Insurer Responses to Changes in Average Credit Information: Windfall or Wash?

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ABSTRACT

One stated goal of insurance regulators is to protect consumers from potential anti-competitive practices resulting from information asymmetry. Several studies conclude that insurance markets are highly competitive, mitigating potential anticompetitive practices even without regulation (e.g. Joskow, 1973; Powell, 2008). However, others find evidence consistent with collusion among insurance companies to the detriment of consumers (Bajtelsmit and Bouzouita, 1998). In this article, we measure insurer responses to new exogenous ratemaking information – changes in average credit risk – to determine if market competition effectively drives profits to the cost of capital. Results of our analysis address the public policy debate regarding efficacy and appropriateness of insurance credit scoring. Evidence is consistent with adequate competition in private passenger automobile insurance markets.

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Introduction

Market competition drives prices from the highest market clearing price to the lowest price at which sellers will participate. Insurance markets display the four characteristics of competitive markets.[1] There are multiple independent sellers, multiple independent buyers, relatively homogenous products, and moderate barriers to entry and exit.[2] Although competition suggests limiting the role of regulation, the insurance industry faces very strict and complex regulation.

Industry critics assert that, despite exhibiting characteristics of competitive markets, insurers participate in a host of anticompetitive practices to the detriment of consumers.[3] Beyond the stylized rhetoric of so-called "consumer advocates," the literature suggests a few structural issues in insurance markets that could limit competition. However, such findings in the literature rely on "antique data," that precede many technological innovations consistent with increased efficiency and competition.

Dahlby and West (1986), for example, find that search costs in private passenger automobile insurance markets leads to price dispersion. Their sample of Canadian data spans the period 1974 to 1981. Today, a consumer can get multiple online quotes for automobile insurance in about fifteen minutes. Similarly, using U.S. data from 1984 to 1992, Bajtelsmit and Bouzouita (1998) point to concentration in state automobile insurance markets as barriers to adequate competition. Again, efficient consumer interface systems should mitigate this problem in today's market.

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[1] Competition is defined as "workable competition" in the sense suggested by Clark (1940).
[2] See Powell (2008) for expanded discussion of competitive insurance markets.
[3] See, for example, testimony of J. Robert Hunter before the Senate Judiciary Committee, 10/14/2009. Available from http://judiciary.senate.gov/pdf/10-14-09%20Hunter%20Testimony.pdf accessed 4/19/2011.

In this study, we evaluate competition in private passenger automobile insurance markets by observing insurer behavior in response to an exogenous shock to consumer credit information, one of the most accurate and controversial rating variables. As we describe fully in the following section, most insurers use Credit-Based Insurance Scores (CBIS) as one of many variables in their rating models. Several studies show CBIS to be among the most accurate and powerful predictors of risk (Texas Department of Insurance, 2004; FTC, 2007; Powell, 2009, and others).

In 2006, several factors, including speculation in credit markets and a bursting bubble of housing prices, precipitated an abrupt decline in economic conditions. From 2006 to 2009, home foreclosures increased by more than 225%. During this period, an index of average consumer credit risk[4] in the U.S. increased by almost six percent and the percentage of U.S. consumers with credit scores below 421 (approximately the 5^{th} percentile in holdout samples) increased by more than 20% (from .091 to .111). Figure 1 shows the distribution of credit scores over time in the U.S.

[Figure 1 here]

Industry critics and some regulators have voiced concerns that the use of credit information to price insurance, in light of the recent increase in average credit risk, represents a potential windfall for insurers at consumers' expense.[5] Marginal deterioration of one's credit score does not necessarily indicate increase in insurance risk. Therefore, in the absence of competition, insurers could earn excessive profits if they do not recalibrate their credit scoring models.

[4] The credit risk index is collected from the TransUnion Trends database.

[5] See, for example, Birney Birnbaum's testimony before an NAIC Committee in March, 2008. http://www.cej-online.org/cej%20naic%20subprime%20insurance%20scoring%20080329.pdf accessed 4/19/2011; and http://www.insurancejournal.com/news/west/2010/07/16/111627.htm accessed 4/20/2011.

Our analytical approach keys on this concept that CBISs are indicators of insurance risk relative to the rest of the population. Therefore, the change in average credit risk of the population does not suggest a coinciding change in the underlying insurance risk. When an external shock, such as an economic crisis, causes a change in average credit, drivers do not immediately become more risky. Instead, more people with underlying risk characteristics are revealed through credit information. In other words, the signal credit information provides to insurance underwriters is diluted.

Figure 2 presents evidence consistent with our intuitive assumption that insurance risk changes very little over time relative to credit risk. It shows the average credit risk and the average automobile insurance risk in the three states (AZ, FL, and NV) that experienced the largest changes in credit risk. While credit risk changes substantially over time, automobile insurance risk does not change noticeably.

[Figure 2 here]

We test for adequate competition in insurance markets by analyzing the correlation between average credit information and the unit price of private passenger automobile insurance. A positive relation between credit and price would be consistent with a windfall for insurance companies. Any other result would suggest these markets are competitive.

