTER 13

Data and Econometric Model

I use data compiled by the A.M. Best Company in its Best's Insurance Reports Property/Casualty United States 2005 Edition Volumes I&II. The 2005 edition of Best's Insurance Reports compiles data from the year 2004. I combine this data with data from the National Association of Insurance Commissioners 2004 data tapes to investigate a total of 77 firms that operate in the California automobile insurance market.

The California Department of Insurance (CDI) has been collecting data since 1994 about where California insurers are and are not writing homeowners, automobile, and commercial policies. Pursuant to its authority under Proposition 103, the CDI promulgated a regulation requiring the public disclosure of the data described above. In 1999, the insurance industry led by State Farm sued claiming that the data constituted a trade secret. On April 26, 2003 in State Farm v. Garamendi (Case # S102251) the California Supreme Court unanimously ruled that the state insurance commissioner did not exceed his statutory authority under Proposition 103 when he promulgated the public disclosure regulation. Therefore, 2004 is the first year after the ruling that the data has been made public. There is more recent data but data from 2004 is the best year to use because this year is the closest in time to the year 2000 in which the last United States Census was taken.

There are 213 insurance firms that operate in the private passenger auto market in California. Only 103 firms reported data to the CDI revealing their earned exposure numbers for underserved and non underserved areas. Of these 103 firms, 77 reported the requisite service

office or agency data to the California Department of Insurance in order to be included in the study. These 77 firms represent over 81% of the private passenger auto insurance market in California.

Using this data I will construct a model to identify which factors are more likely to affect whether a firm operates in underserved areas. Any firm will operate in an area in which it can sell its product for a reasonable profit. Insurance companies sell policies for a price that will enable them to cover the risk transferred by the policy plus their expenses and enable them to realize a profit. If an area is underserved it means that either the demand for insurance is insufficient or that insurance companies have for some reason decided not to supply that area with insurance. If the latter is the case then there is an issue of lack of access to insurance for residents of these underserved areas.

This study is an attempt to ascertain what factors may cause an insurance firm to avoid these underserved areas. I will do this by examining traits of the firms that do operate in these areas and compare them with the traits of firms that operate in non-underserved areas and in California as a whole to discover if there are differences that can be found between these sets of firms. Using firm level data, the analysis proposed here takes the form

$$Y = f(X,Z,V)$$

where Y is the supply of automobile insurance supplied by a firm in a certain area. X is a vector of firm specific accounting variables, Z is a vector of firm operating variables, and V is a vector of firm descriptive variables.

The X variables are firm size, capacity, leverage, and the inverse of the firm's loss ratio. The Z variables are the amount of a firm's California earned exposures, the number of service offices the firm has in underserved and non-underserved areas, and the number of agencies a firm has in underserved and non-underserved areas. The V variables are the firm's business mix and the firm's ownership structure.

The variables in the model were chosen because in other contexts they have been shown to have an effect on the manner in which firms operate or supply insurance. As discussed below, firm size has been found to be related to success and previous literature has found that capacity, leverage, business mix and ownership structure seem to impact the amount of risk taken on by some firms. I have included variables for service offices and agents in order to examine whether the size and characteristics of the distribution network or channel has a measurable impact on the amount of insurance supplied to a particular area. I include a loss ratio variable to determine what effect the price of insurance has on the amount of insurance written in a given area. In the context of automobile insurance perhaps low cost insurers would fare better in underserved areas.

The model is specified as follows:

$$\text{Log(Earned Exposures)}_{i,j} = \beta_0 + \beta_1(\text{CA Exposures})_i + \beta_2(\text{Offices})_{i,j} + \beta_3(\text{Agents})_{i,j} + \beta_4(\text{Size})_i + \beta_5(\text{Loss Ratio})_i + \beta_6(\text{Structure})_i + \beta_7(\text{Capacity})_i + \beta_8(\text{Leverage})_i + \beta_9(\text{Business Mix})_i$$

where:

Earned Exposures $_{i,j}$ = the amount of earned exposures for firm i in area j normalized by the amount of registered vehicles in area j,

CA Exposures $_{i}$ = the amount of direct premiums for firm i in California,

Offices $_{i,j}$ = the number of service offices for firm i in area j,

Agents $_{i,j}$ = the number of agents for firm i in area j,

Size $_{i}$ = the size of firm i,

Loss Ratio $_{i}$ = the inverse of the loss ratio for firm i,

Structure $_{i}$ = the ownership structure of firm i,

Capacity$_{i}$ = the inverse of solvency of firm i,

Leverage$_{i}$ = the leverage of firm i,

Business Mix$_{i}$ = the percentage of firm i's business that is devoted to auto insurance.

Following Butler (1994), I log the explanatory variable proxying for insurance supply to reduce the positive skewness in the regression's error term. We can also examine the characteristics of firms that operate in underserved areas and compare them with the characteristics of the firms that don't operate in these areas. This may help us determine if there are other reasons that may explain why some firms choose to operate in underserved areas while other firms don't. Lower sales may not be the only reason firms have for avoiding underserved areas. Perhaps firms that operate in underserved areas pay another price such as having a lower A.M. Best rating and this also deters them from operating in underserved areas.

Investigating the demand side of the equation by examining the underserved market and investigating the supply side of the equation by examining the characteristics of different California insurance firms should help us understand whether there are true economic reasons for some areas to be underserved or whether this problem is due simply to discrimination.

I will apply the model to discover whether there are certain characteristics that are common to firms that tend to avoid underserved areas. Conversely, I will investigate whether there are characteristics common to firms that tend to write business in underserved areas. Combining these results with what is found by examining the demand side of the equation will help to provide policymakers with a better idea of why certain areas tend to be underserved and why certain firms tend not to write business in those areas. The goal is to provide a better understanding of these underserved areas so that ideas can be formulated that will help increase access to automobile insurance.

In the following discussion of the variables used in the model there are references to how each variable is expected to be related to insurance supply. The expectations are for underserved areas. For non-underserved areas the expectations for capacity, leverage, business mix, size, ownership structure (form) and loss ratio are reversed.

Earned Exposures

I use earned exposures to proxy for the supply of insurance. The term "earned" is defined by the California Department of Insurance as a condition where the exposure is recognized by the insurance company after time has passed and the insurance company has delivered the services promised under the insurance policy. Furthermore, an exposure is defined

as the risk or loss potential an insurance company assumes from its policyholder in exchange for premium (an automobile or home are examples of exposures).

Earned exposures are an appropriate proxy for supply because they measure the service supplied by the insurance company to the insured. Specifically, they measure the number of times that the insurance company agrees to accept a transfer of risk from the insured. Because insurance involves a transfer of risk from the insured to the insurer, the number of earned exposures generated by a particular company is a proper measure for the supply of insurance generated by that company.

The earned exposures variable is normalized by dividing the number of earned exposures by the number of registered vehicles in the appropriate area.

Firm Size

I control for the effect that size has on the ability of firms to be more successful and thereby realize more net income. Many prior studies have investigated the effect of large organizational size on firm success and failure rates (Ranger-Moore, 1997). Large organizational size has been found to be a source of several advantages. Large firms have access to a greater supply of resources and have the ability to bargain for more favorable tax treatment (Aldrich and Auster, 1986). Large firms can better adapt to a wider range of environments because of their deeper and more complicated performance repertoire (Nelson and Winter, 1982). Large firms are also advantaged relative to smaller firms because they are better able to withstand competition (Barnett and Amburgey, 1990). Large firms can also exert a greater influence on their own environments, either through monopolizing important environmental

resources or by influencing their own institutional environment (Ranger-Moore, 1997). The natural log of total firm assets is used to define the size variable (Sommer, 1996).

Due to their size, large firms are more likely to have more service offices and agencies. Therefore, these large firms are more likely to have service offices and agencies in underserved areas and sell more insurance there. For this reason size may be positively related to insurance supply. However, smaller firms are more likely to specialize in certain areas. To the extent that underserved areas are places where these smaller firms face less competition they may choose to operate in these areas to avoid larger firms. If this is the case supply may be negatively related to size. I think the former explanation is more likely than the latter so size should be positively related to insurance supply.

Loss Ratio

I use the inverse of the loss ratio to proxy for price charged for insurance. The loss ratio is computed by adding incurred losses and loss adjustment expenses and dividing this sum by the premiums earned. The inverse of the loss ratio can also be described as premiums per unit of benefit payments to the insured population (Grabowski, Viscusi, and Evans, 1989). It is important to account for the price that firms charge for their insurance because *ceteris paribus* those firms that charge lower prices for insurance can be expected to sell more. This is especially true in the context of auto insurance because many insureds buy insurance solely because it is required by law in order to drive.

I expect that there will be a negative relationship between the inverse of the loss ratio and the supply of insurance. As noted before, firms that charge lower prices for their insurance should be able to sell more all things being equal.

Ownership Structure

The two dominant ownership structures in the insurance industry are stocks and mutuals. Stock companies are those companies in which the owners and the customers can be different people. Mutual companies are those companies in which the customers are the owners of the company.

The literature investigating the impact of ownership structure has faced fundamental problems because of the endogenous nature of ownership structure (Mayers and Smith, 1990). However, Lamm-Tennant and Starks were able to show that stock insurers write relatively more business in riskier lines and states than mutuals (Lamm-Tennant and Starks, 1993). I control for differences in the ownership structure between stocks and mutuals by using dummy variables.

Two firms in the sample were classified as reciprocals by the National Association of Insurance Commissioners. For purposes of this analysis there should be no substantive difference in behavior between these two reciprocal firms and their mutual cousins. Therefore, I have categorized those two firms as mutuals. I assign a value of 1 for stocks and 0 for mutuals.

Following previous research, stock insurers should write more business in underserved areas so there should be a direct relationship found in those areas and the opposite relationship found in non-underserved areas.

Agencies/Service Offices

I include variables for the number of agencies and service offices that each firm has in underserved areas and in California. This measure is meant to investigate whether certain firms are providing access to insurance in underserved areas. The more service offices or agencies a firm has in underserved areas the more insurance the firm should be able to supply to those areas. The expectation is that there should be a positive relation between the number of agencies or service offices and the supply of insurance because if there are more agencies in an underserved area there will be greater access to insurance in those areas. Studies in the health insurance field have found that access is strongly related to utilization (Solis et al., 1990).

California Exposures

This variable is a measure of direct premiums each company writes in California. It is a percentage computed by dividing the amount of premiums written in California by the total amount of premiums written by the company in its entire geographic book of business. This variable is included to account for the fact that some insurers may not be writing much insurance in underserved areas simply because they don't write a high percentage of their insurance in California. There should be a positive relationship between the California exposures variable and insurance supply in underserved areas. This relationship should be found because insurers that write more insurance in California are more likely to write insurance in underserved areas.

Capacity

The capacity variable (sometimes called operating leverage) is included to measure the financial stability of the companies in the sample (Carson and Hoyt, 2000). This variable will

shed light on whether stable firms are more likely to operate in underserved areas because they are better positioned financially to handle the increased risk incurred by writing business in these areas. Alternatively, less stable firms may choose to write business in underserved areas because they may view these areas as opportunities for growing their business because of decreased competition from other firms. This variable is a measure of inverse solvency so the lower the variable the more solvent the firm. Therefore, I predict a positive relationship between the capacity variable and insurance supply because I expect that less stable firms will choose to operate in underserved areas because of the opportunities afforded them to grow their business.

Leverage

This variable is computed by dividing the firm's assets by its liabilities. An insurer's leverage level will have an impact on its appetite for risk. As an insurer's leverage declines, its cost of risk bearing should decline. As the insurer's level of leverage increases, so should that insurer's loss of value increase in the event that the insurer engages in poor project selection (Kleffner and Doherty, 1996). Therefore, the higher an individual insurer's leverage, the more pain it will incur from bad business decisions. This should make these highly leveraged insurers even more risk averse than normal. This will make them more likely to avoid underserved areas. Because of this I expect that there will be an inverse relationship between leverage and insurance supply. This variable is sometimes called financial leverage.

Business Mix

This variable is computed by dividing a firm's auto premiums by its direct premiums written. An insurer's business mix may impact whether or not it decides to write business in

underserved areas. The variety of lines of business engaged in by a firm can have an important impact on that firm's risk tolerance (Choi and Weiss, 2005). Insurers that derive a higher percentage of their business from auto insurance may not feel the need to grow their business into new areas because they are doing well in their current markets. Providing insurance in underserved areas may be seen as taking on unnecessary risk. For this reason I expect that the business mix variable will be inversely related to insurance supply.

Table 1 reports the independent variables with their predicted signs.

Table 1

Summary of the Predicted Signs
of the Independent Variables

Variable	Definition	Hypothesized Sign
Size	Firm Size (log of total firm assets)	+
Inverse Loss Ratio	premiums per unit of benefit payments to insureds	-
Structure	Ownership Structure	+ or -
Agencies	Number of Agencies	+
Offices	Number of Service Offices	+
CA Exposures	Direct Premiums Written in CA	+
Capacity	Net Premiums Written/Surplus	+
Leverage	Liabilities/Assets	-
Business Mix	Auto Premiums/ Total Direct Premiums Written	-

Table 2 reports the total earned exposures for California automobile insurers in the state as a whole and specifically in served and underserved areas. Table 3 reports the agencies and service offices in served and underserved areas for California automobile insurers.

Table 2

Summary Statistics for California Automobile Insurers

Firm	Total Earned Exposures - California	Total Earned Exposures - Underserved	Total Earned Exposures - Served
21st Century Ins (American International Group)	1269329	139897	1129432
Aegis Security	14581	3486	11095
AIG	94131	5692	88439
Allied Prop & Cas (Nationwide Group)	100809	3375	97434
ALLSTATE IND (Allstate Insurance Group)	1044960	121306	923654
ALLSTATE INS (Allstate Insurance Group)	608122	33978	574144
ALLSTATE PROP & CAS INS (Allstate Insurance Group)	100015	14039	85976
AMCO INS (Nationwide Group)	117093	2828	114265
AMERICAN HOME ASSUR	47391	4052	43339
AMERICAN INTL INS CO OF CA (American International Group)	45228	3426	41802
AMERICAN SECURITY GROUP	15097	1125	13972
AMEX ASSUR	109575	6681	102894
AMICA MUT INS	45536	1002	44534
ANCHOR GEN INS	30561	4227	26334
ARGONAUT INS	6359	265	6094
CALIFORNIA CASUALTY GROUP	164747	6873	157874
CALIFORNIA INS GROUP	34582	1016	33566
CALIFORNIA STATE AUTO ASN INTER-INS (California State Auto Group)	1764874	61583	1703291
CENTURY NATL INS	5838	437	5401
C N A INS GROUP	88289	6925	81364
COAST NATL INS (Bristol West Ins Group)	358960	81550	277410
COMMERCE WEST INS	51322	5471	45851
CONVERIUM INS NORTH AMERICA (Converium Group)	3211	1192	2019
Civil Service Employees INS GROUP	65035	4361	60674
DEERBROOK INS	19386	3282	16104
DEPOSITORS INS (Nationwide Group)	16775	347	16428
DIAMOND STATE INS	3144	349	2795
ELECTRIC INS	6365	286	6079

