Information Shocks and Competition in Insurance Markets: Evidence from the Great Recession*

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Abstract

We measure insurer responses to new exogenous ratemaking information — changes in credit risk beginning in 2007 — to determine if market competition is effective in protecting consumers. Extant literature yields mixed conclusions regarding efficiency and competition in insurance markets. We find that insurers proactively adjust pricing models in response to new information. In fact, results suggest increasing certainty from new information reduces the price of insurance. This is consistent with competition in automobile insurance markets.

Keywords: Automobile Insurance, Market Competition, Credit-Based Insurance Scoring

JEL Classifications: D22; G28

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*We appreciate helpful comments on an earlier version of this paper from Cameron Ellis, Steve Fier, Martin Grace, Ben McMichaels, and seminar participants at University of Alabama, University of Georgia, University of Mississippi, Temple University, and the 2017 American Risk and Insurance Association annual meeting in Toronto, Ontario, Canada. The usual caveat applies. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Electronic copy available at: https://ssrn.com/abstract=4013925

1 Introduction

Complex and stringent price regulation in the U.S. market for automobile insurance suggests market failure; however, the market displays characteristics consistent with competition and efficiency. The market is large, collecting \$299 billion to cover 254 million vehicles in 2019.[1] There are many buyers and sellers (NAIC 2012), low search costs (Honka 2014), and barriers to entry and exit are reasonable (NAIC 2012). Although extant literature finds evidence consistent with market problems (Dahlby and West 1986; Bajtelsmit and Bouzouita 1998), these studies analyze data preceding innovations, such as online shopping, which are known to reduce price levels and price dispersion in insurance markets (Brown and Goolsbee 2002).

We evaluate competition in automobile insurance markets by measuring insurers' reactions to new underwriting information in a scenario that could facilitate tacit collusion.[2] Specifically, we observe changes in the price of automobile insurance during the economic downturn from 2007 through 2011. Because insurers use Credit-Based Insurance Scores (CBIS) as a factor in setting rates, the economic recession represents an exogenous shock of new information.[3] CBIS use information from a person's credit file (e.g. number of accounts, balance-to-limit ratio, late payments) to predict insured losses.[4] It is a measure of driver risk relative to other drivers, but a driver's probability of loss does not necessarily change when her credit information changes. Instead, when an event causes an increase in overall credit risk, such as increasing unemployment or decreasing supply of credit, credit data become more accurate. For example, in a strong economy with increasing wages and asset values, a person can be financially reckless without consequences to their credit. In this scenario, CBIS misclassifies a "high risk" driver as a "low risk" driver. When unemployment increases and asset values fall, the same person is likely to miss payments and borrow money, creating negative information in her credit file. Similarly, as more "high risk" drivers are identified, the classification of "low risk" drivers becomes more accurate as well.

When an exogenous event increases the granularity of insurance rating data, the magnitude of coefficient estimates for rating variables decreases. In the absence of market

[1] Expenditure amount from NAIC database, number of vehicles from *Highway Statistics*. Not all registered vehicles are insured.

[2] Tacit collusion is collusion without communication. See Rees (1993) for more detail.

[3] Several studies show CBIS to be among the most accurate and powerful predictors of automobile insurance risk ((Texas Department of Insurance 2004; FTC 2007); and others).

[4] See the technical appendix to FTC (2007) for a review of CBIS calculations.

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competition, if insurance companies do not re-calibrate their pricing models to recognize such changes, they will overprice insurance policies and potentially earn excess profits. This scenario presents an opportunity for tacit collusion among insurers, because they do not have to take any action to collude. However, in a competitive market, if an insurance company calibrates its rating models to reflect the new granularity of information, it will gain profitable market share from tacit colluders. Moreover, colluders will experience adverse selection unless they also re-calibrate their rating models. Therefore, evidence that insurers re-calibrate rating models would be consistent with substantial competition in automobile insurance markets.

As a preview of results, we find a *negative* correlation between credit risk and the price of automobile insurance, suggesting not only do insurers re-calibrate models to incorporate new information, but increased accuracy from new information allows them to decrease the average price.

The number of people affected by automobile insurance and the amount of money changing hands in this market suggest our research is economically important. However, the project is also timely, given recent efforts to eliminate CBIS from insurance pricing due to the concern of discrimination (Colorado S.B. 21-169 2021) and the effects of COVID-19 on the economy.[5]

The remainder of our article is organized as follows. Section 2 provides background information and briefly reviews relevant literature. Section 3 describes CBIS. Section 4 presents a simple theoretical model and a numerical example to clarify our hypotheses and conceptual approach. Section 5 includes descriptions of our data and empirical tests, and discussion of results. Section 6 summarizes our conclusions.