As a preview of our results, we do not find a positive relation between the price of insurance and average credit risk, suggesting insurance markets are competitive. The remainder of this paper is organized as follows. Section 2 describes background information on CBIS and our conceptual approach to the research question. Section 3 describes our data and empirical models. Section 4 presents results from empirical analysis. Section 5 discusses our conclusions.

2. Background and Conceptual Approach

2.1 Credit-based insurance scores

The correlation between driving outcomes and credit information appears in academic literature as early as 1949 (Tillman and Hobbs, 1949). Insurance companies and third-party venders calculate credit-based insurance scores by estimating the relation between credit information and insurance outcomes. The process of calculating a CBIS is conceptually similar to calculating a traditional credit score used to underwrite loans.

The most important difference between traditional credit scores and credit based insurance scores is the dependent variable. A credit score calculation uses a potential borrower's credit information to estimate the probability of defaulting on a loan. A CBIS calculation uses similar credit information to estimate an insurance applicant's probability of filing a claim.

In 1991, Progressive Insurance Company became the first to use credit information in rating and underwriting private passenger automobile insurance.[6] Over the following decade, the practice of insurance scoring became nearly universal in states that do not prohibit the use of CBIS.[7]

Accuracy in rating is very important to an insurance company's success. Insurers that can predict future losses more accurately than other insures have a distinct competitive advantage. Adverse selection limits potential profits of less accurate insurers. Several studies confirm CBIS is among the most powerful predictors of insurance outcomes (TDI, 2005; Miller and Smith, 2003, FTC, 2007). Hence, an insurer choosing not to use CBIS, or any other accurate and legal pricing variable, would struggle to compete in the private passenger insurance market.

[6] See http://www.progressive.com/progressive-insurance/first.aspx accessed 4/19/2011.

[7] Hawaii has a specific statutory ban on CBIS. Existing rate regulations in Massachusetts and California effectively ban the use of CBIS. New Jersey has banned use of CBIS in the past, but it is currently legal. Other states allow CBIS but restrict the effect of CBIS on insurance rates in certain circumstances.

Consistent with this assertion, Figure 3 shows that Progressive Insurance Company outperformed the rest of the market in growth and profitability by a wide margin throughout the next decade.

[Figure 3 here]

2.2 The exogenous shock

Beginning in 2006, the United States economy experienced a serious downturn resulting in increased incidences of foreclosures and broad, extended unemployment. From here, it is a straight shot to significant changes in the distribution of credit information. Figure 4 shows the average credit risk in the U.S. and in three states that were hit especially hard by the recession. While tragic, this economic nosedive provides an opportunity to evaluate the level of competition in insurance markets.

[Figure 4 here]

Insurers use information from credit models to classify prospective insureds and, perhaps to a lesser extent, renewing policyholders[8] into rate categories. Thus, the classification process implicitly compares individuals being scored to their contemporaries in the market.

A significant shift in average credit risk will lead to decreases in average loss ratio (i.e. increases in average profits) if insurers do not recalibrate their credit models. While the insurer identifies a larger share of the population as having credit information relevant to its scoring model, the insurance risk of the population does not change. Therefore, the predicted effect of credit activity on insurance outcomes is necessarily dampened.

The underlying explanation for the relation between credit and insurance risk is that credit behavior is a proxy for risk aversion. If a person stretches her credit to the limit relative to her ability to pay, this clearly indicates an appetite for risk. However, if the populations' average

[8] Some states restrict the use of credit information at renewal. Other states require insurers to re-score policyholders at specified intervals.

ability to pay is reduced by external factors, the quantitative relation between credit activity and insurance risk must change as well.

2.3 Research Question

Our primary hypothesis is that insurance markets are competitive. Because the insurance industry exhibits the four characteristics of competitive markets, we expect insurers to face adequate competition. The literature identifies two factors that could reduce competition in the insurance industry. The first is search costs. The second is local market concentration.

If search costs are sufficiently high, consumers will not seek adequate information to make the best insurance purchasing decisions. To the extent that consumers are naively satisfied with their insurance price (i.e. they could find a better combination of price and service if they looked), insurers do not have to compete with each other on price to sell new policies or renew existing policies.

In concentrated markets, there are fewer competitors, decreasing the expected price of collusion. While there are more than 2,500 firms selling insurance in the U.S., local markets can have substantially different structures. Insurance is regulated by the states and territories, creating 56 separate jurisdictions. In addition, the vast majority of automobile insurance is underwritten by insurers of common ownership. Therefore, within each state, consumers may find a much smaller number of decision-making entities from which to purchase insurance.

Table 1 presents the number of insurance groups underwriting at least $1 million of private passenger automobile insurance premium in each state over several years. Consistent with competitive markets, each state has numerous independent insurers. In addition, the number changes from year to year, demonstrating that barriers to market entry and exit are reasonable.