ENSURANCE PROP & CAS INS	25881	1613	24268
EXECUTIVE RISK IND INC (Chubb Group)	49734	19057	30677
FARMERS INS COS	1989063	122133	1866930
FIDELITY NATL INS CO (Fidelity National Group)	389	5	384
FINANCIAL IND CO (Unitrin Inc)	100835	9429	91406
FIREMANS INS GROUP	20915	345	20570
GEICO CAS CO	29884	874	29010
GEICO GENERAL INS	308134	10665	297469
GEICO IND	73075	3151	69924
GMAC INS CO ONLINE INC	5703	266	5437
GOVERNMENT EMPLOYEES INS	203886	7782	196104
GRANGE INS GROUP	23620	150	23470
GRANITE STATE INS	129371	37097	92274
GREAT AMERICAN INS (Great American P&C Insurance Group)	6015	136	5879
GREENWICH INS CO	27449	4769	22680
HARBOR SPECIALTY INS	65178	8961	56217
HARTFORD INS GROUP	357050	19601	337449
HORACE MANN INS (Horace Mann Ins Group)	20217	1498	18719
HORACE MANN PROP & CAS INS	17556	1847	15709
HUDSON INS CO (Fairfax Financial -USA- Group)	42557	10839	31718
ICW INS GROUP	68340	6132	62208
INFINITY INS COS (Infinity P&C Group)	465189	177816	287373
INSURANCE CO OF THE STATE OF PA	582	6	576
INSURANCE CORP OF HANOVER	8183	846	7337
INTEGON PREFERRED INS CO (GMAC Insurance Group)	11256	569	10687
INTERINS EXCH OF THE AUTOMOBILE CLUB (Automobile Club of Southern Calif Group)	1692819	116874	1575945
LIBERTY MUTUAL GROUP	227778	9875	217903
LINCOLN GENERAL INS CO (Kingsway America Group)	71165	26119	45046
LUBERMANS MUTUAL CASUALTY GP (PERSONAL)	43837	636	43201
MERASTAR INS CO	6277	587	5690
MERCURY INS GROUP	1708641	203876	1504765
METROPOLITAN DRT PROP & CAS INS CO	47529	3010	44519
MIC GENERAL INS	17814	1770	16044
NATIONAL ALLIANCE INS CO	13977	496	13481
NATIONAL AMERICAN INS CO OF CA (DHC Group)	35102	5849	29253
NATIONAL GENERAL INS CO (GMAC Insurance Group)	137254	5309	131945
NATIONWIDE INS GROUP	126200	5262	120938
NATIONWIDE INS GROUP (ALLIED DIVISION)	39836	1967	37869
NORTHWESTERN PACIFIC IND CO (Chubb Group of Insurance Cos)	7452	144	7308
OCEAN HARBOR CAS INS CO	1843	676	1167
OREGON MUT INS CO	5411	386	5025
PACIFIC PIONEER INS CO	817	54	763

PACIFIC PROP & CAS (American National P&C Group)	10130	410	9720
PACIFIC SPECIALTY INS (Pacific Specialty Ins Group)	4067	741	3326
PERMANENT GENERAL ASSUR CORP (Permanent General Insurance Group)	68461	8507	59954
PROGRESSIVE INS GROUP	342290	22773	319517
QBE INS CORP (QBE Re Group - US)	8196	2733	5463
QBE REINS CORP	5507	1924	3583
REPUBLIC IND CO OF CA (Great American P&C Ins Group)	27679	7457	20222
RESPONSE WORLDWIDE INS CO	3649	169	3480
SAFECO INS GROUP	331798	13941	317857
SAFEWAY DIRECT INS CO	6320	955	5365
SAFEWAY INS CO (Safeway Insurance Group)	58056	23180	34876
SEQUOIA INS CO	16212	213	15999
SIRIUS AMER INS CO (White Mountains Ins Group)	12380	1924	10456
SOUTHERN INS CO (Republic Companies Group)	3324	598	2726
STARNET INS CO	42856	9188	33668
STATE FARM INS GROUP	2759880	145573	2614307
STERLING CAS INS CO	72300	15322	56978
SUTTER INS CO	9881	862	9019
TOKIO MARINE & FIRE INS CO LTD US BR	14477	1656	12821
TRAVELERS INS COS	72533	4984	67549
TRINITY UNIVERSAL INS CO	4953	389	4564
UNITED SERVICES AUTO ASSOC	394196	6711	387485
UNITRIN DIRECT INS CO	12777	1252	11525
UNITRIN DIRECT PROP & CAS INS CO	21460	604	20856
UNITRIN INS GROUP	6819	106	6713
USAA CAS INS CO	326604	8210	318394
USAA GENERAL INS CO	8451	223	8228
VALLEY INS CO	7756	39	7717
VIKIING INS CO OF WI	236238	41436	194802
WAWANESA INS GROUP	324660	27882	296778
WESTERN GENERAL INS CO	32917	6054	26863
WESTERN UNITED INS CO (California State Auto Group)	105210	13017	92193
WORKMENS AUTO INS CO	45963	2979	42984

Table 3

Agencies and Service Offices in Served and Underserved Areas for California Automobile Insurers

Firm	Service Offices - California	Service Offices - Underserved	Agencies in California	Agencies in Underserved
21st Century Ins (American International Group)	20	4	287	0
Aegis Security				
AIG				
Allied Prop & Cas (Nationwide Group)	3	0	483	18
ALLSTATE IND (Allstate Insurance Group)	1294	88	1363	93
ALLSTATE INS (Allstate Insurance Group)	1294	88	1363	93
ALLSTATE PROP & CAS INS (Allstate Insurance Group)	1294	88	1363	93
AMCO INS (Nationwide Group)	3	0	1105	47
AMERICAN HOME ASSUR	1	0		
AMERICAN INTL INS CO OF CA (American International Group)	4	1	94	7
AMERICAN SECURITY GROUP	1842	116	1842	116
AMEX ASSUR				
AMICA MUT INS				
ANCHOR GEN INS				
ARGONAUT INS				
CALIFORNIA CASUALTY GROUP				
CALIFORNIA INS GROUP	6	0	419	16
CALIFORNIA STATE AUTO ASN INTER-INS (California State Auto Group)	122	3	502	0
CENTURY NATL INS	2	2	181	102
C N A INS GROUP	4	0	215	12
COAST NATL INS (Bristol West Ins Group)	1	0	1310	309
COMMERCE WEST INS	1	0	1508	242
CONVERIUM INS NORTH AMERICA (Converium Group)	2	0	3707	608
Civil Service Employees INS GROUP	3	0	399	10
DEERBROOK INS				
DEPOSITORS INS (Nationwide Group)	3	0	1096	33
DIAMOND STATE INS				
ELECTRIC INS				
ENSURANCE PROP & CAS INS				
EXECUTIVE RISK IND INC (Chubb Group)	1	0	115	34
FARMERS INS COS	5677	303	5642	301
FIDELITY NATL INS CO (Fidelity National Group)	1	0	10	0
FINANCIAL IND CO (Unitrin Inc)	2203	269	2203	269
FIREMANS INS GROUP	493	28	491	27

GEICO CAS CO				
GEICO GENERAL INS	1	0		
GEICO IND				
GMAC INS CO ONLINE INC	5	1		
GOVERNMENT EMPLOYEES INS	1	0		
GRANGE INS GROUP	1	0	12	0
GRANITE STATE INS	1	1		
GREAT AMERICAN INS (Great American P&C Insurance Group)	24	1	710	42
GREENWICH INS CO				
HARBOR SPECIALTY INS				
HARTFORD INS GROUP	3	0	2274	212
HORACE MANN INS (Horace Mann Ins Group)			57	2
HORACE MANN PROP & CAS INS			57	2
HUDSON INS CO (Fairfax Financial -USA-Group)	661	162	652	160
ICW INS GROUP	1	0	1522	96
INFINITY INS COS (Infinity P&C Group)	8019	1502	7994	1500
INSURANCE CO OF THE STATE OF PA				
INSURANCE CORP OF HANOVER				
INTEGON PREFERRED INS CO (GMAC Insurance Group)	211	9	40	2
INTERINS EXCH OF THE AUTOMOBILE CLUB (Automobile Club of Southern Calif Group)	78	8	717	43
LIBERTY MUTUAL GROUP	23	1	142	4
LINCOLN GENERAL INS CO (Kingsway America Group)			1259	106
LUBERMANS MUTUAL CASUALTY GP (PERSONAL)	382	20	379	20
MERASTAR INS CO				
MERCURY INS GROUP	70	0	1606	77
METROPOLITAN DRT PROP & CAS INS CO				
MIC GENERAL INS	5	1		
NATIONAL ALLIANCE INS CO	5	1		
NATIONAL AMERICAN INS CO OF CA (DHC Group)	2	1	1	0
NATIONAL GENERAL INS CO (GMAC Insurance Group)	13	2	8	1
NATIONWIDE INS GROUP				
NATIONWIDE INS GROUP (ALLIED DIVISION)	3	0	1105	34
NORTHWESTERN PACIFIC IND CO (Chubb Group of Insurance Cos)	7	2	174	12
OCEAN HARBOR CAS INS CO	1	0	150	25
OREGON MUT INS CO	224	7	218	6
PACIFIC PIONEER INS CO				
PACIFIC PROP & CAS (American National P&C Group)	43	1	43	1

PACIFIC SPECIALTY INS (Pacific Specialty Ins Group)	5120	431	5120	431
PERMANENT GENERAL ASSUR CORP (Permanent General Insurance Group)	9	1	36	6
PROGRESSIVE INS GROUP	13	1	2751	219
QBE INS CORP (QBE Re Group - US)	2	0	885	180
QBE REINS CORP				
REPUBLIC IND CO OF CA (Great American P&C Ins Group)	15	2	717	119
RESPONSE WORLDWIDE INS CO				
SAFECO INS GROUP	3	0	1411	70
SAFEWAY DIRECT INS CO				
SAFEWAY INS CO (Safeway Insurance Group)	1	0	359	103
SEQUOIA INS CO	1	0	58	2
SIRIUS AMER INS CO (White Mountains Ins Group)	590	111	1	0
SOUTHERN INS CO (Republic Companies Group)	2	0	3706	608
STARNET INS CO				
STATE FARM INS GROUP	1937	69	1874	68
STERLING CAS INS CO	1122	247	22	3
SUTTER INS CO			312	22
TOKIO MARINE & FIRE INS CO LTD US BR	9	0	32	10
TRAVELERS INS COS	9	1	813	52
TRINITY UNIVERSAL INS CO				
UNITED SERVICES AUTO ASSOC				
UNITRIN DIRECT INS CO	1	0	1	0
UNITRIN DIRECT PROP & CAS INS CO	1	0	1	0
UNITRIN INS GROUP	391	20	387	20
USAA CAS INS CO				
USAA GENERAL INS CO				
VALLEY INS CO	52	2	52	2
VIKIING INS CO OF WI	2	0	1281	220
WAWANESA INS GROUP				
WESTERN GENERAL INS CO				
WESTERN UNITED INS CO (California State Auto Group)	1060	185	2735	447
WORKMENS AUTO INS CO	2	1	209	11

Table 4 reports the organizational form, inverse loss ratio, and total firm assets for California automobile insurers. I have assigned a value of 1 for stocks, 0 for mutuals, and 2 for

combined. None of the insurers with a combined organizational structure were included in the sample because they failed to report all of the statistics required to be included in the model.

Table 4

Total Earned Premium for California, Organizational Form, Inverse Loss Ratio, and Total Firm Assets for California Automobile Insurers

Firm	Total Earned Premium CA	Form	Inverse Loss Ratio	Total Firm Assets
21st Century Ins (American International Group)	674870877	1	0.0163132	1500378000
Aegis Security	7221517	1	0.090541	68151000
AIG	35866818	1	0.0001192	88582718000
Allied Prop & Cas (Nationwide Group)	39843854	1		85301000
ALLSTATE IND (Allstate Insurance Group)	411307844	1		98913000
ALLSTATE INS (Allstate Insurance Group)	222844616	1	0.0179856	44711746000
ALLSTATE PROP & CAS INS (Allstate Insurance Group)	69071611	1		19085000
AMCO INS (Nationwide Group)	51662546	1		969700000
AMERICAN HOME ASSUR	19239217	1	0.0003452	19477874000
AMERICAN INTL INS CO OF CA (American International Group)	20930554	1	0.0145138	68647000
AMERICAN SECURITY GROUP	1641374	1		
AMEX ASSUR	42774092	1	0.073575	283613000
AMICA MUT INS	20230584	0	0.0007452	3384387000
ANCHOR GEN INS	16406800	1	0.1933023	25112000
ARGONAUT INS	3195231	1	0.0013638	1195883000
CALIFORNIA CASUALTY GROUP	71304874	2	0.0186973	538366000
CALIFORNIA INS GROUP	26577612	2		423469709
CALIFORNIA STATE AUTO ASN INTER-INS (California State Auto Group)	775893636	0	0.0176991	4727824000
CENTURY NATL INS	3216643	1	0.0186916	495116000
C N A INS GROUP	35560125	1	0.0238663	37579698000
COAST NATL INS (Bristol West Ins Group)	241009026	1	0.0184502	565989000
COMMERCE WEST INS	22474352	1	0.0181159	117693000
CONVERIUM INS NORTH AMERICA (Converium Group)	980162	1	0.0004675	85085000
Civil Service Employees INS GROUP	29052290	1	0.0306748	180638000
DEERBROOK INS	13363440	1		32208000
DEPOSITORS INS (Nationwide Group)	9442719	1		43198000
DIAMOND STATE INS	1630217	1	0.0281797	151802000
ELECTRIC INS	2795457	1	0.000401	1144333000

ENSURANCE PROP & CAS INS	14715751			
EXECUTIVE RISK IND INC (Chubb Group)	17145923	1	0.017331	2225389000
FARMERS INS COS	1017079266	1	1.3846394	166927081
FIDELITY NATL INS CO (Fidelity National Group)	198018	1	0.0175439	116158000
FINANCIAL IND CO (Unitrin Inc)	58127233	1	0.2174746	64452000
FIREMANS INS GROUP	14013953	1		
GEICO CAS CO	26700071	1	0.0217603	261923000
GEICO GENERAL INS	133790301	1		125939000
GEICO IND	34879887	1	0.0011977	3409350000
GMAC INS CO ONLINE INC	3319005	1	0.1125788	17003000
GOVERNMENT EMPLOYEES INS	79876299	1	0.0008075	11160614000
GRANGE INS GROUP	8175008	0	0.016	191295000
GRANITE STATE INS	52580732	1		33474000
GREAT AMERICAN INS (Great American P&C Insurance Group)	5651098	1	0.026738	5084577000
GREENWICH INS CO	9717090	1	0.0231533	674630000
HARBOR SPECIALTY INS	27384203	1	0.0679297	262018000
HARTFORD INS GROUP	113493233			34473270000
HORACE MANN INS (Horace Mann Ins Group)	7298316	1	0.0139082	452477000
HORACE MANN PROP & CAS INS	7160538	1	0.0169492	92037000
HUDSON INS CO (Fairfax Financial -USA- Group)	20493951	1	0.0174216	219951000
ICW INS GROUP	27447153	1	0.015674	703340000
INFINITY INS COS (Infinity P&C Group)	215135193	1	0.0220751	901858000
INSURANCE CO OF THE STATE OF PA	387701	1	6.026E-06	3156975000
INSURANCE CORP OF HANOVER	3406964	1	0.008791	732545000
INTEGON PREFERRED INS CO (GMAC Insurance Group)	6645339	1		30643000
INTERINS EXCH OF THE AUTOMOBILE CLUB (Automobile Club of Southern Calif Group)	849636608	0	0.0211416	4400067000
LIBERTY MUTUAL GROUP	96650847	0	0.0153846	37951435000
LINCOLN GENERAL INS CO (Kingsway America Group)	37421683	1	0.0152672	513451000
LUBERMANS MUTUAL CASUALTY GP (PERSONAL)	21814309	2	0.0019911	3776441000
MERASTAR INS CO	3435158	1	0.0114366	105090000
MERCURY INS GROUP	908600174		0.1521026	3079415870
METROPOLITAN DRT PROP & CAS INS CO	17293987	1		25573000
MIC GENERAL INS	6396108	1		69082000
NATIONAL ALLIANCE INS CO	4492916	1	0.223752	27332000
NATIONAL AMERICAN INS CO OF CA (DHC Group)	14919896	1	0.0280899	58630000
NATIONAL GENERAL INS CO (GMAC Insurance Group)	43952366	1	0.0978493	130278000
NATIONWIDE INS GROUP	59658408	2	0.0003066	33705160000
NATIONWIDE INS GROUP (ALLIED DIVISION)	16570591			30362299174
NORTHWESTERN PACIFIC IND CO (Chubb Group of Insurance Cos)	4643721	1		43400000