[5]Legislators, regulators, and advocates argue that CBIS are not appropriate in the wake of COVID-19 effects on the economy. These arguments are documented in legislative testimony provided in Washington (Washington S.B. 5010 2021) and New Jersey (New Jersey S.B. 111 2020), and in NAIC committee discussions.

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2 Background and Prior Literature

2.1 Competition in Insurance Markets

Insurance markets display the four characteristics of competitive markets.[6] There are multiple independent sellers, multiple independent buyers, relatively homogeneous products, and moderate barriers to entry and exit.[7] In addition, insurance markets demonstrate moderate returns and relatively large investment in advertising.[8] Market competition drives prices from the highest market-clearing price towards the lowest price at which sellers will participate. Although observed competition suggests limiting the role of regulation, the insurance industry faces regulation that is very strict and complex.

Industry critics assert that, despite exhibiting characteristics of competitive markets, insurers participate in anti-competitive practices to the detriment of consumers.[9] Beyond the rhetoric of consumer advocates, the literature suggests certain structural issues in insurance markets that could limit competition. However, such findings in the literature are produced from 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 lead to price dispersion. Their sample of Canadian data spans the period 1974 to 1981. Today, with the benefit of new technologies, a consumer can obtain multiple online quotes for automobile insurance in less than fifteen minutes, suggesting search costs have decreased. In fact, Dahlby and West (1986) estimate search costs in 1974 between \$181 and \$804 (adjusted for inflation to 2019 and foreign currency exchange); while more recently, Honka (2014) estimates search costs below \$40.

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 could mitigate this problem in today's market. Moreover, several authors assert that market concentration is a poor proxy for competition (e.g.

[6] Competition is defined as "workable competition" in the sense suggested by Clark (1940).
[7] See Powell (2008) for expanded discussion of competitive insurance markets.
[8] In 2019, property and liability insurers spent more than \$7.9 billion on advertising.
[9] See, for example, testimony of J. Robert Hunter before the Senate Judiciary Committee, 10/14/2009. Available from `https://www.judiciary.senate.gov/download/testimony-of-hunterpdf` accessed 01/04/2022.

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Peltzman (1977) and Demsetz (1973)); suggesting the need for additional research.

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.[10] As we describe fully in Section 3, most insurers use CBIS as one of many variables in their rating models.

2.2 Changes in Credit Information during the Economic Recession

Economic conditions deteriorated sharply at the end of 2007. Household credit risk changed from 2007 to 2009. We saw home foreclosures increasing by more than 225%. An index of average consumer credit risk[11] in the U.S. increased by almost 6% and the percentage of U.S. consumers with credit scores below 421 (approximately the 5$^{\text{th}}$ percentile in holdout samples) increased by more than 20%. Figure 1 compares a measure of average credit risk across three states with the highest increases in credit risk (AZ, FL, and NV) and the U.S. average.

During the economic recession from 2007 through 2011, and more recently as the COVID-19 pandemic affected consumer credit quality, industry critics and some regulators voiced concerns that the use of credit information to set insurance prices represented a potential windfall for insurers at consumers' expense.[12] Because a marginal deterioration of one's credit score does not necessarily indicate an increase in insurance risk, in the absence of competition, insurers could earn excessive profits if they do not recalibrate their CBIS models.

Our analytical approach relies on this concept that CBIS 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 recession, causes a change in the distribution of credit scores, drivers do not immediately become riskier. Instead, more people with underlying

[10] FTC (2007) demonstrates that CBIS rank first or second in predictive power among all rating variables for each type of automobile insurance coverage.

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

[12] See, for example, Birny Birnbaum's testimony before an NAIC Committee in March 2008. `http://www.cej-online.org/cejnaicsubprimeinsurancescoring080329.pdf` accessed 01/04/2022; and statements of Washington Insurance Commissioner Mike Kreidler in 2010 `http://www.insurancejournal.com/news/west/2010/07/16/111627.htm` accessed 01/04/2022.