Despite these clear signals of market competition, industry critics and some policy makers maintain that insurance markets are not sufficiently competitive to provide meaningful consumer protection. Powell (2008) concludes that concerns of anticompetitive pricing are exacerbated by populist misconceptions of the limited antitrust exemption provided to the business of insurance in the McCarran Ferguson Act of 1945 (Powell, 2008). Nonetheless, and given the immense regulatory burden faced by insurers, the level of competition in insurance markets remains an interesting empirical question.

We test for competition in automobile insurance markets by measuring correlation between credit risk and the price of insurance. If insurers compete on price actively, they will recalibrate their rating models to incorporate exogenous changes in rating information. A positive correlation between average credit risk and price would be consistent with lack of competition. In our model, we also control for market concentration, traffic congestion, and miles travelled per vehicle.

3. Data and Model

3.1 Data

We collect most of our data from two sources. Insurance company information is from the National Association of Insurance Commissioners (NAIC) InfoPro database.[9] We observe automobile insurance premiums and losses of individual insurance companies by company and by state. These are summed to the state level for analysis.

[9] This database contains the statutory annual statement accounting data that are filed with the NAIC by virtually all insurers in the U.S. These data are used with permission of the NAIC. The NAIC does not endorse any analysis or conclusions based upon the use of its data.

Our source of credit information is TransUnion's Trends database.[10] Trends data include quarterly measures of average credit risk and the distribution of credit scores at the state level. The average credit risk measure is an index of the default risk of consumers' credit across all industries relative to a base year, 1996. We average quarterly observations to match the annual observations in other variables. Data on traffic conditions are collected from *Highway Statistics*.[11]

Because we are interested in the effects of the most recent recession, we limit our sample to observations in years 2006 through 2010. Thus, we have 255 state / year observations.

3.2 Analysis

We want to test for a relationship between the price of insurance and average credit risk, all else equal. Thus, we need measures of each, and adequate control variables. Our proxy for the price of automobile insurance is premium divided by losses. Our measure of credit risk is the average credit default risk across all industries reported by TransUnion.

We also control for control for market concentration, traffic congestion, and miles driven. Market concentration is a Herfindahl index of automobile insurance premium written by insurance groups in each state.[12] While a concentrated market may reduce the expected cost of collusion among insurers, it may also occur because the a small number of insurers have a competitive advantage over other insurers (Demsetz, 199X). Therefore, the relation between price and concentration is left as an empirical question.

[10] http://www.transunion.com/corporate/business/solutions/financialservices/trend-data.page?ref=b_a

[11] http://www.fhwa.dot.gov/policyinformation/statistics

[12] The Herfindahl index for each state is calculated as follows: $\sum_{i=1}^{n}\left(\frac{C_i}{S}\right)^2$, where C equals premium written by company i, S equals total premium written in the state, and n equals the number of insurers writing automobile insurance in the state.

Traffic congestion is total miles driven divided by lane-miles. This variable also presents competing hypotheses. A higher ratio of vehicles to road surface is known to increase the frequency of collisions. However, traffic congestion slows the speed of travel and may decrease loss severity. Finally, we control for miles of travel per licensed driver. All else equal, we expect a positive relation between price and miles driven. Table 2 presents descriptive statistics for our sample.

Table 2: Descriptive statistics

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Price	255	1.60	0.16	0.84	2.07
Credit risk	255	1.17	0.21	0.79	1.67
Market Concentration	255	0.11	0.02	0.06	0.19
Travel	255	0.01	0.00	0.01	0.02
Traffic	255	0.39	0.25	0.04	1.09

In the multivariate analysis, we regress credit risk, market concentration, and traffic conditions on the price of insurance using a standard state and time fixed effects model described in Equation 1

$$Price_{st} = \beta_0 + \beta_1 CreditRisk_{st} + \beta_2 Concentration_{st} + \beta_3 Traffic_{st} + \beta_4 Travel_{st} + \gamma_s + \delta_t + \epsilon_{st} \quad (1)$$

where S and T denote states and years, respectively.

4 Results

Table 3 presents results from the regression analysis.

Table 3: Regression results

Variable	Parameter estimate	Standard error	
Credit risk	0.22	0.18	
Market concentration	-2.22	1.30	*
Traffic	1.30	0.69	*
Travel	4.13	14.05	
State fixed effects	YES		
Year fixed effects	YES		
R2	0.74		

Dependent variable, Price, is premium divided by losses.
* indicates statistical significance at the 10% level.

The coefficient estimate for the independent variable of primary interest is not significantly different from zero. The lack of positive relation between price and credit risk is consistent with our hypothesis that automobile insurance markets are competitive. Bolstering this result, we also find that market concentration shows a negative relation to price. While this is only significant at the 10% level, it suggests firms are not colluding to inflate prices in concentrated markets. We also find a positive relation between price and traffic congestion.