OCEAN HARBOR CAS INS CO	1609448	1	0.0152439	76706000
OREGON MUT INS CO	2931864	0	0.0190476	158910000
PACIFIC PIONEER INS CO	607397	1	0.0427431	21910000
PACIFIC PROP & CAS (American National P&C Group)	7085088	1	0.0149254	30605000
PACIFIC SPECIALTY INS (Pacific Specialty Ins Group)	1851534	1	0.046729	231026000
PERMANENT GENERAL ASSUR CORP (Permanent General Insurance Group)	32060462	1	0.015456	79735000
PROGRESSIVE INS GROUP	258035754	1		15387116019
QBE INS CORP (QBE Re Group - US)	3309246	1	0.0034865	357534000
QBE REINS CORP	2293688	1	0.003522	1255954000
REPUBLIC IND CO OF CA (Great American P&C Ins Group)	12653080	1	0.0190476	36926000
RESPONSE WORLDWIDE INS CO	1105406	1	0.0028921	62040000
SAFECO INS GROUP	166800264		0.0023232	11296309000
SAFEWAY DIRECT INS CO	2598977	1	0.133389	9986000
SAFEWAY INS CO (Safeway Insurance Group)	27630992	1	0.0181159	360459000
SEQUOIA INS CO	4331122	1	0.0246914	148641000
SIRIUS AMER INS CO (White Mountains Ins Group)	5141696	1	0.019802	287900000
SOUTHERN INS CO (Republic Companies Group)	1213111	1		9171000
STARNET INS CO	15724889	1	1.058239	410095000
STATE FARM INS GROUP	1503605270	0	0.0169205	1.05977E+11
STERLING CAS INS CO	35924693	1	0.0157729	33125000
SUTTER INS CO	3914906	1	0.0223714	76014000
TOKIO MARINE & FIRE INS CO LTD US BR	6627440	1	0.0163399	1349878000
TRAVELERS INS COS	33559016			
TRINITY UNIVERSAL INS CO	2283892	1	0.0001659	3271968000
UNITED SERVICES AUTO ASSOC	162459786	0	0.0011241	14383720000
UNITRIN DIRECT INS CO	5538826	1	0.3298645	47735000
UNITRIN DIRECT PROP & CAS INS CO	9840993	1	0.0492124	30945000
UNITRIN INS GROUP	3671696		5.251E-05	3495056440
USAA CAS INS CO	138016020	1	0.0022031	4721088000
USAA GENERAL INS CO	5722767		0.0012229	394605000
VALLEY INS CO	2750758	1	0.0115863	22680000
VIKIING INS CO OF WI	101022768	1	0.0172414	257362000
WAWANESA INS GROUP	106061842	2		
WESTERN GENERAL INS CO	17254208	1	0.1098072	77248000
WESTERN UNITED INS CO (California State Auto Group)	53354021	1	0.0176991	80182000
WORKMENS AUTO INS CO	21313957	1	0.017331	66193000

CHAPTER 14

Results

Table 5 reports the correlation matrix for each of the variables in the model for the insurance companies.

Table 5

Correlation Matrix of Insurance Company Model Variables

	Supply	Office	Agent	Size	Loss Ratio	Form	Capacity	Leverage	Busmix
Supply	1.0000								
Office	0.2730	1.0000							
Agent	0.2748	0.8996	1.0000						
Size	0.4493	0.0214	-0.0001	1.0000					
LossRatio	0.1846	0.3574	0.2946	-0.1618	1.0000				
Form	-0.1575	-0.0425	-0.0557	-0.0680	0.0073	1.0000			
Capacity	0.3563	0.4583	0.4393	-0.2507	0.5809	0.0101	1.0000		
Leverage	0.0251	-0.0104	-0.0654	0.1963	-0.3097	0.2205	-0.0041	1.0000	
Busmix	-0.2993	-0.0520	-0.0759	0.1409	-0.0593	0.0185	-0.0905	0.0243	1.0000

The matrix supports most of the predictions made in Table 1 regarding the relationship between supply and the other variables in the model. The only variables that seem to experience a high amount of cross-correlation are the service office and agents variables.

Table 6 reports the results for the insurance companies from the dataset that comprises the entire state of California.

Table 6

Results from Insurance Supply Model on California Insurance Firms

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.36169	1.257248	-13.01	0.000		
Offices	-.0000272	.0003063	-0.09	0.929	5.76	+
Agents	.0000715	.0003007	0.24	0.813	5.56	+
Size	.5238216	.0712721	7.35	0.000	1.18	+
Loss Ratio	-.5615617	.8011767	-0.70	0.486	1.88	-
Form	-.4568606	.4634412	-0.99	0.328	1.08	+
Capacity	6.463915	1.498626	4.31	0.000	1.96	+
Leverage	-.8201155	1.250634	-0.66	0.514	1.35	-
Busmix	-.0002279	.0000373	-6.11	0.000	1.03	-

n = 76
R^2 = .5715

The results reported in Table 6 provide some support for the previously stated hypotheses. The size variable is also positive and significant which agrees with what was expected. The capacity variable is positive and significant. The business variable is negative and significant. Both of these results are in line with expectations. The coefficient estimates for the remaining variables are not statistically different from zero.

Because Table 5 reports that the offices variable and the agents variable are highly correlated there is a possibility that multicollinearity is present with regard to these two variables. The relatively high VIF values for those two variables that are reported in Table 6 also seem to strongly indicate that there is multicollinearity present in the model. Tables 6a and 6b estimate the same model as Table 6 except that in Table 6a the offices variable has been dropped and in Table 6b the agents variable has been dropped.

Table 6a

Results from Insurance Supply Model on California Insurance Firms

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.34422	1.222965	-13.36	0.000		
Agents	.0000493	.0001173	0.42	0.676	1.28	+
Size	.5236184	.0696104	7.52	0.000	1.17	+
Loss Ratio	-.5841885	.7716658	-0.76	0.452	1.79	-
Form	-.4555161	.4581531	-0.99	0.324	1.08	+
Capacity	6.462794	1.483602	4.36	0.000	1.96	+
Leverage	-.8374504	1.219551	-0.69	0.495	1.31	-
Busmix	-.0002281	.0000371	-6.15	0.000	1.03	-
n = 77						
R^2 = .5740						

Table 6b

Results from Insurance Supply Model on California Insurance Firms

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.32398	1.248392	-13.08	0.000		
Offices	.0000403	.0001166	0.35	0.731	1.33	+
Size	.5241691	.070668	7.42	0.000	1.18	+
Loss Ratio	-.6126851	.7768837	-0.79	0.433	1.82	-
Form	-.4561202	.4596461	-0.99	0.325	1.08	+
Capacity	6.524321	1.47158	4.43	0.000	1.92	+
Leverage	-.8671195	1.230446	-0.70	0.483	1.31	-
Busmix	-.0002288	.0000373	-6.14	0.000	1.03	-
n = 76						
R^2 = .5711						

The results reported in Tables 6a and 6b do not seem to have experienced significant change when compared to the results reported in Table 6. Both of the newer tables agree with the original Table 6 in that the size, capacity, and business mix variables are all significant and consistent with expectations. None of the remaining variables are consistent in any iteration of Table 6.

Table 7 reports the correlation matrix for each of the variables in the model for the insurance companies that operate in underserved ZIP codes.

Table 7

Correlation Matrix of Insurance Company Model Variables in Underserved ZIP codes

	Supply	CAExp	Office	Agent	Size	Loss Ratio	Form	Capacity	Leverage	Mix
Supply	1.0000									
CA Exp	0.8869	1.0000								
Offices	0.2890	0.2077	1.0000							
Agents	0.3230	0.1823	0.8727	1.0000						
Size	0.3028	0.4493	-0.0101	-0.0440	1.0000					
Loss Ratio	0.1933	0.1846	0.1139	0.0650	-0.1618	1.0000				
Form	-0.1666	-0.1575	-0.0039	-0.0033	-0.0680	0.0073	1.0000			
Capacity	0.4365	0.3563	0.3227	0.3032	-0.2507	0.5809	0.0101	1.0000		
Leverage	0.0159	0.0251	-0.0016	-0.0657	0.1963	-0.3097	0.2205	-0.0041	1.0000	
Busmix	-0.4074	-0.2993	-0.0454	-0.0673	0.1409	-0.0593	0.0185	-0.0905	0.0243	1.00

Overall, there doesn't seem to be a high amount of correlation in any of the variables reported in the matrix in Table 7 except for supply and CA exposures and offices and agents. It makes sense that these four variables would have some correlation. Supply is measured by earned exposures in underserved areas while CA exposures measures the number of earned exposures in California as a whole therefore a degree of correlation is to be expected. Similarly,

agents and service offices have a correlation because agents often work out of service offices and frequently there will be only one agent assigned to each office, especially in underserved areas where the volume of business will be lower.

Table 8 reports the results for the insurance companies from the underserved dataset.

Table 8

Results from Insurance Supply Model in Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.56977	.9731745	-17.03	0.000		
CA Exposures	.8775127	.0732342	11.98	0.000	2.34	+
Offices	-.0017351	.0006534	-2.66	0.010	4.40	+
Agents	.0028134	.0006404	4.39	0.000	4.45	+
Size	.0167812	.0591901	0.28	0.778	2.07	+
Loss Ratio	-.3345352	.8570688	-0.39	0.698	1.88	-
Form	-.2639078	.3047651	-0.87	0.390	1.10	+
Capacity	2.096349	.9717212	2.16	0.035	2.54	+
Leverage	.1806028	.5564686	0.32	0.747	1.38	-
Busmix	-.0001236	.0000314	-3.94	0.000	1.30	-
n = 76						
R^2 = .8519						

The results found in Table 8 ratify some of the previously stated expectations. The California exposures and capacity variables are positive and significant. The California exposures variable confirms the theory that firms that write more business in California also write more business in underserved areas. The capacity variable indicates that more stable firms do tend to write less business in underserved areas. The business mix variable remains negative and significant. This result supports the theory that insurers that derive more of their business from auto insurance do not feel as compelled to operate in underserved areas. The agents

variable is positive and significant which is in line with expectations. The offices variable is negative and significant. This result is contrary to expectations. It will be interesting to see if this result remains the same in the succeeding specification. The coefficient estimates for the rest of the variables are not significant.

Because of the rather high correlation and possible multicollinearity observed with regard to the agents and offices variables, Tables 8a and 8b have been prepared. Tables 8a and 8b estimate the same model as Table 8 except that in Table 8a the offices variable has been removed and in Table 8b the agents variable has been removed.

Table 8a

Results from Insurance Supply Model in Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.37201	.946616	-17.30	0.000		
CA Exposures	.8720042	.0729172	11.96	0.000	2.35	+
Agents	.0014363	.0003714	3.87	0.000	1.16	+
Size	.014968	.0582277	0.26	0.798	2.07	+
Loss Ratio	-.4476642	.8085803	-0.55	0.582	1.86	-
Form	-.2530811	.3089276	-0.82	0.416	1.10	+
Capacity	2.063112	.7771796	2.65	0.010	2.53	+
Leverage	.0520027	.5560074	0.09	0.926	1.35	-
Busmix	-.0001265	.0000318	-3.97	0.000	1.30	-

n = 77
R^2 = .8473

Table 8b

Results from Insurance Supply Model in Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-16.28439	.9936256	-16.39	0.000		
CA Exposures	.8742823	.0759808	11.51	0.000	2.34	+
Offices	.0008904	.0001712	5.20	0.000	1.14	+
Size	.0169559	.0600999	0.28	0.779	2.07	+
Loss Ratio	-.6826137	.8222002	-0.83	0.409	1.81	-
Form	-.2308089	.320111	-0.72	0.473	1.10	+
Capacity	2.484641	.8605562	2.89	0.005	2.49	+
Leverage	-.143109	.612899	-0.23	0.816	1.33	-
Busmix	-.0001293	.0000332	-3.89	0.000	1.29	-

n = 76

R^2 = .8362

The results reported in Tables 8a & 8b are consistent with each other. In both tables the California exposures variable is positive and significant. This result is consistent with expectations. The offices and agents variables are also positive and significant which is what was expected. The offices variable did switch signs from Table 8 to Table 8b. In Table 8 it was negative and significant. In Table 8b it was positive and significant. The capacity and business mix variables are also significant and they both match expectations. None of the other variables are significant.

In Table 8 both the agents and the offices variables had VIF values above 4. In Tables 8a & 8b the agents and the offices variables both had VIF values slightly above 1. Therefore, Tables 8a & 8b seem to ratify the concerns about multicollinearity. However, with the exception of the aforementioned offices variable, the results reported in Tables 8a and 8b generally confirm

the results reported in Table 8. The results in Tables 8a & 8b are also consistent with expectations.

Taken together, these results show that more stable firms do tend to write less business in underserved areas. Also, these results support the theory that insurers that derive more of their business from auto insurance do not feel as compelled to operate in underserved areas. The results for the service offices and agencies are also interesting. These results indicate strongly that providing more agents and service offices in underserved communities would positively impact the amount of insurance supply provided to those communities.

Table 9 reports the correlation matrix for each of the variables in the model for the insurance companies that operate in non-underserved ZIP codes.

Table 9

Correlation Matrix of Insurance Company Model Variables in Non-Underserved ZIP codes

	Supply	CAExp	Office	Agent	Size	Loss Ratio	Form	Capacity	Leverage	Mix
Supply	1.0000									
CA Exp	0.9975	1.0000								
Offices	0.2640	0.2784	1.0000							
Agents	0.2618	0.2852	0.9055	1.0000						
Size	0.4581	0.4493	0.0261	0.0074	1.0000					
Loss Ratio	0.1838	0.1846	0.3904	0.3280	-0.1618	1.0000				
Form	-0.1566	-0.1575	-0.0480	-0.0636	-0.0680	0.0073	1.0000			
Capacity	0.3407	0.3563	0.4715	0.4539	-0.2507	0.5809	0.0101	1.0000		
Leverage	0.0315	0.0251	-0.0116	-0.0640	0.1963	-0.3097	0.2205	-0.0041	1.0000	
Busmix	-0.2857	-0.2993	-0.0521	-0.0759	0.1409	-0.0593	0.0185	-0.0905	0.0243	1.00

The results in Table 9 largely mirror the results found in Table 7. Once again there is a strong correlation between supply and CA exposures and offices and agents. However, the overall correlation between most of the variables is relatively low.

Table 10 reports the results for the insurance companies from the non-underserved dataset. For non-underserved areas the expectations for capacity, leverage, business mix, size, ownership structure (form) and loss ratio are opposite from what they were for underserved areas.

Table 10

Results from Insurance Supply Model in Non Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-17.18358	.10458	-164.31	0.000		
CA Exposures	1.020928	.0109014	93.65	0.000	2.33	+
Offices	.0000539	.0000305	1.77	0.082	6.15	+
Agents	-.0000798	.0000243	-3.28	0.002	5.90	+
Size	-.0041874	.007764	-0.54	0.591	2.09	-
Loss Ratio	.153693	.1259426	1.22	0.227	1.91	+
Form	-.0051711	.0230573	-0.22	0.823	1.10	-
Capacity	-.2901453	.1222785	-2.37	0.021	2.55	-
Leverage	.0913191	.0908809	1.00	0.319	1.37	+
Busmix	.0000103	3.92e-06	2.63	0.011	1.30	+
n = 76						
R^2 = .9962						

Table 10 reports some interesting results. As before the California exposures variable is positive and significant. Although the offices variable matches expectations, the results from the agents variable are somewhat surprising. The coefficient is negative and significant which is

contrary to expectations. ZIP codes in non-underserved areas tend to be more affluent. People who live in these areas would presumably have more resources at their disposal like the internet. Perhaps these resources help them research their insurance purchases so that they don't have as much of a need for insurance service offices in their communities. The capacity variable is negative and significant. The business mix variable is positive and significant. Both of these results match expectations. None of the other variables is significant.