5 Conclusions

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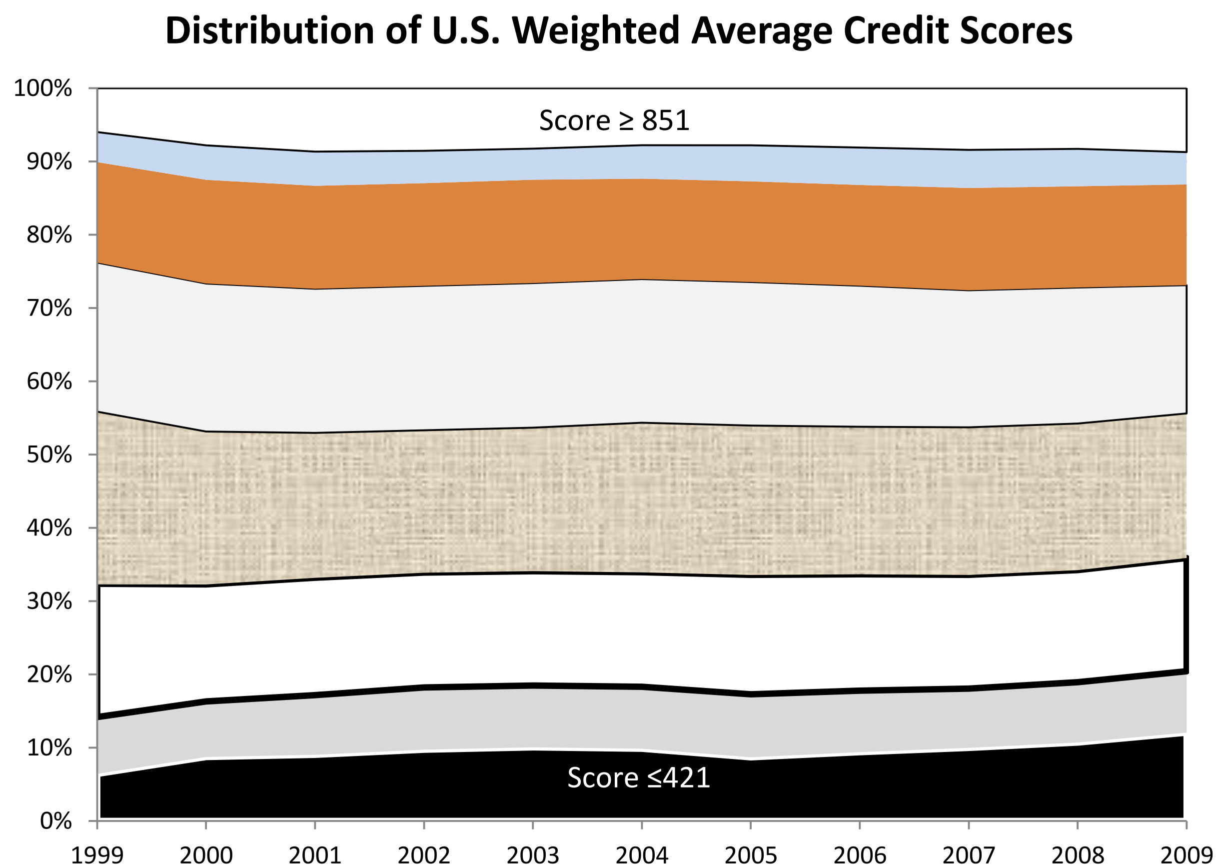
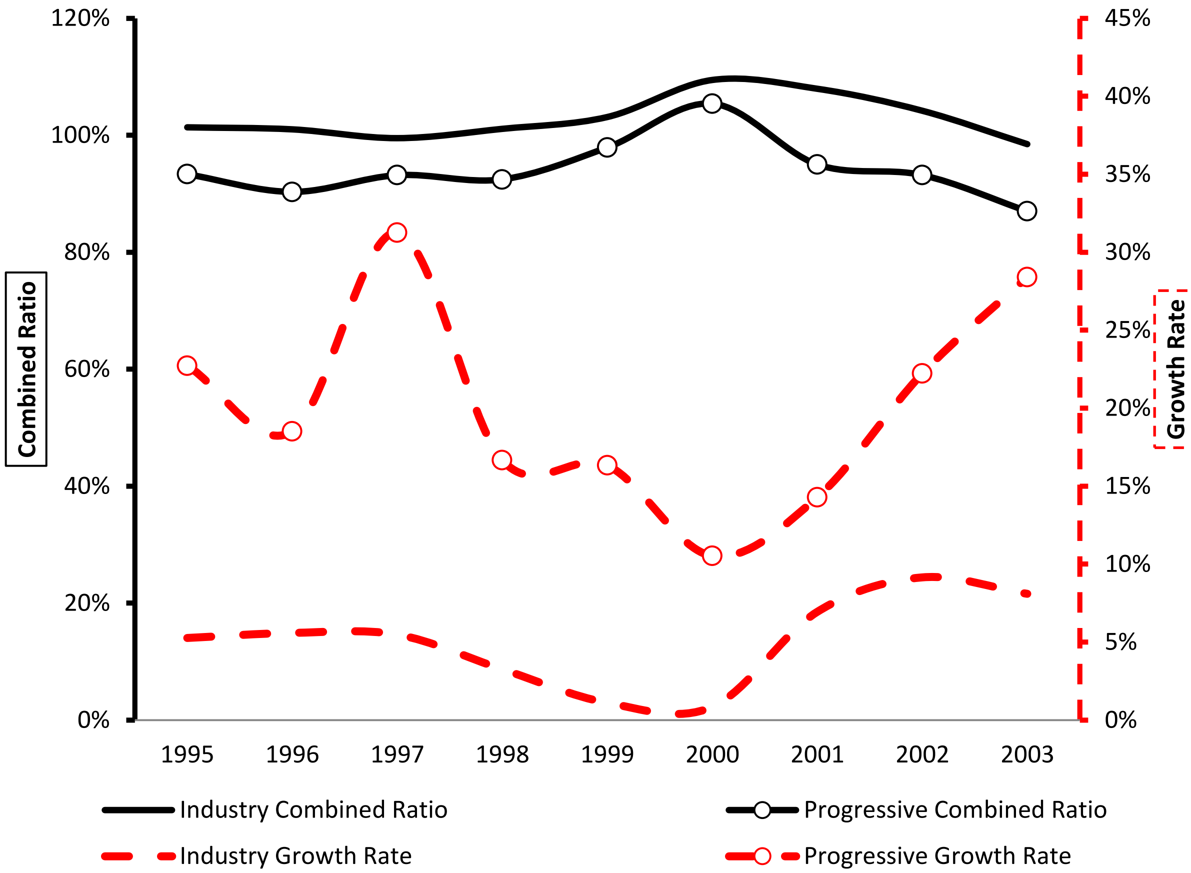
Figure 1: Distribution of Average Credit Scores



Source: TransUnion Trends database provides the percentage of scores in each range at the state level. Each observation is weighted by population and summed across all states.

Figure 3: Performance of Progressive Insurance Company vs. Industry Average



Source: NAIC InfoPro Database 1995 - 2003

Figure 2: Credit Risk versus Insurance Risk, Selected States: 2006-2011

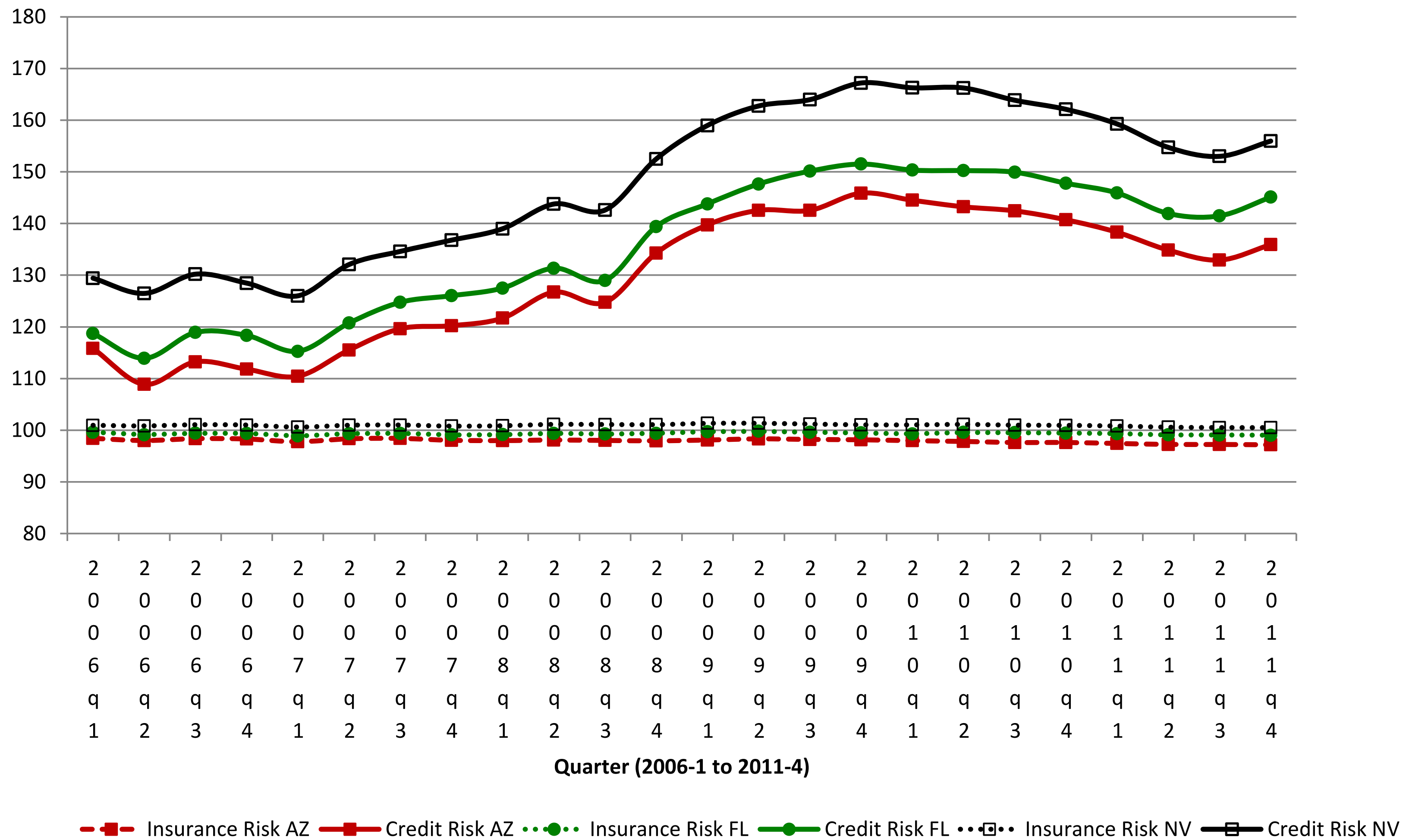
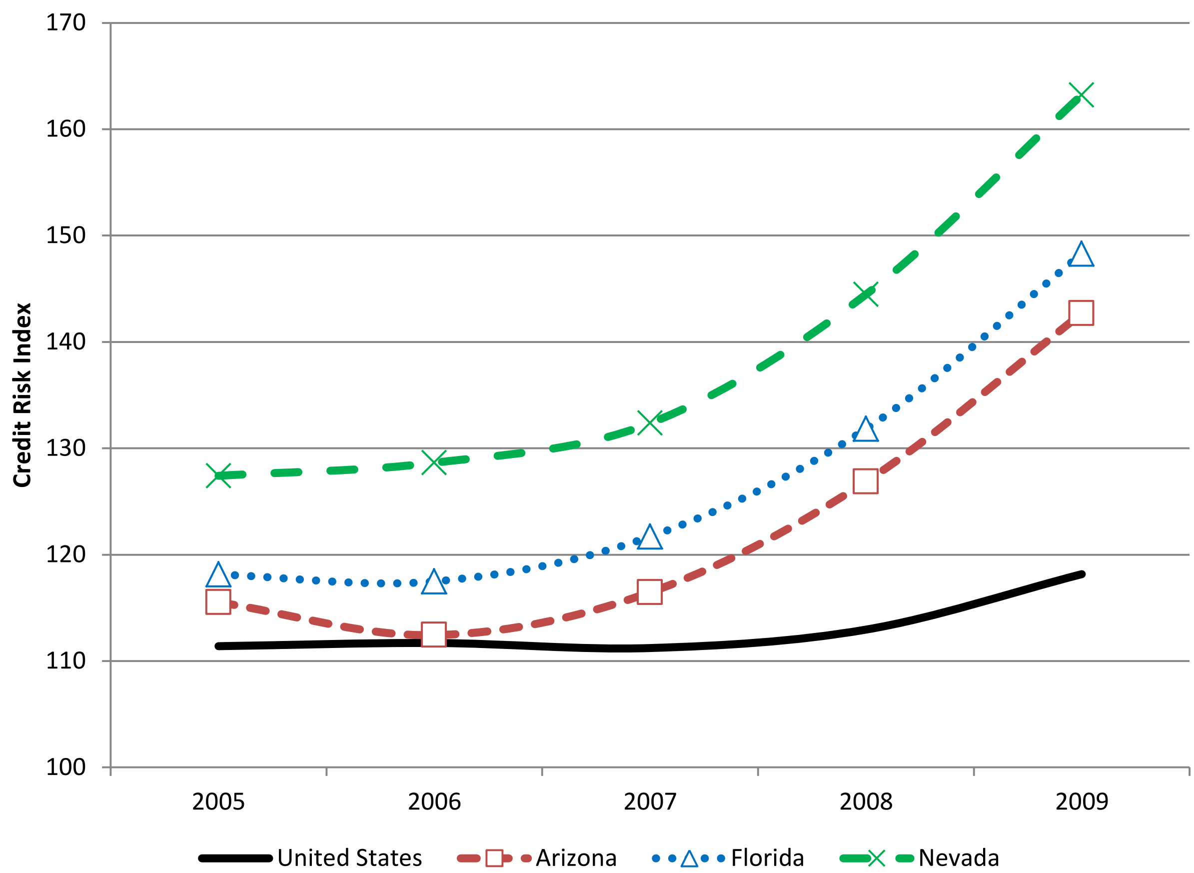


Figure 4: Credit Risk Index, U.S. and Selected States, 2005 – 2009



Source: TransUnion Trends database. The credit risk index tracks the average credit risk in a state from the base year 1996. U.S. figure is the population-weighted average of all states.