Table 10 is consistent with Tables 6 & 8 in that there appears to be multicollinearity present with regard to the offices and agents variables. Tables 10a & 10b correct for this possibility by presenting models that have deleted either the offices or the agents variable. Tables 10a and 10b estimate the same model as Table 10 except that in Table 10a the offices variable has been dropped and in Table 10b the agents variable has been dropped.

Table 10a

Results from Insurance Supply Model in Non Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-17.21444	.1077825	-159.71	0.000		
CA Exposures	1.020457	.0110519	92.33	0.000	2.35	+
Agents	-.0000354	.0000141	-2.51	0.014	1.31	+
Size	-.0035406	.0075686	-0.47	0.641	2.09	+
Loss Ratio	.1938558	.1244202	1.56	0.124	1.80	-
Form	-.0073904	.0244748	-0.30	0.764	1.10	+
Capacity	-.2854116	.1052431	-2.71	0.008	2.54	-
Leverage	.1198903	.0957869	1.25	0.215	1.32	-
Busmix	.0000105	3.98e-06	2.64	0.010	1.30	+

n = 77
R^2 = .9960

Table 10b

Results from Insurance Supply Model in Non Underserved ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	VIF	Expected Sign
Intercept	-17.21688	.115606	-148.93	0.000		
CA Exposures	1.01956	.0113748	89.63	0.000	2.33	+
Offices	-.0000215	.0000177	-1.22	0.227	1.37	+
Size	-.0038909	.0076852	-0.51	0.614	2.09	+
Loss Ratio	.2004084	.123985	1.62	0.111	1.85	-
Form	-.005678	.0265334	-0.21	0.831	1.10	+
Capacity	-.3379709	.1179526	-2.87	0.006	2.52	-
Leverage	.1335562	.1019259	1.31	0.195	1.33	-
Busmix	.0000109	4.15e-06	2.62	0.011	1.29	+

n = 76

R^2 = .9958

The results reported in Tables 10a & 10b are generally consistent with each other. In both tables the coefficient for California exposures is positive and significant.

The offices variable is not significant but the agents variable remains negative and significant. This result is contrary to expectations but when taken together with what was observed in the underserved areas this result is interesting. In the underserved areas we observed that both the offices and agents variables were positive and significant. This result supported the theory that more agents and service offices in an area would lead to more business being written in that area. Perhaps these results reveal that the presence of agents and service offices is more important in underserved areas than in other areas. The capacity variable is negative and significant and the business mix variable is positive and significant in both specifications. This matches expectations. None of the other variables is significant.

These results seem to ratify the efficient structure hypothesis. The efficient structure hypothesis indicates that firms that can generate superior efficiency in certain markets can use this efficiency to gain greater market share (Bajtelsmit and Bouzouita, 1998). The capacity variable suggests that more financially stable firms are concentrating in the less risky non-underserved market while less financially stable firms are more likely to do business in the comparatively riskier underserved market.

CHAPTER 15

Conclusion

The state of California has directed the California Department of Insurance to collect data from all automobile insurers that operate in underserved areas. This data is combined with data from the NAIC data tapes and Best's Insurance Reports to analyze the behavior of insurers that operate in this market to determine if there are reasons why underserved areas continue to experience problems accessing automobile insurance.

This study estimates a model that contains several different firm characteristics in order to determine whether there are factors that are common to firms that do or do not operate in underserved areas. The model is designed in order to investigate whether or not these characteristics have a measurable impact on the supply of insurance supplied to these areas.

The model is performed on three different areas; the entire state of California, only underserved ZIP codes, and only non-underserved ZIP codes. These areas were studied independently to determine if there are factors common to firms that operate in underserved areas that we don't observe in firms that operate in non-underserved areas and vice versa.

The results for the entire state of California were inconclusive in answering the question of whether the number of agents and service offices is positively correlated with insurance supply. Size and capacity were found to be positively correlated with insurance supply while business mix was negatively correlated with insurance supply. All of these results were consistent with expectations. The size variable confirms previous research by Ranger-Moore and others that found that larger firms have several advantages over smaller firms.

In underserved areas, agents and service offices were found to be positively correlated with insurance supply. This finding confirms previous research performed by Solis that found a strong link between access and utilization. The capacity variable is positively correlated with insurance demand and business mix variable is negatively correlated with insurance demand. These results were consistent with expectations.

In non-underserved areas the agents variable was inversely related to insurance supply while service offices variable was inconclusive. Capacity is also inversely related to insurance supply and business mix is positively related to insurance supply.

Comparing the results obtained from the different areas yields some interesting findings. It seems that there are differences between underserved areas and non-underserved areas. The presence of service offices and agencies can make a positive difference in providing more insurance in underserved areas but they seem to have the opposite effect or are inconclusive elsewhere. This result validates the efforts of the CDI to increase auto insurance access to underserved areas. This research shows that underserved areas are different from other areas in that they are more likely to respond positively to the presence of more service offices and agencies. This indicates that an investment to put more agencies and offices in underserved areas could be an effective way to increase access to auto insurance and help California in its efforts to deal with the uninsured motorist problem.

This result can also provide guidance to insurance firms. Perhaps they will be more motivated to hire agents and open service offices in underserved areas because they will see a greater return on their investment in these areas in the form of a greater volume of business.

This study is based in part on data provided to the public by the California Department of Insurance. This is the first time that this data has been made publicly available by the CDI. It would be interesting to conduct further research to determine if making this data public has an appreciable effect on the behavior of California automobile firms with regard to their operations in underserved areas.

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APPENDIX A

LEGAL HISTORY OF IMPORTANT CIVIL RIGHTS CASES

I will ignore the slavery cases and the cases that came out of the Reconstruction. Therefore, I will not discuss admittedly important cases such as Dred Scott v. Sanford 60 U.S. (19 How.) 393 (1857) or The Slaughter-House Cases 83 U.S. (16 Wall.) 36 (1873). While these cases are extremely important historically, they have little relevance to the problems of access that the CDI is currently seeking to remedy.

In Plessy v. Ferguson 163 U.S. 537 (1896) at issue was a Louisiana statute that required railroad companies to provide "equal but separate accommodations for the white and colored races". A passenger using facilities intended for the other race was made criminally liable. Plessy, who claimed to be 7/8 Caucasian, was prosecuted under the statute when he failed to leave the coach reserved for whites.

The Supreme Court upheld the constitutionality of the statute. Justice Henry B. Brown delivered the opinion of the court. It reads in part:

> The object of the fourteenth amendment was undoubtedly to enforce the absolute equality of the two races before the law, but, in the nature of things, it could not have been intended to abolish distinctions based upon color, or to enforce social, as distinguished from political, equality, or a commingling of the two races upon terms unsatisfactory to either. Laws permitting, and even requiring, their separation, in places where they are liable to be brought into contact, do not necessarily imply the inferiority of either race to the other, and have been generally, if not universally, recognized as within the competency of the sate legislatures in the exercise of their police power.

Even though the court in *Plessy* doesn't explicitly mention the words "separate but equal", this case is often mentioned as the one that established that doctrine as the law of the land. In so doing it hindered the rights of minorities in general and Blacks in particular to equal access to facilities in the United States for more than a generation.

In Cumming v. Board of Education 175 U.S. 528 (1899) the court again confronted the issue of equal access. In *Cumming*, the plaintiffs were black taxpayers and parents who challenged their tax assessment on the ground that the money was being used to support a high school open only to white students. In an opinion written by the first Justice John Marshall Harlan, the court rejected this challenge:

> The substantial relief asked is an injunction that would either impair the efficiency of the high school provided for white children or compel the Board to close it. But if that were done, the result would only be to take from white children educational privileges enjoyed by them, without giving to colored children additional opportunities for the education furnished in high schools.

In these opinions and others like them the Court thwarted the intent of the framers of the Reconstruction amendments. These amendments were intended to protect the rights of newly freed slaves. The Court defied this intent by giving effect to an older version of federalism. At the same time there was a collapse of political consensus in favor of civil rights legislation.

Slowly but surely the tide began to turn. In Missouri Ex Rel Gaines v. Canada 305 U.S. 337 (1938) the court confronted the question of access in education. Missouri law mandated separate educational facilities for whites and blacks. Although the University of Missouri operated a law school, the parallel black institution, Lincoln University did not. However, a Missouri statute authorized the board of curators to arrange for attendance of black residents at

institutions in neighboring states and to pay reasonable tuition rates for such attendance when no black in state facility was available. Lloyd Gaines was the plaintiff in this case. He was a black man denied admission to the University of Missouri law school. He sued for admittance. Chief Justice Charles Evans Hughes delivered the opinion of the Court. It read in part:

> The basic consideration is not as to what sort of opportunities other states provide, or whether they are as good as those in Missouri, but as to what opportunities Missouri itself furnishes to white students and denies to negroes solely upon the ground of color. [By] the operation of the laws of Missouri a privilege has been created for white law students which is denied to negroes by reason of their race. The white resident is afforded legal education within the state; the negro resident having the same qualifications is refused it there and must go outside the state to obtain it. That is a denial of the equality of legal right to the enjoyment of the privilege which the state has set up and the provision for the payment of tuition fees in another state does not remove the discrimination.

This decision by the Court in *Gaines* set the stage for the famous *Brown v. Board of Education* case because the Court began to come to the conclusion that as a practical matter it was almost impossible to set up a structure to determine whether or not separate facilities are equal. Therefore, the Court ultimately comes to the conclusion that the whole "separate but equal" framework is unworkable and must be discarded. This brings us to *Brown*.

In Brown v. Board of Education of Topeka 347 U.S. 483 (1954) the Supreme Court combined four different cases under the heading of one case because each of the cases dealt with the same subject matter and the plaintiffs in each case were seeking the same remedy. The cases were Briggs et al. v. Elliott et al. 342 U.S. 350 (1952), Davis v. County School Board of Prince Edward County 103 F. Supp. 337 (1952), Gebhardt v. Belton 33 Del. Ch. 144, 87 A.2d 862 (Del. Ch. 1952), and *Brown*. Bolling v. Sharpe 347 U.S. 497 (1954) was decided on the same day as

Brown and is considered a companion case to *Brown*. *Bolling* was a school desegregation case originating in the District of Columbia. It dealt with the same issues as Brown and the ultimate result was identical to *Brown* but it was decided using the due process clause of the Fifth Amendment because the Fourteenth Amendment only applies to the states, not the District of Columbia.

In *Brown*, the plaintiffs were thirteen Topeka parents who were contesting Kansas' policy of school racial segregation. The named plaintiff was Oliver Brown who had a daughter that was refused admittance to a white school seven blocks from her house. She was forced to walk to a bus stop six blocks from her house and then was bused to a black school that was a mile away. This segregation was permitted under a Kansas law that permitted districts to maintain separate but equal elementary school facilities for black and white children.

Chief Justice Earl Warren delivered the opinion for a unanimous Court. It reads in part:

> We come then to the question presented: Does segregation of children in public schools solely on the basis of race, even though the physical facilities and other "tangible" factors may be equal, deprive the children of the minority group of equal educational opportunities? We believe that it does.
>
> In [*Sweatt v. Painter*], in finding that a segregated law school for Negroes could not provide them equal educational opportunities, this Court relied in large part on "those qualities which are incapable of objective measurement but which make for greatness in a law school". In [*McLaurin v. Oklahoma State Regents*], the Court, in requiring that a Negro admitted to a white graduate school be treated like all other students, again resorted to intangible considerations: "…his ability to study, to engage in discussions and exchange views with other students, and, in general to learn his profession." Such considerations apply with added force to children in grade and high schools. To separate them from others of similar age and qualifications solely because of their race generates a feeling of inferiority as to their status in the community that may affect their hearts and minds in a way unlikely ever to be undone.

The Court finishes by stating:

> We conclude that in the field of public education the doctrine of "separate but equal" has no place. Separate educational facilities are inherently unequal. Therefore, we hold that the plaintiffs and others similarly situated for whom the actions have been brought are, by reason of the segregation complained of, deprived of the equal protection of the laws guaranteed by the Fourteenth Amendment.

Brown deals only with public school education but the Court affirmed and extended *Brown* when it held segregation to be unconstitutional in a wide variety of other public facilities including buses, municipal golf courses, and public beaches and bathhouses. See also *Boynton v. Virginia*, 364 U.S. 454 (1960) where the Court held that racial discrimination in public transportation was illegal, and *Heart of Atlanta Motel v. United States*, 379 U.S. 241 (1964) where the Court affirmed the constitutionality of Title II of the 1964 Civil Rights act and held that the motel must offer rooms to all clientele regardless of race.

APPENDIX B

RESULTS OF INSURANCE DEMAND MODEL INCLUDING THE ASIAN VARIABLE

The Asian variable reports the percentage of people in each ZIP code who claimed that they were of Asian descent. In California, 4,471,394 people identified themselves as Asians. Therefore, Asians comprise 12.3% of the population of California (U.S. Census Bureau, 2006-2008 American Community Survey). Asians accounted for 4.4% of the total United States population. Because of the comparatively outsized impact that the Asian community has in California it is important to consider them in any analysis of insurance demand in California. I am unsure what the relationship will be between this variable and insurance demand. It is also interesting to determine whether this ethnic group has a different demand for insurance than the other ethnic groups included in this study. Analysis of the various models that include the Asian variable reveals that including this variable would introduce a significant level of multicollinearity into the models.

Table 11 reports the correlation matrix for all California ZIP codes including the Asian variable.

Table 11

Correlation Matrix of Model Variables for all California ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	H.S.	Asian
Demand	1.0000								
Urban	-0.1792	1.0000							
Hispanic	-0.4929	0.0341	1.0000						
Minority	-0.5265	0.3087	0.8253	1.0000					
Income	0.2324	0.3562	-0.3512	-0.2508	1.0000				
Poverty	-0.4299	-0.1239	0.5667	0.5328	-0.6291	1.0000			
Language	-0.5115	0.3242	0.8510	0.8900	-0.1704	0.4671	1.0000		
High School	0.5414	0.1036	-0.8825	-0.7470	0.5514	-0.7350	-0.7547	1.0000	
Asian	-0.0973	0.5089	-0.0444	0.3831	0.1489	-0.1010	0.4056	0.0727	1.0000

The Asian variable isn't particularly highly correlated with the other variables in the model although it is most correlated with the urban variable.

Table 12 reports the results for the full universe of California ZIP codes with all of the variables including the Asian variable in the model.

Table 12

Results from Insurance Demand Model on all California ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	1.654577	.2377566	6.96	0.000		
Urban	-.1149543	.0255156	-4.51	0.000	–	1.98
Hispanic	.6029405	.1782888	3.38	0.001	-	18.92
Minority	-.5350178	.1188988	-4.50	0.000	-	9.04
Income	-4.66e-06	1.83e-06	-2.55	0.011	+	2.28
Poverty	-.3423382	.2137283	-1.60	0.109	-	2.54
Language	-.1867027	.1902091	-0.98	0.326	-	15.91
High School	1.410696	.2992736	4.71	0.000	+	8.69
Asian	.5182071	.1771667	2.92	0.003	+/-	5.24
n = 1553						
R^2 = .3746						

Table 12 reveals that introducing the Asian variable into the model significantly increases the VIF for several variables. Including the Asian variable in the other models also increases the VIF for many of the variables by comparable amounts. Therefore, while these models produce some interesting results they aren't reliable because of the likely presence of multicollinearity.

Table 13 reports results from a model containing the Asian variable that excludes all of the variables from Table 12 that exhibit high levels of multicollinearity.

Table 13

Results from Insurance Demand Model on all California ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	2.701561	.0513654	52.59	0.000		
Urban	-.2000363	.024061	-8.31	0.000	-	1.49
Poverty	-1.896125	.2369492	-8.00	0.000	-	1.50
Income	2.17e-06	1.25e-06	1.73	0.084	+	1.64
Asian	-.1159458	.0750946	-1.54	0.123	+/-	1.36

n = 1553
R^2 = .2405

The results from Table 13 confirm the previously held expectations regarding the urban, poverty and income variables. The Asian variable was not significant. Therefore, while the Asian population is a significant and growing percentage of the population of California; it is difficult to reach a definitive conclusion about their effect on automobile insurance demand in California.

APPENDIX C

RESULTS OF INSURANCE DEMAND MODEL INCLUDING THE THEFTS VARIABLE

The thefts variable reports the motor vehicle theft rate by county per 100,000 people for the year of 2004. The state of California doesn't tabulate this statistic at the ZIP code level. Therefore, county level data is the next most precise data available for study. Each ZIP code in a county was assigned the motor vehicle theft rate reported by that county. For instance, the motor vehicle theft rate per 100,000 people in the county of Alameda was 1022.4 therefore because ZIP codes 94544 and 94608 are both in Alameda they were both assigned theft rates of 1022.4.

The data was compiled by the Department of Justice of the state of California. The rates are based on annual population estimates provided by the Demographic Research Unit of the California Department of Finance. This dataset contains 1358 observations instead of the customary 1553 because the counties of Alpine, Amador, Calaveras, Colusa, Del Norte, Glenn, Inyo, Lake, Lassen, Mariposa, Mendocino, Modoc, Mono, Nevada, Plumas, San Benito, Sierra, Siskyou, Sutter, Tehama, Trinity, Tuolomne, and Yuba did not report information to the Department of Justice.

It is interesting to examine the effect that motor vehicle theft has on the demand for automobile insurance. Residing in a high crime area could make residents more likely to want automobile insurance because they realize that there is a greater chance that their car could be stolen so they may see the need to protect their asset through automobile insurance. Alternatively, insurance companies are aware of which areas tend to experience higher crime

rates and will price their policies accordingly. Higher premiums could deincentivize the purchase of insurance and lead to residents being less likely to purchase insurance. Because of these two opposite considerations, I am unsure what the relationship will be between this variable and insurance demand.

Table 14 reports the correlation matrix for all California ZIP codes including the Asian variable.

Table 14

Correlation Matrix of Model Variables for all California ZIP codes

	Demand	Urban	Hispanic	Minority	Income	Poverty	Language	H.S.	Theft
Demand	1.0000								
Urban	-0.1654	1.0000							
Hispanic	-0.5026	-0.0463	1.0000						
Minority	-0.5485	0.2319	0.8144	1.0000					
Income	0.2541	0.2969	-0.5808	-0.5323	1.0000				
Poverty	-0.4640	-0.1290	0.6094	0.5842	-0.5810	1.0000			
Language	-0.5313	0.2484	0.8402	0.8806	-0.4027	0.5196	1.0000		
High School	0.5528	0.1382	-0.8976	-0.7669	0.6638	-0.7592	-0.7761	1.0000	
Theft	-0.2181	0.1727	0.1089	0.2218	-0.1691	0.2141	0.1273	-0.1740	1.0000

The theft variable isn't particularly highly correlated with any of the other variables in the model.

Table 15 reports the results for the full universe of California ZIP codes with all of the variables including the theft variable in the model.

Table 15

Results from Insurance Demand Model on all California ZIP codes

Variable	Coefficient	Standard Error	t-stat	P>|t|	Expected Sign	VIF
Intercept	1.849273	.2411584	7.67	0.000		
Urban	-.1084298	.0268733	-4.03	0.000	–	1.85
Hispanic	.2108581	.1172098	1.80	0.072	-	7.91
Minority	-.4144588	.1089925	-3.80	0.000	-	6.33
Income	-5.62e-06	1.92e-06	-2.93	0.003	+	2.29
Poverty	-.491525	.2570394	-1.91	0.056	-	2.67
Language	.0530733	.1355596	0.39	0.695	-	7.26
High School	1.339422	.316998	4.23	0.000	+	8.69
Theft	-.0001183	.0000417	-2.84	0.005	+/-	1.16

n = 1358
R^2 = .3994

The results reported in Table 15 reveal virtually no change in the sign or significance of the variables in the original model when the theft variable in included. The theft variable itself is negative and significant. This indicates that automobile insurance demand tends to drop when the motor vehicle theft rate in an area rises.

APPENDIX D

UNDERSERVED ZIP CODES

The following ZIP codes were designated by the California Department of Insurance as underserved because they meet the following three criteria:

1. The proportion of uninsured motorists is ten percentage points above the statewide average,

2. The per capita income of the community (as measured in the most recent U.S. Census), is below the fiftieth (50th) percentile for California, and

3. The community (as measured in the most recent U.S. Census), is predominantly minority (2004 Commissioner's Report on Underserved Communities).

zip	city	county
90001	LOS ANGELES	LOS ANGELES
90002	LOS ANGELES	LOS ANGELES
90003	LOS ANGELES	LOS ANGELES
90004	LOS ANGELES	LOS ANGELES
90005	LOS ANGELES	LOS ANGELES
90006	LOS ANGELES	LOS ANGELES
90007	LOS ANGELES	LOS ANGELES
90011	LOS ANGELES	LOS ANGELES
90012	LOS ANGELES	LOS ANGELES
90013	LOS ANGELES	LOS ANGELES
90014	LOS ANGELES	LOS ANGELES
90015	LOS ANGELES	LOS ANGELES
90016	LOS ANGELES	LOS ANGELES
90017	LOS ANGELES	LOS ANGELES
90018	LOS ANGELES	LOS ANGELES
90019	LOS ANGELES	LOS ANGELES
90020	LOS ANGELES	LOS ANGELES
90021	LOS ANGELES	LOS ANGELES
90022	LOS ANGELES	LOS ANGELES
90023	LOS ANGELES	LOS ANGELES

90026	LOS ANGELES	LOS ANGELES
90029	LOS ANGELES	LOS ANGELES
90031	LOS ANGELES	LOS ANGELES
90032	LOS ANGELES	LOS ANGELES
90033	LOS ANGELES	LOS ANGELES
90037	LOS ANGELES	LOS ANGELES
90038	LOS ANGELES	LOS ANGELES
90040	LOS ANGELES	LOS ANGELES
90042	LOS ANGELES	LOS ANGELES
90043	LOS ANGELES	LOS ANGELES
90044	LOS ANGELES	LOS ANGELES
90047	LOS ANGELES	LOS ANGELES
90057	LOS ANGELES	LOS ANGELES
90058	LOS ANGELES	LOS ANGELES
90059	LOS ANGELES	LOS ANGELES
90061	LOS ANGELES	LOS ANGELES
90062	LOS ANGELES	LOS ANGELES
90063	LOS ANGELES	LOS ANGELES
90065	LOS ANGELES	LOS ANGELES
90201	BELL	LOS ANGELES
90220	COMPTON	LOS ANGELES
90221	COMPTON	LOS ANGELES
90222	COMPTON	LOS ANGELES
90247	GARDENA	LOS ANGELES
90250	HAWTHORNE	LOS ANGELES
90255	HUNTINGTON PARK	LOS ANGELES
90262	LYNWOOD	LOS ANGELES
90270	MAYWOOD	LOS ANGELES
90280	SOUTH GATE	LOS ANGELES
90301	INGLEWOOD	LOS ANGELES
90302	INGLEWOOD	LOS ANGELES
90303	INGLEWOOD	LOS ANGELES
90304	INGLEWOOD	LOS ANGELES
90501	TORRANCE	LOS ANGELES
90716	HAWAIIAN GARDENS	LOS ANGELES
90723	PARAMOUNT	LOS ANGELES
90744	WILMINGTON	LOS ANGELES
90806	LONG BEACH	LOS ANGELES
90810	LONG BEACH	LOS ANGELES
90813	LONG BEACH	LOS ANGELES
91204	GLENDALE	LOS ANGELES
91303	CANOGA PARK	LOS ANGELES
91331	PACOIMA	LOS ANGELES
91340	SAN FERNANDO	LOS ANGELES
91343	NORTH HILLS	LOS ANGELES

91352	SUN VALLEY	LOS ANGELES
91402	PANORAMA CITY	LOS ANGELES
91405	VAN NUYS	LOS ANGELES
91406	VAN NUYS	LOS ANGELES
91601	NORTH HOLLYWOOD	LOS ANGELES
91605	NORTH HOLLYWOOD	LOS ANGELES
91606	NORTH HOLLYWOOD	LOS ANGELES
91706	BALDWIN PARK	LOS ANGELES
91731	EL MONTE	LOS ANGELES
91733	SOUTH EL MONTE	LOS ANGELES
91746	LA PUENTE	LOS ANGELES
91761	ONTARIO	SAN BERNADINO
91767	POMONA	LOS ANGELES
91950	NATIONAL CITY	SAN DIEGO
92102	SAN DIEGO	SAN DIEGO
92105	SAN DIEGO	SAN DIEGO
92113	SAN DIEGO	SAN DIEGO
92173	SAN YSIDRO	SAN DIEGO
92231	CALEXICO	IMPERIAL
92233	CALIPATRIA	IMPERIAL
92236	COACHELLA	RIVERSIDE
92249	HEBER	IMPERIAL
92254	MECCA	RIVERSIDE
92309	BAKER	SAN BERNADINO
92324	COLTON	SAN BERNADINO
92401	SAN BERNARDINO	SAN BERNADINO
92408	SAN BERNARDINO	SAN BERNADINO
92410	SAN BERNARDINO	SAN BERNADINO
92411	SAN BERNARDINO	SAN BERNADINO
92701	SANTA ANA	ORANGE
92703	SANTA ANA	ORANGE
92704	SANTA ANA	ORANGE
92707	SANTA ANA	ORANGE
92805	ANAHEIM	ORANGE
93036	OXNARD	VENTURA
93206	BUTTONWILLOW	KERN
93219	EARLIMART	TULARE
93239	KETTLEMAN CITY	KINGS
93241	LAMONT	KERN
93256	PIXLEY	TULARE
93272	TIPTON	TULARE
93458	SANTA MARIA	SANTA BARBARA
93608	CANTUA CREEK	FRESNO
93609	CARUTHERS	FRESNO
93615	CUTLER	TULARE

93616	DEL REY	FRESNO
93622	FIREBAUGH	FRESNO
93640	MENDOTA	FRESNO
93646	ORANGE COVE	FRESNO
93648	PARLIER	FRESNO
93656	RIVERDALE	FRESNO
93660	SAN JOAQUIN	FRESNO
93668	TRANQUILITY	FRESNO
93701	FRESNO	FRESNO
93702	FRESNO	FRESNO
93703	FRESNO	FRESNO
93706	FRESNO	FRESNO
93721	FRESNO	FRESNO
93725	FRESNO	FRESNO
93925	CHUALAR	MONTEREY
94063	REDWOOD CITY	SAN MATEO
94124	SAN FRANCISCO	SAN FRANCISCO
94134	SAN FRANCISCO	SAN FRANCISCO
94601	OAKLAND	ALAMEDA
94603	OAKLAND	ALAMEDA
94606	OAKLAND	ALAMEDA
94607	OAKLAND	ALAMEDA
94612	OAKLAND	ALAMEDA
94621	OAKLAND	ALAMEDA
94710	BERKELEY	ALAMEDA
94801	RICHMOND	CONTRA COSTA
95019	FREEDOM	SANTA CRUZ
95110	SAN JOSE	SANTA CLARA
95112	SAN JOSE	SANTA CLARA
95116	SAN JOSE	SANTA CLARA
95122	SAN JOSE	SANTA CLARA
95202	STOCKTON	SAN JOAQUIN
95205	STOCKTON	SAN JOAQUIN
95351	MODESTO	STANISLAUS
95824	SACRAMENTO	SACRAMENTO
95838	SACRAMENTO	SACRAMENTO

APPENDIX E

ALMOST UNDERSERVED ZIP CODES

The following ZIP codes have been designated as almost underserved. These are ZIP codes in which the per capita income of the community is below the fiftieth (50th) percentile for California, and the community is predominantly minority but the proportion of uninsured motorists is *not* ten percentage points above the statewide average.

zip	city	county
90241	DOWNEY	LOS ANGELES
90242	DOWNEY	LOS ANGELES
90249	GARDENA	LOS ANGELES
90250	HAWTHORNE	LOS ANGELES
90260	LAWNDALE	LOS ANGELES
90502	TORRANCE	LOS ANGELES
90602	WHITTIER	LOS ANGELES
90605	WHITTIER	LOS ANGELES
90606	WHITTIER	LOS ANGELES
90621	BUENA PARK	ORANGE
90640	MONTEBELLO	LOS ANGELES
90650	NORWALK	LOS ANGELES
90660	PICO RIVERA	LOS ANGELES
90680	STANTON	ORANGE
90701	ARTESIA	LOS ANGELES
90706	BELLFLOWER	LOS ANGELES
90710	HARBOR CITY	LOS ANGELES
90715	LAKEWOOD	LOS ANGELES
90745	CARSON	LOS ANGELES
90802	LONG BEACH	LOS ANGELES
90804	LONG BEACH	LOS ANGELES
90805	LONG BEACH	LOS ANGELES
91010	DUARTE	LOS ANGELES
91103	PASADENA	LOS ANGELES
91342	SYLMAR	LOS ANGELES
91345	MISSION HILLS	LOS ANGELES
91702	AZUSA	LOS ANGELES
91722	COVINA	LOS ANGELES
91732	EL MONTE	LOS ANGELES

91744	LA PUENTE	LOS ANGELES
91748	ROWLAND HEIGHTS	LOS ANGELES
91754	MONTEREY PARK	LOS ANGELES
91755	MONTEREY PARK	LOS ANGELES
91762	ONTARIO	SAN BERNARDINO
91763	MONTCLAIR	SAN BERNARDINO
91764	ONTARIO	SAN BERNARDINO
91767	POMONA	LOS ANGELES
91768	POMONA	LOS ANGELES
91770	ROSEMEAD	LOS ANGELES
91776	SAN GABRIEL	LOS ANGELES
91790	WEST COVINA	LOS ANGELES
91792	WEST COVINA	LOS ANGELES
91801	ALHAMBRA	LOS ANGELES
91803	ALHAMBRA	LOS ANGELES
91911	CHULA VISTA	SAN DIEGO
91950	NATIONAL CITY	SAN DIEGO
92114	SAN DIEGO	SAN DIEGO
92139	SAN DIEGO	SAN DIEGO
92154	SAN DIEGO	SAN DIEGO
92201	INDIO	RIVERSIDE
92227	BRAWLEY	IMPERIAL
92233	CALIPATRIA	IMPERIAL
92243	EL CENTRO	IMPERIAL
92250	HOLTVILLE	IMPERIAL
92251	IMPERIAL	IMPERIAL
92274	THERMAL	RIVERSIDE
92283	WINTERHAVEN	IMPERIAL
92316	BLOOMINGTON	SAN BERNARDINO
92324	COLTON	SAN BERNARDINO
92336	FONTANA	SAN BERNARDINO
92376	RIALTO	SAN BERNARDINO
92377	RIALTO	SAN BERNARDINO
92405	SAN BERNARDINO	SAN BERNARDINO
92507	RIVERSIDE	RIVERSIDE
92551	MORENO VALLEY	RIVERSIDE
92553	MORENO VALLEY	RIVERSIDE
92570	PERRIS	RIVERSIDE