Table 1: Insurers per State Underwriting >$1MM Auto Insurance

State	2004	2005	2006	2007	2008	2009	2010
AL	42	46	45	47	44	45	42
AK	13	13	13	13	12	13	11
AZ	61	61	67	64	65	68	63
AR	45	42	39	40	37	39	37
CA	78	75	75	74	75	70	67
CO	45	45	46	46	47	48	44
CT	47	45	46	44	45	43	40
DE	27	28	28	27	27	26	23
DC	16	15	15	15	15	16	15
FL	71	72	70	69	65	65	61
GA	67	63	63	66	66	68	66
HI	14	14	13	15	15	16	15
ID	32	34	32	31	31	32	27
IL	79	78	82	80	81	81	78
IN	71	72	73	71	72	74	68
IA	52	52	53	51	50	49	44
KS	45	43	43	41	41	40	34
KY	46	44	43	41	43	43	41
LA	40	38	37	40	40	41	36
ME	35	34	35	34	34	33	31
MD	46	41	44	42	41	41	40
MA	22	23	21	20	21	25	24
MI	57	58	53	49	50	49	46
MN	61	59	56	55	56	54	53
MS	37	36	36	34	33	34	33
MO	62	61	62	58	57	57	55
MT	27	28	28	27	28	28	25
NE	45	45	46	40	38	36	35
NV	43	43	45	46	46	49	48
NH	40	39	37	37	35	34	32
NJ	47	46	43	47	41	41	37
NM	36	35	35	34	36	34	31
NY	65	63	59	62	55	52	51
NC	52	53	53	49	49	48	43
ND	28	27	27	27	27	27	27
OH	66	65	66	64	64	65	64
OK	52	49	53	48	45	50	41
OR	42	39	41	41	40	39	36
PA	70	68	66	66	67	67	65
RI	36	35	31	31	29	29	28
SC	44	45	48	48	47	50	49
SD	39	39	39	39	37	40	34
TN	60	56	58	57	53	55	56
TX	49	50	54	65	66	68	65
UT	42	39	39	36	38	42	42
VT	28	28	29	30	28	26	25
VA	59	54	58	56	54	56	54
WA	45	44	44	43	44	44	41
WV	30	28	26	25	24	24	24
WI	66	64	64	62	60	59	54
WY	21	21	21	20	18	18	15

Source: NAIC InfoPro database

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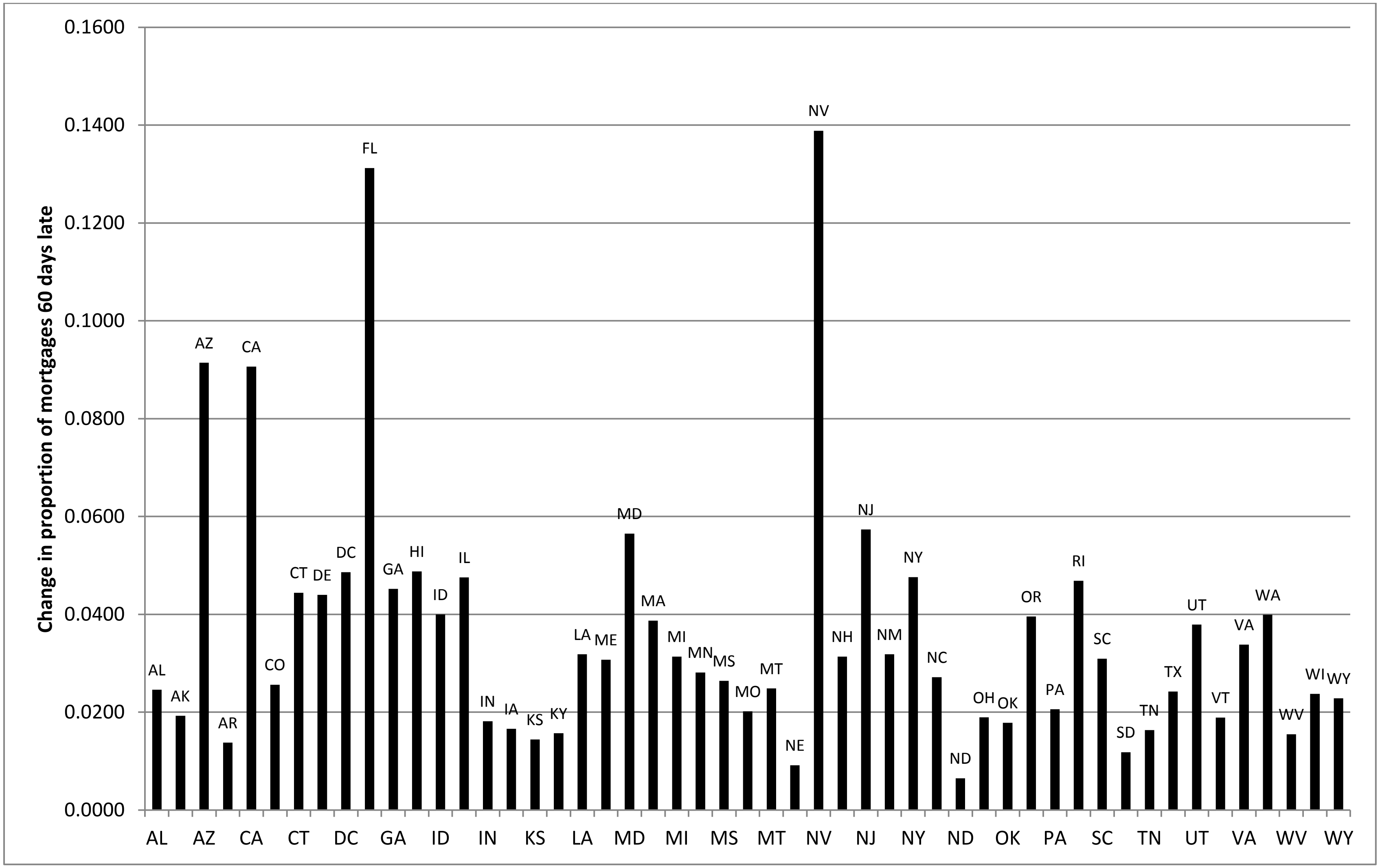
Travel	4.13	14.05	
State fixed effects	YES		
Year fixed effects	YES		
R2	0.74		