92571	PERRIS	RIVERSIDE
92655	MIDWAY CITY	ORANGE
92706	SANTA ANA	ORANGE
92801	ANAHEIM	ORANGE
92802	ANAHEIM	ORANGE
92840	GARDEN GROVE	ORANGE
92843	GARDEN GROVE	ORANGE
92844	GARDEN GROVE	ORANGE
93015	FILLMORE	VENTURA
93030	OXNARD	VENTURA
93033	OXNARD	VENTURA
93040	PIRU	VENTURA
93060	SANTA PAULA	VENTURA
93203	ARVIN	KERN
93204	AVENAL	KINGS
93212	CORCORAN	KINGS
93215	DELANO	KERN
93223	FARMERSVILLE	TULARE
93235	IVANHOE	TULARE
93247	LINDSAY	TULARE
93249	LOST HILLS	KERN
93250	MC FARLAND	KERN
93263	SHAFTER	KERN
93266	STRATFORD	KINGS
93270	TERRA BELLA	TULARE
93280	WASCO	KERN
93286	WOODLAKE	TULARE
93305	BAKERSFIELD	KERN
93307	BAKERSFIELD	KERN
93434	GUADALUPE	SANTA BARBARA
93552	PALMDALE	LOS ANGELES
93615	CUTLER	TULARE
93618	DINUBA	TULARE
93622	FIREBAUGH	FRESNO
93625	FOWLER	FRESNO
93630	KERMAN	FRESNO
93638	MADERA	MADERA
93647	OROSI	TULARE
93654	REEDLEY	FRESNO
93657	SANGER	FRESNO
93662	SELMA	FRESNO
93905	SALINAS	MONTEREY
93906	SALINAS	MONTEREY
93926	GONZALES	MONTEREY

93927	GREENFIELD	MONTEREY
93930	KING CITY	MONTEREY
93960	SOLEDAD	MONTEREY
94544	HAYWARD	ALAMEDA
94565	PITTSBURG	CONTRA COSTA
94589	VALLEJO	SOLANO
94608	EMERYVILLE	ALAMEDA
94804	RICHMOND	CONTRA COSTA
94806	SAN PABLO	CONTRA COSTA
95012	CASTROVILLE	MONTEREY
95076	WATSONVILLE	SANTA CRUZ
95111	SAN JOSE	SANTA CLARA
95203	STOCKTON	SAN JOAQUIN
95206	STOCKTON	SAN JOAQUIN
95210	STOCKTON	SAN JOAQUIN
95333	LE GRAND	MERCED
95334	LIVINGSTON	MERCED
95365	PLANADA	MERCED
95546	HOOPA	HUMBOLDT
95822	SACRAMENTO	SACRAMENTO
95823	SACRAMENTO	SACRAMENTO
95832	SACRAMENTO	SACRAMENTO
95838	SACRAMENTO	SACRAMENTO
95951	HAMILTON CITY	GLENN
95987	WILLIAMS	COLUSA

APPENDIX F

CALIFORNIA ZIP CODES

The following ZIP codes are the rest of the ZIP codes in California that were used in the sample. These ZIP codes are not considered to be either underserved or almost underserved. Those ZIP codes in which the California Department of Insurance did not report uninsured motorist statistics or those ZIP codes that were too small were omitted from the sample.

city	county
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES - UCLA / UCLA MEDICAL PLAZA	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES
WEST HOLLYWOOD	LOS ANGELES
LOS ANGELES	LOS ANGELES
LOS ANGELES	LOS ANGELES

BEVERLY HILLS	LOS ANGELES
BEVERLY HILLS	LOS ANGELES
BEVERLY HILLS	LOS ANGELES
CULVER CITY	LOS ANGELES
CULVER CITY	LOS ANGELES
DOWNEY	LOS ANGELES
EL SEGUNDO	LOS ANGELES
GARDENA	LOS ANGELES
HERMOSA BEACH	LOS ANGELES
MALIBU	LOS ANGELES
MANHATTAN BEACH	LOS ANGELES
PACIFIC PALISADES	LOS ANGELES
PALOS VERDES PENINSULA	LOS ANGELES
RANCHO PALOS VERDES	LOS ANGELES
REDONDO BEACH	LOS ANGELES
REDONDO BEACH	LOS ANGELES
TOPANGA	LOS ANGELES
VENICE	LOS ANGELES
MARINA DEL REY	LOS ANGELES
PLAYA DEL REY	LOS ANGELES
INGLEWOOD	LOS ANGELES
SANTA MONICA	LOS ANGELES
SANTA MONICA	LOS ANGELES
SANTA MONICA	LOS ANGELES
SANTA MONICA	LOS ANGELES
SANTA MONICA	LOS ANGELES
TORRANCE	LOS ANGELES
TORRANCE	LOS ANGELES
TORRANCE	LOS ANGELES
WHITTIER	LOS ANGELES
WHITTIER	LOS ANGELES
WHITTIER	LOS ANGELES
BUENA PARK	ORANGE
LA PALMA	ORANGE
CYPRESS	ORANGE
LA HABRA	ORANGE
LA MIRADA	LOS ANGELES
SANTA FE SPRINGS	LOS ANGELES
CERRITOS	LOS ANGELES
AVALON	LOS ANGELES
LAKEWOOD	LOS ANGELES
LAKEWOOD	LOS ANGELES
LOMITA	LOS ANGELES
LOS ALAMITOS	ORANGE
SAN PEDRO	LOS ANGELES

SAN PEDRO	LOS ANGELES
SEAL BEACH	ORANGE
SUNSET BEACH	ORANGE
SURFSIDE	ORANGE
CARSON	LOS ANGELES
LONG BEACH	LOS ANGELES
LONG BEACH	LOS ANGELES
LONG BEACH	LOS ANGELES
LONG BEACH	LOS ANGELES
LONG BEACH	LOS ANGELES
ALTADENA	LOS ANGELES
ARCADIA	LOS ANGELES
ARCADIA	LOS ANGELES
LA CANADA FLINTRIDGE	LOS ANGELES
MONROVIA	LOS ANGELES
MONTROSE	LOS ANGELES
SIERRA MADRE	LOS ANGELES
SOUTH PASADENA	LOS ANGELES
SUNLAND	LOS ANGELES
TUJUNGA	LOS ANGELES
PASADENA	LOS ANGELES
PASADENA	LOS ANGELES
PASADENA	LOS ANGELES
PASADENA	LOS ANGELES
PASADENA	LOS ANGELES
SAN MARINO	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
GLENDALE	LOS ANGELES
LA CRESCENTA	LOS ANGELES
AGOURA HILLS	LOS ANGELES
CALABASAS	LOS ANGELES
CANOGA PARK	LOS ANGELES
WINNETKA	LOS ANGELES
WEST HILLS	LOS ANGELES
CHATSWORTH	LOS ANGELES
ENCINO	LOS ANGELES
NEWBURY PARK	VENTURA
NEWHALL	LOS ANGELES
NORTHRIDGE	LOS ANGELES
NORTHRIDGE	LOS ANGELES

NORTHRIDGE	LOS ANGELES
RESEDA	LOS ANGELES
GRANADA HILLS	LOS ANGELES
SANTA CLARITA	LOS ANGELES
CANYON COUNTRY	LOS ANGELES
VALENCIA	LOS ANGELES
VALENCIA	LOS ANGELES
TARZANA	LOS ANGELES
THOUSAND OAKS	VENTURA
WESTLAKE VILLAGE	VENTURA / L.A.
THOUSAND OAKS	VENTURA
WOODLAND HILLS	LOS ANGELES
WOODLAND HILLS	LOS ANGELES
OAK PARK	VENTURA
STEVENSON RANCH	LOS ANGELES
CASTAIC	LOS ANGELES
VAN NUYS	LOS ANGELES
SHERMAN OAKS	LOS ANGELES
VAN NUYS	LOS ANGELES
SHERMAN OAKS	LOS ANGELES
ENCINO	LOS ANGELES
BURBANK	LOS ANGELES
BURBANK	LOS ANGELES
BURBANK	LOS ANGELES
BURBANK	LOS ANGELES
BURBANK	LOS ANGELES
NORTH HOLLYWOOD	LOS ANGELES
STUDIO CITY	LOS ANGELES
VALLEY VILLAGE	LOS ANGELES
RANCHO CUCAMONGA	SAN BERNARDINO
CHINO HILLS	SAN BERNARDINO
CHINO	SAN BERNARDINO
CLAREMONT	LOS ANGELES
COVINA	LOS ANGELES
COVINA	LOS ANGELES
EL MONTE	LOS ANGELES
RANCHO CUCAMONGA	SAN BERNARDINO
RANCHO CUCAMONGA	SAN BERNARDINO
GLENDORA	LOS ANGELES
GLENDORA	LOS ANGELES
HACIENDA HEIGHTS	LOS ANGELES

LA VERNE	LOS ANGELES
MIRA LOMA	RIVERSIDE
DIAMOND BAR	LOS ANGELES
POMONA	LOS ANGELES
SAN DIMAS	LOS ANGELES
SAN GABRIEL	LOS ANGELES
TEMPLE CITY	LOS ANGELES
UPLAND	SAN BERNARDINO
UPLAND	SAN BERNARDINO
WALNUT	LOS ANGELES
WEST COVINA	LOS ANGELES
ALPINE	SAN DIEGO
BONITA	SAN DIEGO
BOULEVARD	SAN DIEGO
CAMPO	SAN DIEGO
CHULA VISTA	SAN DIEGO
CHULA VISTA	SAN DIEGO
CHULA VISTA	SAN DIEGO
CHULA VISTA	SAN DIEGO
DESCANSO	SAN DIEGO
DULZURA	SAN DIEGO
GUATAY	SAN DIEGO
IMPERIAL BEACH	SAN DIEGO
JACUMBA	SAN DIEGO
JAMUL	SAN DIEGO
LA MESA	SAN DIEGO
LA MESA	SAN DIEGO
LEMON GROVE	SAN DIEGO
PINE VALLEY	SAN DIEGO
POTRERO	SAN DIEGO
SPRING VALLEY	SAN DIEGO
SPRING VALLEY	SAN DIEGO
BONSALL	SAN DIEGO
BORREGO SPRINGS	SAN DIEGO
CARDIFF BY THE SEA	SAN DIEGO
CARLSBAD	SAN DIEGO
CARLSBAD	SAN DIEGO
DEL MAR	SAN DIEGO
EL CAJON	SAN DIEGO
EL CAJON	SAN DIEGO
EL CAJON	SAN DIEGO
ENCINITAS	SAN DIEGO
ESCONDIDO	SAN DIEGO

ESCONDIDO	SAN DIEGO
ESCONDIDO	SAN DIEGO
FALLBROOK	SAN DIEGO
ESCONDIDO	SAN DIEGO
JULIAN	SAN DIEGO
LA JOLLA	SAN DIEGO
LAKESIDE	SAN DIEGO
OCEANSIDE	SAN DIEGO
OCEANSIDE	SAN DIEGO
OCEANSIDE	SAN DIEGO
PALA	SAN DIEGO
PALOMAR MOUNTAIN	SAN DIEGO
PAUMA VALLEY	SAN DIEGO
POWAY	SAN DIEGO
RAMONA	SAN DIEGO
RANCHITA	SAN DIEGO
SAN MARCOS	SAN DIEGO
SANTA YSABEL	SAN DIEGO
SANTEE	SAN DIEGO
SOLANA BEACH	SAN DIEGO
SAN MARCOS	SAN DIEGO
VALLEY CENTER	SAN DIEGO
VISTA	SAN DIEGO
VISTA	SAN DIEGO
WARNER SPRINGS	SAN DIEGO
RANCHO SANTA FE	SAN DIEGO
SAN DIEGO	SAN DIEGO
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SAN DIEGO	SAN DIEGO
CORONADO	SAN DIEGO
SAN DIEGO	SAN DIEGO
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SAN DIEGO	SAN DIEGO
SAN DIEGO	SAN DIEGO
INDIO	RIVERSIDE
INDIAN WELLS	RIVERSIDE
PALM DESERT	RIVERSIDE
BANNING	RIVERSIDE
BEAUMONT	RIVERSIDE
BLYTHE	RIVERSIDE
CABAZON	RIVERSIDE
CATHEDRAL CITY	RIVERSIDE
DESERT CENTER	RIVERSIDE
DESERT HOT SPRINGS	RIVERSIDE
DESERT HOT SPRINGS	RIVERSIDE
EARP	SAN BERNARDINO
JOSHUA TREE	SAN BERNARDINO
LA QUINTA	RIVERSIDE
MORONGO VALLEY	SAN BERNARDINO
NILAND	IMPERIAL
NORTH PALM SPRINGS	RIVERSIDE
OCOTILLO	IMPERIAL
PALM DESERT	RIVERSIDE
PALM SPRINGS	RIVERSIDE
PALM SPRINGS	RIVERSIDE
PALO VERDE	IMPERIAL
PARKER DAM	SAN BERNARDINO
PIONEERTOWN	SAN BERNARDINO
RANCHO MIRAGE	RIVERSIDE
SEELEY	IMPERIAL
SALTON CITY	RIVERSIDE
THOUSAND PALMS	RIVERSIDE
TWENTYNINE PALMS	SAN BERNARDINO
TWENTYNINE PALMS MCB (MARINE CRP BS)	SAN BERNARDINO
WESTMORLAND	IMPERIAL
WHITE WATER	RIVERSIDE
YUCCA VALLEY	SAN BERNARDINO

LANDERS	SAN BERNARDINO
ADELANTO	SAN BERNARDINO
ANGELUS OAKS	SAN BERNARDINO
APPLE VALLEY	SAN BERNARDINO
APPLE VALLEY	SAN BERNARDINO
FORT IRWIN	SAN BERNARDINO
BARSTOW	SAN BERNARDINO
GRAND TERRACE	SAN BERNARDINO
BIG BEAR CITY	SAN BERNARDINO
BLUE JAY	SAN BERNARDINO
BRYN MAWR	SAN BERNARDINO
CALIMESA	RIVERSIDE
CEDAR GLEN	SAN BERNARDINO
CRESTLINE	SAN BERNARDINO
DAGGETT	SAN BERNARDINO
DEATH VALLEY	INYO
ESSEX	SAN BERNARDINO
FAWNSKIN	SAN BERNARDINO
FONTANA	SAN BERNARDINO
FONTANA	SAN BERNARDINO
FOREST FALLS	SAN BERNARDINO
GREEN VALLEY LAKE	SAN BERNARDINO
HELENDALE	SAN BERNARDINO
HESPERIA	SAN BERNARDINO
HIGHLAND	SAN BERNARDINO
HINKLEY	SAN BERNARDINO

LAKE ARROWHEAD	SAN BERNARDINO
LOMA LINDA	SAN BERNARDINO
LUCERNE VALLEY	SAN BERNARDINO
LYTLE CREEK	SAN BERNARDINO
MENTONE	SAN BERNARDINO
NEEDLES	SAN BERNARDINO
NIPTON	SAN BERNARDINO
NEWBERRY SPRINGS	SAN BERNARDINO
ORO GRANDE	SAN BERNARDINO
PHELAN	SAN BERNARDINO
PINON HILLS	SAN BERNARDINO
REDLANDS	SAN BERNARDINO
REDLANDS	SAN BERNARDINO
RUNNING SPRINGS	SAN BERNARDINO
SUGARLOAF	SAN BERNARDINO
VICTORVILLE	SAN BERNARDINO
VICTORVILLE	SAN BERNARDINO
WRIGHTWOOD	SAN BERNARDINO
YERMO	SAN BERNARDINO
YUCAIPA	SAN BERNARDINO
SAN BERNARDINO	SAN BERNARDINO
SAN BERNARDINO	SAN BERNARDINO
RIVERSIDE	RIVERSIDE
RIVERSIDE	RIVERSIDE
RIVERSIDE	RIVERSIDE
RIVERSIDE	RIVERSIDE
RIVERSIDE	RIVERSIDE

RIVERSIDE	RIVERSIDE
RIVERSIDE	RIVERSIDE
MARCH AIR RESERVE BASE	RIVERSIDE
LAKE ELSINORE	RIVERSIDE
LAKE ELSINORE	RIVERSIDE
AGUANGA	RIVERSIDE
ANZA	RIVERSIDE
HEMET	RIVERSIDE
HEMET	RIVERSIDE
HEMET	RIVERSIDE
HOMELAND	RIVERSIDE
IDYLLWILD	RIVERSIDE
MORENO VALLEY	RIVERSIDE
MORENO VALLEY	RIVERSIDE
MOUNTAIN CENTER	RIVERSIDE
MURRIETA	RIVERSIDE
MURRIETA	RIVERSIDE
NUEVO	RIVERSIDE
SAN JACINTO	RIVERSIDE
SAN JACINTO	RIVERSIDE
MENIFEE	RIVERSIDE
SUN CITY	RIVERSIDE
SUN CITY	RIVERSIDE
SUN CITY	RIVERSIDE
TEMECULA	RIVERSIDE
TEMECULA	RIVERSIDE
TEMECULA	RIVERSIDE
WILDOMAR	RIVERSIDE
WINCHESTER	RIVERSIDE
IRVINE	ORANGE
IRVINE	ORANGE
IRVINE	ORANGE
FOOTHILL RANCH	ORANGE
IRVINE	ORANGE
IRVINE	ORANGE
IRVINE	ORANGE
IRVINE	ORANGE
CAPISTRANO BEACH	ORANGE
CORONA DEL MAR	ORANGE
COSTA MESA	ORANGE
COSTA MESA	ORANGE
DANA POINT	ORANGE
LAKE FOREST	ORANGE
HUNTINGTON BEACH	ORANGE
HUNTINGTON BEACH	ORANGE

HUNTINGTON BEACH	ORANGE
HUNTINGTON BEACH	ORANGE
LAGUNA BEACH	ORANGE
LAGUNA HILLS	ORANGE
ALISO VIEJO	ORANGE
NEWPORT COAST	ORANGE
NEWPORT BEACH	ORANGE
NEWPORT BEACH	ORANGE
NEWPORT BEACH	ORANGE
NEWPORT BEACH	ORANGE
SAN CLEMENTE	ORANGE
SAN CLEMENTE	ORANGE
SAN JUAN CAPISTRANO	ORANGE
SILVERADO	ORANGE
LAGUNA NIGUEL	ORANGE
TRABUCO CANYON	ORANGE
WESTMINSTER	ORANGE
RANCHO SANTA MARGARITA	ORANGE
MISSION VIEJO	ORANGE
MISSION VIEJO	ORANGE
LADERA RANCH	ORANGE
SANTA ANA	ORANGE
FOUNTAIN VALLEY	ORANGE
TUSTIN	ORANGE
TUSTIN	ORANGE
ANAHEIM	ORANGE
ANAHEIM	ORANGE
ANAHEIM	ORANGE
ANAHEIM	ORANGE
BREA	ORANGE
BREA	ORANGE
FULLERTON	ORANGE
FULLERTON	ORANGE
FULLERTON	ORANGE
FULLERTON	ORANGE
GARDEN GROVE	ORANGE
GARDEN GROVE	ORANGE
NORCO	RIVERSIDE
VILLA PARK	ORANGE
ORANGE	ORANGE
ORANGE	ORANGE
ORANGE	ORANGE
ORANGE	ORANGE
ORANGE	ORANGE
PLACENTIA	ORANGE

CORONA	RIVERSIDE
CORONA	RIVERSIDE
CORONA	RIVERSIDE
CORONA	RIVERSIDE
CORONA	RIVERSIDE
YORBA LINDA	ORANGE
YORBA LINDA	ORANGE
VENTURA	VENTURA
VENTURA	VENTURA
VENTURA	VENTURA
CAMARILLO	VENTURA
CAMARILLO	VENTURA
CARPINTERIA	SANTA BARBARA
MOORPARK	VENTURA
OAK VIEW	VENTURA
OJAI	VENTURA
OXNARD	VENTURA
PORT HUENEME	VENTURA
SIMI VALLEY	VENTURA
SIMI VALLEY	VENTURA
SOMIS	VENTURA
SUMMERLAND	SANTA BARBARA
SANTA BARBARA	SANTA BARBARA
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SANTA BARBARA	SANTA BARBARA
SANTA BARBARA	SANTA BARBARA
SANTA BARBARA	SANTA BARBARA
GOLETA	SANTA BARBARA
ALPAUGH	TULARE
ARMONA	KINGS
BODFISH	KERN
CALIFORNIA HOT SPRINGS	TULARE
CAMP NELSON	TULARE
COALINGA	FRESNO
DUCOR	TULARE

EXETER	TULARE
FELLOWS	KERN
FRAZIER PARK	KERN
GLENNVILLE	KERN
HANFORD	KINGS
HURON	FRESNO
KERNVILLE	KERN
LAKE ISABELLA	KERN
LATON	FRESNO
LEBEC	KERN
LEMON COVE	TULARE
LEMOORE	KINGS
MC KITTRICK	KERN
MARICOPA	KERN
NEW CUYAMA	SANTA BARBARA
ONYX	KERN
PORTERVILLE	TULARE
POSEY	TULARE
RICHGROVE	TULARE
SPRINGVILLE	TULARE
STRATHMORE	TULARE
TAFT	KERN
THREE RIVERS	TULARE
TULARE	TULARE
TUPMAN	KERN
VISALIA	TULARE
WELDON	KERN
WOFFORD HEIGHTS	KERN
VISALIA	TULARE
VISALIA	TULARE
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
BAKERSFIELD	KERN
SAN LUIS OBISPO	SAN LUIS OBISPO
LOS OSOS	SAN LUIS OBISPO
SAN LUIS OBISPO	SAN LUIS OBISPO
ARROYO GRANDE	SAN LUIS

	SAN LUIS OBISPO
ATASCADERO	SAN LUIS OBISPO
AVILA BEACH	SAN LUIS OBISPO
BRADLEY	MONTEREY
BUELLTON	SANTA BARBARA
CAMBRIA	SAN LUIS OBISPO
CASMALIA	SANTA BARBARA
CAYUCOS	SAN LUIS OBISPO
CRESTON	SAN LUIS OBISPO
GROVER BEACH	SAN LUIS OBISPO
LOMPOC	SANTA BARBARA
LOMPOC	SANTA BARBARA
LOS ALAMOS	SANTA BARBARA
LOS OLIVOS	SANTA BARBARA
MORRO BAY	SAN LUIS OBISPO
NIPOMO	SAN LUIS OBISPO
OCEANO	SAN LUIS OBISPO
PASO ROBLES	SAN LUIS OBISPO
PISMO BEACH	SAN LUIS OBISPO
SAN ARDO	MONTEREY
SAN MIGUEL	SAN LUIS OBISPO
SAN SIMEON	SAN LUIS OBISPO
SANTA MARGARITA	SAN LUIS OBISPO
SANTA MARIA	SANTA BARBARA
SANTA MARIA	SANTA BARBARA
SANTA YNEZ	SANTA BARBARA
SHANDON	SAN LUIS

SOLVANG	SANTA BARBARA
TEMPLETON	SAN LUIS OBISPO
MOJAVE	KERN
CALIFORNIA CITY	KERN
ACTON	LOS ANGELES
BENTON	MONO
BIG PINE	INYO
BISHOP	INYO
BORON	KERN
BRIDGEPORT	MONO
CALIENTE	KERN
EDWARDS	KERN
INDEPENDENCE	INYO
INYOKERN	KERN
JOHANNESBURG	KERN
JUNE LAKE	MONO
KEENE	KERN
LAKE HUGHES	LOS ANGELES
LANCASTER	LOS ANGELES
LANCASTER	LOS ANGELES
LANCASTER	LOS ANGELES
LEE VINING	MONO
LITTLEROCK	LOS ANGELES
LLANO	LOS ANGELES
LONE PINE	INYO
MAMMOTH LAKES	MONO
OLANCHA	INYO
PALMDALE	LOS ANGELES
PALMDALE	LOS ANGELES
PEARBLOSSOM	LOS ANGELES
RIDGECREST	KERN
ROSAMUND	KERN
TEHACHAPI	KERN
TRONA	SAN BERNARDINO
VALYERMO	LOS ANGELES
PALMDALE	LOS ANGELES
AHWAHNEE	MADERA
AUBERRY	FRESNO
BADGER	TULARE
BASS LAKE	MADERA
BIG CREEK	FRESNO
BIOLA	FRESNO

CHOWCHILLA	MADERA
CLOVIS	FRESNO
CLOVIS	FRESNO
COARSEGOLD	MADERA
DOS PALOS	MERCED
DUNLAP	FRESNO
FIVE POINTS	FRESNO
FRIANT	FRESNO
KINGSBURG	FRESNO
LOS BANOS	MERCED
MADERA	MADERA
MIRAMONTE	FRESNO
NORTH FORK	MADERA
OAKHURST	MADERA
FRESNO	FRESNO
PRATHER	FRESNO
RAISIN	FRESNO
RAYMOND	MADERA
SHAVER LAKE	FRESNO
SOUTH DOS PALOS	MERCED
SULTANA	TULARE
TOLLHOUSE	FRESNO
WISHON	MADERA
TRAVER	TULARE
SQUAW VALLEY	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
FRESNO	FRESNO
SALINAS	MONTEREY
SALINAS	MONTEREY
SALINAS	MONTEREY
BIG SUR	MONTEREY
CARMEL	MONTEREY
CARMEL VALLEY	MONTEREY
JOLON	MONTEREY
LOCKWOOD	MONTEREY
MARINA	MONTEREY
MONTEREY	MONTEREY
PACIFIC GROVE	MONTEREY

PEBBLE BEACH	MONTEREY
SAN LUCAS	MONTEREY
SEASIDE	MONTEREY
SPRECKELS	MONTEREY
BELMONT	SAN MATEO
BRISBANE	SAN MATEO
BURLINGAME	SAN MATEO
DALY CITY	SAN MATEO
DALY CITY	SAN MATEO
HALF MOON BAY	SAN MATEO
LA HONDA	SAN MATEO
LOS ALTOS	SANTA CLARA
LOS ALTOS	SANTA CLARA
MENLO PARK	SAN MATEO
ATHERTON	SAN MATEO
PORTOLA VALLEY	SAN MATEO
MILLBRAE	SAN MATEO
MONTARA	SAN MATEO
MOSS BEACH	SAN MATEO
MOUNTAIN VIEW	SANTA CLARA
MOUNTAIN VIEW	SANTA CLARA
MOUNTAIN VIEW	SANTA CLARA
PACIFICA	SAN MATEO
PESCADERO	SAN MATEO
REDWOOD CITY	SAN MATEO
REDWOOD CITY	SAN MATEO
REDWOOD CITY	SAN MATEO
SAN BRUNO	SAN MATEO
SAN CARLOS	SAN MATEO
SAN GREGORIO	SAN MATEO
SOUTH SAN FRANCISCO	SAN MATEO
SUNNYVALE	SANTA CLARA
SUNNYVALE	SANTA CLARA
SUNNYVALE	SANTA CLARA
SAN FRANCISCO	SAN FRANCISCO
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PALO ALTO	SANTA CLARA
PALO ALTO	SAN MATEO
PALO ALTO	SANTA CLARA
STANFORD	SANTA CLARA
PALO ALTO	SANTA CLARA
SAN MATEO	SAN MATEO
SAN MATEO	SAN MATEO
SAN MATEO	SAN MATEO
SAN MATEO	SAN MATEO
ALAMEDA	ALAMEDA
ALAMEDA	ALAMEDA
DANVILLE	CONTRA COSTA
ALAMO	CONTRA COSTA
ANGWIN	NAPA
ANTIOCH	CONTRA COSTA
BENICIA	SOLANO
BETHEL ISLAND	CONTRA COSTA
BRENTWOOD	CONTRA COSTA
BYRON	CONTRA COSTA
CALISTOGA	NAPA
CLAYTON	CONTRA COSTA
CONCORD	CONTRA COSTA
CONCORD	CONTRA COSTA
CONCORD	CONTRA COSTA
CONCORD	CONTRA COSTA
PLEASANT HILL	CONTRA COSTA
CROCKETT	CONTRA COSTA
DANVILLE	CONTRA COSTA
EL CERRITO	CONTRA COSTA
FAIRFIELD	SOLANO
TRAVIS AFB	SOLANO
FREMONT	ALAMEDA

FREMONT	ALAMEDA
FREMONT	ALAMEDA
HAYWARD	ALAMEDA
HAYWARD	ALAMEDA
HAYWARD	ALAMEDA
CASTRO VALLEY	ALAMEDA
HERCULES	CONTRA COSTA
LAFAYETTE	CONTRA COSTA
LIVERMORE	ALAMEDA
CASTRO VALLEY	ALAMEDA
MARTINEZ	CONTRA COSTA
FREMONT	ALAMEDA
MORAGA	CONTRA COSTA
NAPA	NAPA
NAPA	NAPA
NEWARK	ALAMEDA
OAKLEY	CONTRA COSTA
ORINDA	CONTRA COSTA
PINOLE	CONTRA COSTA
PLEASANTON	ALAMEDA
POPE VALLEY	NAPA
DUBLIN	ALAMEDA
RIO VISTA	SOLANO
RODEO	CONTRA COSTA
SAINT HELENA	NAPA
DEER PARK	NAPA
SAN LEANDRO	ALAMEDA
SAN LEANDRO	ALAMEDA
SAN LEANDRO	ALAMEDA
SAN LORENZO	ALAMEDA
SAN RAMON	CONTRA COSTA
SUISUN CITY	SOLANO
SUNOL	ALAMEDA
UNION CITY	ALAMEDA
PLEASANTON	ALAMEDA
VALLEJO	SOLANO
VALLEJO	SOLANO
WALNUT CREEK	CONTRA COSTA
WALNUT CREEK	CONTRA COSTA
WALNUT CREEK	CONTRA COSTA
YOUNTVILLE	NAPA
OAKLAND	ALAMEDA
OAKLAND	ALAMEDA
OAKLAND	ALAMEDA
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OAKLAND	ALAMEDA
OAKLAND	ALAMEDA
BERKELEY	ALAMEDA
BERKELEY	ALAMEDA
BERKELEY	ALAMEDA
BERKELEY	ALAMEDA
ALBANY	ALAMEDA
BERKELEY	ALAMEDA
BERKELEY	ALAMEDA
BERKELEY	ALAMEDA
EL SOBRANTE	CONTRA COSTA
RICHMOND	CONTRA COSTA
SAN RAFAEL	MARIN
SAN RAFAEL	MARIN
GREENBRAE	MARIN
BELVEDERE TIBURON	MARIN
BODEGA	SONOMA
BODEGA BAY	SONOMA
BOLINAS	MARIN
CORTE MADERA	MARIN
ROHNERT PARK	SONOMA
DILLON BEACH	MARIN
FAIRFAX	MARIN
COTATI	SONOMA
FOREST KNOLLS	MARIN
INVERNESS	MARIN
LAGUNITAS	MARIN
LARKSPUR	MARIN
MARSHALL	MARIN
MILL VALLEY	MARIN
NOVATO	MARIN
NICASIO	MARIN
NOVATO	MARIN
NOVATO	MARIN
OLEMA	MARIN
PENNGROVE	SONOMA
PETALUMA	SONOMA
PETALUMA	SONOMA
POINT REYES STATION	MARIN
SAN ANSELMO	MARIN
SAN GERONIMO	MARIN
SAUSALITO	MARIN
STINSON BEACH	MARIN
TOMALES	MARIN