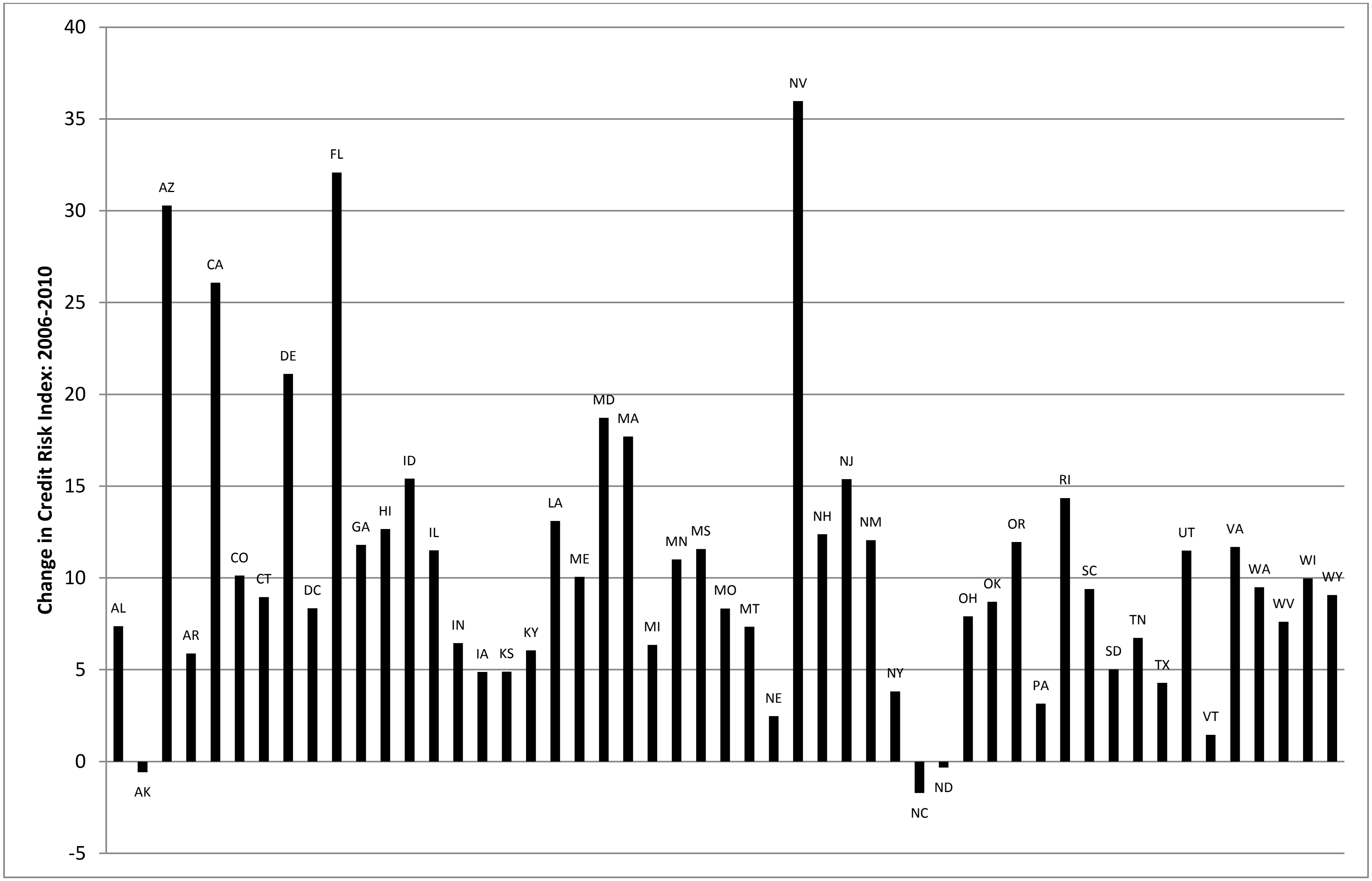
Dependent variable, Price, is premium divided by losses.
* indicates statistical significance at the 10% level.

Change in Proportion of Mortgages 60 Days Overdue: 2006 – 2010



Source: TransUnion Trends database

Figure X - Change in Credit Risk Index by State: 2006-2010



Source: TransUnion Trends Database