WOODACRE	MARIN
ALVISO	SANTA CLARA
APTOS	SANTA CRUZ
AROMAS	MONTEREY
BEN LOMOND	SANTA CRUZ
BOULDER CREEK	SANTA CRUZ
BROOKDALE	SANTA CRUZ
CAMPBELL	SANTA CLARA
CAPITOLA	SANTA CRUZ
CUPERTINO	SANTA CLARA
DAVENPORT	SANTA CRUZ
FELTON	SANTA CRUZ
GILROY	SANTA CLARA
HOLLISTER	SAN BENITO
LOS GATOS	SANTA CLARA
LOS GATOS	SANTA CLARA
LOS GATOS	SANTA CLARA
MILPITAS	SANTA CLARA
MORGAN HILL	SANTA CLARA
MOSS LANDING	MONTEREY
PAICINES	SAN BENITO
SAN JUAN BAUTISTA	SAN BENITO
SAN MARTIN	SANTA CLARA
SANTA CLARA	SANTA CLARA
SANTA CLARA	SANTA CLARA
SANTA CLARA	SANTA CLARA
SANTA CRUZ	SANTA CRUZ
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SANTA CRUZ	SANTA CRUZ
SCOTTS VALLEY	SANTA CRUZ
SARATOGA	SANTA CLARA
SOQUEL	SANTA CRUZ
SAN JOSE	SANTA CLARA
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SAN JOSE	SANTA CLARA
SAN JOSE	SANTA CLARA
STOCKTON	SAN JOAQUIN
STOCKTON	SAN JOAQUIN
STOCKTON	SAN JOAQUIN
STOCKTON	SAN JOAQUIN
STOCKTON	SAN JOAQUIN
STOCKTON	SAN JOAQUIN
ACAMPO	SAN JOAQUIN
ALTAVILLE	CALAVERAS
ANGELS CAMP	CALAVERAS
ARNOLD	CALAVERAS
CLEMENTS	SAN JOAQUIN
COPPEROPOLIS	CALAVERAS
FARMINGTON	SAN JOAQUIN
FRENCH CAMP	SAN JOAQUIN
HATHAWAY PINES	CALAVERAS
LINDEN	SAN JOAQUIN
LOCKEFORD	SAN JOAQUIN
LODI	SAN JOAQUIN
LODI	SAN JOAQUIN
MOKELUMNE HILL	CALAVERAS
MOUNTAIN RANCH	CALAVERAS
MURPHYS	CALAVERAS
SAN ANDREAS	CALAVERAS
VALLECITO	CALAVERAS
VALLEY SPRINGS	CALAVERAS
WALLACE	CALAVERAS
WEST POINT	CALAVERAS
WILSEYVILLE	CALAVERAS
WOODBRIDGE	SAN JOAQUIN
ATWATER	MERCED
BALLICO	MERCED
CATHEYS VALLEY	MARIPOSA
CERES	STANISLAUS
COLUMBIA	TUOLUMNE

COULTERVILLE	MARIPOSA
CROWS LANDING	STANISLAUS
DELHI	MERCED
DENAIR	STANISLAUS
EL NIDO	MERCED
EL PORTAL	MARIPOSA
ESCALON	SAN JOAQUIN
GROVELAND	TUOLUMNE
GUSTINE	MERCED
HICKMAN	STANISLAUS
HILMAR	MERCED
HUGHSON	STANISLAUS
JAMESTOWN	TUOLUMNE
KEYES	STANISLAUS
LA GRANGE	STANISLAUS
LATHROP	SAN JOAQUIN
LONG BARN	TUOLUMNE
MANTECA	SAN JOAQUIN
MANTECA	SAN JOAQUIN
MARIPOSA	MARIPOSA
MERCED	MERCED
MIDPINES	MARIPOSA
MI WUK VILLAGE	TUOLUMNE
MERCED	MERCED
MODESTO	STANISLAUS
MODESTO	STANISLAUS
MODESTO	STANISLAUS
MODESTO	STANISLAUS
MODESTO	STANISLAUS
MODESTO	STANISLAUS
NEWMAN	STANISLAUS
OAKDALE	STANISLAUS
PATTERSON	STANISLAUS
PINECREST	TUOLUMNE
RIPON	SAN JOAQUIN
RIVERBANK	STANISLAUS
SALIDA	STANISLAUS
SNELLING	MERCED
SONORA	TUOLUMNE
SOULSBYVILLE	TUOLUMNE
STEVINSON	MERCED
TRACY	SAN JOAQUIN
TUOLUMNE	TUOLUMNE
TURLOCK	STANISLAUS
TURLOCK	STANISLAUS

TWAIN HARTE	TUOLUMNE
VERNALIS	SAN JOAQUIN
WATERFORD	STANISLAUS
WESTLEY	STANISLAUS
WINTON	MERCED
YOSEMITE NATIONAL PARK	MARIPOSA
SANTA ROSA	SONOMA
SANTA ROSA	SONOMA
SANTA ROSA	SONOMA
SANTA ROSA	SONOMA
SANTA ROSA	SONOMA
SANTA ROSA	SONOMA
ALBION	MENDOCINO
ANNAPOLIS	SONOMA
BOONVILLE	MENDOCINO
CAMP MEEKER	SONOMA
CASPAR	MENDOCINO
CAZADERO	SONOMA
CLEARLAKE	LAKE
CLEARLAKE OAKS	LAKE
CLOVERDALE	SONOMA
COBB	LAKE
COMPTCHE	MENDOCINO
COVELO	MENDOCINO
ELK	MENDOCINO
FORESTVILLE	SONOMA
FORT BRAGG	MENDOCINO
FULTON	SONOMA
GEYSERVILLE	SONOMA
GLEN ELLEN	SONOMA
GRATON	SONOMA
GUALALA	MENDOCINO
GUERNEVILLE	SONOMA
HEALDSBURG	SONOMA
HOPLAND	MENDOCINO
JENNER	SONOMA
KELSEYVILLE	LAKE
KENWOOD	SONOMA
LAKEPORT	LAKE
LAYTONVILLE	MENDOCINO
LITTLERIVER	MENDOCINO
LOWER LAKE	LAKE
LUCERNE	LAKE
MANCHESTER	MENDOCINO
MENDOCINO	MENDOCINO

MIDDLETOWN	LAKE
MONTE RIO	SONOMA
NICE	LAKE
OCCIDENTAL	SONOMA
PHILO	MENDOCINO
POINT ARENA	MENDOCINO
POTTER VALLEY	MENDOCINO
REDWOOD VALLEY	MENDOCINO
RIO NIDO	SONOMA
SEBASTOPOL	SONOMA
SONOMA	SONOMA
UKIAH	MENDOCINO
UPPER LAKE	LAKE
WESTPORT	MENDOCINO
WILLITS	MENDOCINO
WINSDOR	SONOMA
YORKVILLE	MENDOCINO
THE SEA RANCH	SONOMA
EUREKA	HUMBOLDT
EUREKA	HUMBOLDT
MCKINLEYVILLE	HUMBOLDT
ARCATA	HUMBOLDT
BAYSIDE	HUMBOLDT
BLUE LAKE	HUMBOLDT
BRIDGEVILLE	HUMBOLDT
BURNT RANCH	TRINITY
CARLOTTA	HUMBOLDT
CRESCENT CITY	DEL NORTE
FERNDALE	HUMBOLDT
FORTUNA	HUMBOLDT
GARBERVILLE	HUMBOLDT
GASQUET	DEL NORTE
HYDESVILLE	HUMBOLDT
KLAMATH	DEL NORTE
LOLETA	HUMBOLDT
MIRANDA	HUMBOLDT
MYERS FLAT	HUMBOLDT
ORICK	HUMBOLDT
ORLEANS	HUMBOLDT
REDWAY	HUMBOLDT
RIO DELL	HUMBOLDT
SALYER	TRINITY
SAMOA	HUMBOLDT
SCOTIA	HUMBOLDT
SMITH RIVER	DEL NORTE

REDCREST	HUMBOLDT
TRINIDAD	HUMBOLDT
WILLOW CREEK	HUMBOLDT
LEGGETT	MENDOCINO
WHITETHORN	HUMBOLDT
AUBURN	PLACER
AUBURN	PLACER
WEST SACRAMENTO	YOLO
BROOKS	YOLO
CARMICHAEL	SACRAMENTO
CITRUS HEIGHTS	SACRAMENTO
CLARKSBURG	YOLO
COOL	EL DORADO
COURTLAND	SACRAMENTO
DAVIS	YOLO
DAVIS	YOLO
DIAMOND SPRINGS	EL DORADO
DIXON	SOLANO
CITRUS HEIGHTS	SACRAMENTO
EL DORADO	EL DORADO
ELK GROVE	SACRAMENTO
ELVERTA	SACRAMENTO
ESPARTO	YOLO
FAIR OAKS	SACRAMENTO
FIDDLETOWN	AMADOR
FOLSOM	SACRAMENTO
FORESTHILL	PLACER
GALT	SACRAMENTO
GARDEN VALLEY	EL DORADO
GEORGETOWN	EL DORADO
GREENWOOD	EL DORADO
GRIZZLY FLATS	EL DORADO
HERALD	SACRAMENTO
IONE	AMADOR
ISLETON	SACRAMENTO
JACKSON	AMADOR
KNIGHTS LANDING	YOLO
LINCOLN	PLACER
LOOMIS	PLACER
LOTUS	EL DORADO
MADISON	YOLO
MATHER	SACRAMENTO
NEWCASTLE	PLACER
NICOLAUS	SUTTER
NORTH HIGHLANDS	SACRAMENTO

ROSEVILLE	PLACER
ORANGEVALE	SACRAMENTO
PENRYN	PLACER
PILOT HILL	EL DORADO
PINE GROVE	AMADOR
PIONEER	AMADOR
PLACERVILLE	EL DORADO
PLEASANT GROVE	SUTTER
PLYMOUTH	AMADOR
RANCHO CORDOVA	SACRAMENTO
RESCUE	EL DORADO
RIO LINDA	SACRAMENTO
RIO OSO	SUTTER
RIVER PINES	AMADOR
ROBBINS	SUTTER
ROCKLIN	PLACER
ROSEVILLE	PLACER
SHERIDAN	PLACER
SHINGLE SPRINGS	EL DORADO
SLOUGHHOUSE	SACRAMENTO
SOMERSET	EL DORADO
SUTTER CREEK	AMADOR
THORNTON	SAN JOAQUIN
VACAVILLE	SOLANO
VACAVILLE	SOLANO
VOLCANO	AMADOR
WALNUT GROVE	SACRAMENTO
WEST SACRAMENTO	YOLO
WHEATLAND	YUBA
WILTON	SACRAMENTO
WINTERS	YOLO
WOODLAND	YOLO
ALTA	PLACER
APPLEGATE	PLACER
CAMINO	EL DORADO
COLFAX	PLACER
DUTCH FLAT	PLACER
GOLD RUN	PLACER
MEADOW VISTA	PLACER
POLLOCK PINES	EL DORADO
RANCHO CORDOVA	SACRAMENTO
GRANITE BAY	PLACER
ROSEVILLE	PLACER
ELK GROVE	SACRAMENTO
EL DORADO HILLS	EL DORADO

ROCKLIN	PLACER
WOODLAND	YOLO
SACRAMENTO	SACRAMENTO
SACRAMENTO	SACRAMENTO
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SACRAMENTO	SACRAMENTO
SACRAMENTO	SACRAMENTO
ANTELOPE	SACRAMENTO
SACRAMENTO	SACRAMENTO
MARYSVILLE	YUBA
BEALE AFB	YUBA
ARBUCKLE	COLUSA
BANGOR	BUTTE
BERRY CREEK	BUTTE
BIGGS	BUTTE
BROWNS VALLEY	YUBA
BROWNSVILLE	YUBA
BUTTE CITY	GLENN
CAMPTONVILLE	YUBA
CHALLENGE	YUBA
CHICO	BUTTE
CHICO	BUTTE
CLIPPER MILLS	BUTTE
COLUSA	COLUSA
DOBBINS	YUBA
DOWNIEVILLE	SIERRA
DURHAM	BUTTE
ELK CREEK	GLENN
FORBESTOWN	BUTTE

FOREST RANCH	BUTTE
GLENN	GLENN
GRASS VALLEY	NEVADA
PENN VALLEY	NEVADA
GREENVILLE	PLUMAS
GRIDLEY	BUTTE
GRASS VALLEY	NEVADA
GRIMES	COLUSA
LIVE OAK	SUTTER
MAGALIA	BUTTE
MAXWELL	COLUSA
MEADOW VALLEY	PLUMAS
MERIDIAN	SUTTER
NEVADA CITY	NEVADA
NORTH SAN JUAN	NEVADA
OLIVEHURST	YUBA
OREGON HOUSE	YUBA
ORLAND	GLENN
OROVILLE	BUTTE
OROVILLE	BUTTE
PALERMO	BUTTE
PARADISE	BUTTE
PRINCETON	COLUSA
QUINCY	PLUMAS
CHICO	BUTTE
ROUGH AND READY	NEVADA
SMARTVILLE	YUBA
STONYFORD	COLUSA
SUTTER	SUTTER
TAYLORSVILLE	PLUMAS
WILLOWS	GLENN
YUBA CITY	SUTTER
YUBA CITY	SUTTER
REDDING	SHASTA
REDDING	SHASTA
REDDING	SHASTA
ADIN	MODOC
ANDERSON	SHASTA
BELLA VISTA	SHASTA
BIEBER	LASSEN
BIG BAR	TRINITY
BIG BEND	SHASTA
BURNEY	SHASTA
CALLAHAN	SISKIYOU
CANBY	MODOC

CASSEL	SHASTA
SHASTA LAKE	SHASTA
CHESTER	PLUMAS
CORNING	TEHAMA
COTTONWOOD	SHASTA
DORRIS	SISKIYOU
DOUGLAS CITY	TRINITY
DUNSMUIR	SISKIYOU
ETNA	SISKIYOU
FALL RIVER MILLS	SHASTA
FORT JONES	SISKIYOU
FRENCH GULCH	SHASTA
GAZELLE	SISKIYOU
GERBER	TEHAMA
GREENVIEW	SISKIYOU
GRENADA	SISKIYOU
HAPPY CAMP	SISKIYOU
HAT CREEK	SHASTA
HAYFORK	TRINITY
HORNBROOK	SISKIYOU
HYAMPOM	TRINITY
IGO	SHASTA
JUNCTION CITY	TRINITY
KLAMATH RIVER	SISKIYOU
LAKEHEAD	SHASTA
LEWISTON	TRINITY
LOOKOUT	MODOC
LOS MOLINOS	TEHAMA
MCARTHUR	SHASTA
MCCLOUD	SISKIYOU
MACDOEL	SISKIYOU
MANTON	TEHAMA
MILLVILLE	SHASTA
MONTAGUE	SISKIYOU
MONTGOMERY CREEK	SHASTA
MOUNT SHASTA	SISKIYOU
OAK RUN	SHASTA
PALO CEDRO	SHASTA
PASKENTA	TEHAMA
PAYNES CREEK	TEHAMA
RED BLUFF	TEHAMA
ROUND MOUNTAIN	SHASTA
SEIAD VALLEY	SISKIYOU
SHASTA	SHASTA
SHINGLETOWN	SHASTA

TEHAMA	TEHAMA
TRINITY CENTER	TRINITY
VINA	TEHAMA
WEAVERVILLE	TRINITY
WEED	SISKIYOU
WHITMORE	SHASTA
YREKA	SISKIYOU
ALTURAS	MODOC
BLAIRSDEN-GRAEAGLE	PLUMAS
CEDARVILLE	MODOC
CHILCOOT	PLUMAS
COLEVILLE	MONO
DOYLE	LASSEN
HERLONG	LASSEN
JANESVILLE	LASSEN
LITCHFIELD	LASSEN
LOYALTON	SIERRA
MARKLEEVILLE	ALPINE
MILFORD	LASSEN
PORTOLA	PLUMAS
CALPINE	SIERRA
SIERRA CITY	SIERRA
STANDISH	LASSEN
SUSANVILLE	LASSEN
TULELAKE	SISKIYOU
WESTWOOD	LASSEN
CARNELIAN BAY	PLACER
HOMEWOOD	PLACER
TAHOMA	EL DORADO
KINGS BEACH	PLACER
OLYMPIC VALLEY	PLACER
TAHOE VISTA	PLACER
SOUTH LAKE TAHOE	EL DORADO
TRUCKEE	NEVADA

APPENDIX G

MAP OF INSURANCE DEMAND

The following graphic is a map of California insurance demand by ZIP code divided by thirds. The highest third refers to the ZIP codes with the highest insurance demand while the lowest third refers to the ZIP codes with the lowest insurance demand.