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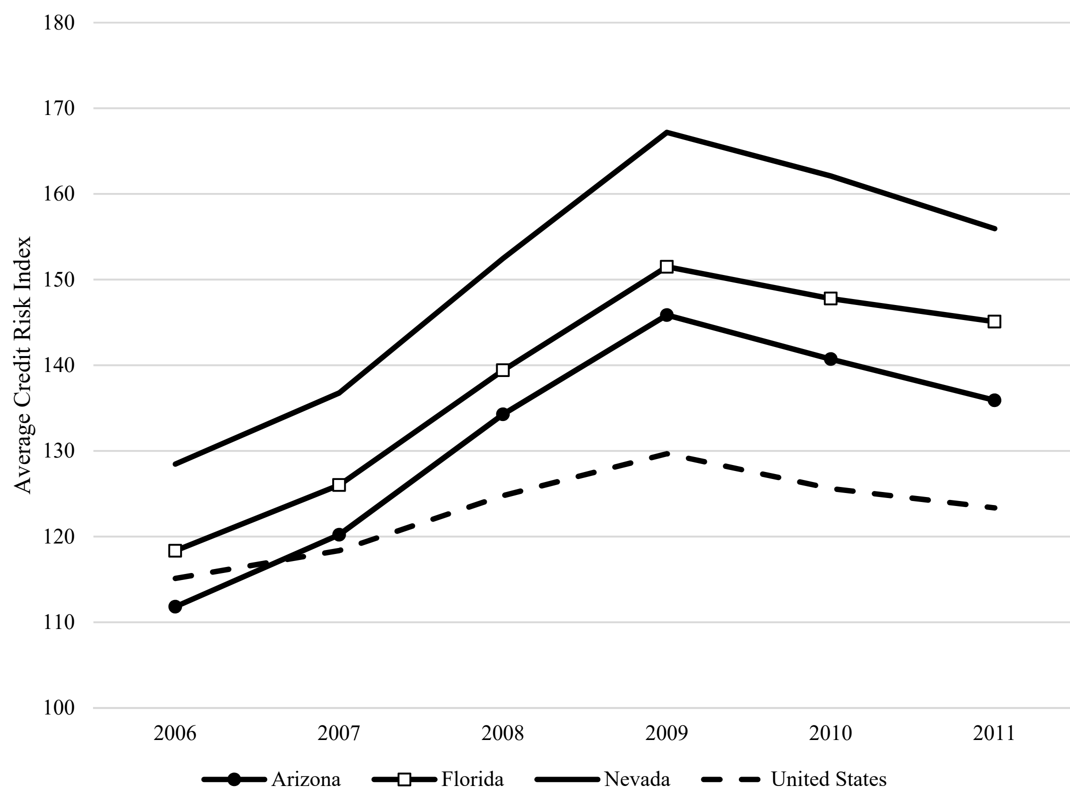
Figure 1: Credit Risk Index, U.S. and Selected States, 2006 - 2011



Source: TransUnion Trends database. The credit risk index tracks the average credit risk in a state from the base year 1996. The United States line represents the population-weighted average of all states.

risk characteristics are revealed through credit information. In other words, the signal that credit information provides to insurance underwriters becomes more accurate. This provides a natural experiment to test the efficacy of market competition in automobile insurance.

3 Credit-Based Insurance Scores

The correlation between driving outcomes and credit information appears in the academic literature as early as 1949 (Tillmann and Hobbs 1949). 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 relative to her ability to pay, this clearly indicates an appetite for risk.

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Insurance companies and third-party vendors calculate CBIS by estimating the relation between credit information and insurance outcomes. The process of calculating CBIS is conceptually similar to calculating a lending credit score used to underwrite loans. However, the most important difference between lending credit scores (e.g. FICO) and CBIS is the dependent variable in the prediction model. A lending 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.[13] Over the following decade, the practice of insurance scoring became nearly universal in states that do not prohibit the use of CBIS.[14]

Accuracy in rating is very important to an insurance company's success. Insurers that can predict future losses more accurately than other insurers 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 (Texas Department of Insurance 2005; Miller, Smith, and Southwood 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 automobile insurance market.

4 Model Calibration

The Great Recession represents a downturn in the U.S. economy that caused significant changes in the distribution of credit information. Insurers use information from credit files to classify prospective insureds and renewing policyholders into rate categories. Thus, the classification process implicitly compares individuals being scored to their contemporaries in the market.

A significant shift in the average credit risk will lead to decreases in the average loss ratio

[13] See `http://www.progressive.com/progressive-insurance/first.aspx` accessed 01/04/2022.

[14] 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 (e.g., domestic violence and collection of medical bills).

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(i.e., increases in average profits) if insurers do not re-calibrate their credit models. Though 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 muted.

We develop a simple theoretical model of the insurance pricing mechanism to clarify our hypotheses and empirical approach. Let the total premium written by insurer k equal $Prem_k$. Denote $\mathbb{Z}_k$ as the set of aggregate, observable characteristics for all the drivers insured by company k (citation history, age, etc.), and CR_k as the aggregate credit risk among these drivers. The expected total loss for insurer k can be written as $L_k(CR_k, \mathbb{Z}_k)$, where L_k represents the first component of the pricing model for insurer k. Through L_k, insurer k uses CR_k directly to measure the insurance risk for its private automobile insurance. The expected total loss of each insurer depends on both the level of aggregate credit risk and the set of aggregate, observable characteristics for all of its insured drivers. Hence, we have the following proposition:

Proposition 4.1. *$\forall L_k$, ceteris paribus, $CR'_k > CR_k \iff L_k(CR'_k, \mathbb{Z}_k) > L_k(CR_k, \mathbb{Z}_k)$.*

Denote f_k as the pricing parameter of insurer k. f_k serves as the second component of the pricing model, and is a function of estimation accuracy, $\mathbb{Q}_k$, and company characteristics, $\mathbb{C}_k$. $\mathbb{C}_k$ is represented in the company fixed-effect in our empirical analysis.[15] The property of f_k can be summarized as the following:

Proposition 4.2. *$\forall f_k(\mathbb{Q}_k, \mathbb{C}_k)$, $\frac{\partial f_k}{\partial \mathbb{Q}_k} < 0$ and $\frac{\partial \mathbb{Q}_k}{\partial CR_k} > 0$.*

Proposition 4.2 states that insurer k's estimation accuracy is increasing in information revealed through credit shocks when it estimates the expected total loss, and that a more accurate estimation of the expected total loss reduces the cost of insuring such risk, thus enabling the company to reduce the price of insurance. The total premium insurer k charges its consumers, $Prem_k$, can be expressed as the insurer's full pricing model:

$$Prem_k = f_k(\mathbb{Q}_k, \mathbb{C}_k) \cdot L_k(CR_k, \mathbb{Z}_k). \tag{1}$$

Therefore, the right hand side of equation (1) can be viewed as the product of the loading factor of the insurance premium and the expected insured loss. If $f_k(\mathbb{Q}_k, \mathbb{C}_k)$ stays

[15] In our empirical model, company fixed-effect also includes $\mathbb{Z}_k$, the set of aggregate, observable characteristics for all its customers.

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the same, for any given loss estimation function L_k, both the expected total loss and the insurance premium increase as CR_k increases.

Now assume that the insured risk does not change during the economic recession, but the aggregate credit risk of insured drivers increases from CR_k to CR'_k.[16] The new total expected loss can be written as $\tilde{L}_k(CR'_k, \mathbb{Z}_k)$, where $\tilde{L}_k$ is the new model insurer k uses to calculate its expected loss. Because the underlying insured risk does not change, $\tilde{L}_k(CR'_k, \mathbb{Z}_k) = L_k(CR_k, \mathbb{Z}_k)$.

In addition, the newly gained information from the changes of credit risk can potentially affect the estimation accuracy of the expected loss ($\mathbb{Q}_k \to \mathbb{Q}'_k$), which will in turn affect the pricing parameter f_k. This happens if the more accurate pricing mechanism reduces parameter uncertainty, thereby decreasing both the required amount of capital and the required return on capital. Thus, the new total premium written can be expressed as $\widetilde{Prem}_k = f_k(\mathbb{Q}'_k, \mathbb{C}_k) \cdot \tilde{L}_k(CR'_k, \mathbb{Z}_k)$.

We define the insurance price for each insurer k, π_k, as the ratio of total premium written over total incurred loss. Let $\pi_k = \frac{Prem_k}{L_k(CR_k, \mathbb{Z}_k)}$ be the price before the recession, and $\tilde{\pi}_k = \frac{\widetilde{Prem}_k}{\tilde{L}_k(CR'_k, \mathbb{Z}_k)} = \frac{\widetilde{Prem}_k}{L_k(CR_k, \mathbb{Z}_k)}$ be the price during the recession. Recall that we assume the changes in the aggregate credit risk of the population during the economic recession does not suggest a coinciding change in the underlying insurance risk, so the actual losses (the denominators of respective insurance prices) before and during the recession are assumed to be the same. Taking the derivative of $\tilde{\pi}_k$ with respect to CR'_k yields the following:

$$\frac{\partial \tilde{\pi}_k}{\partial CR'_k} = \frac{1}{L_k(CR_k, \mathbb{Z}_k)} \{ \frac{\partial f_k}{\partial \mathbb{Q}'_k} \frac{\partial \mathbb{Q}'_k}{\partial CR'_k} \tilde{L}_k(CR'_k, \mathbb{Z}_k) + f_k(\mathbb{Q}'_k, \mathbb{C}_k) \frac{\partial \tilde{L}_k(CR'_k, \mathbb{Z}_k)}{\partial CR'_k} \}, \tag{2}$$

where the first term inside the brackets (before the +) represents the changes in insurer k's pricing parameter caused by the new information revealed from the changes in credit scores, and the second term represents the changes in the insurer's calculated expected loss resulting from such information.

If the insurance market is not competitive, we can consider a special case where insurance companies do not re-calibrate their pricing models. Instead, they continue using pricing models calibrated without the new information revealed by the change from CR_k to CR'_k. In this case (i.e. $L^{\$}$ in the calibration example), $f_k(\mathbb{Q}'_k, \mathbb{C}_k) = f_k(\mathbb{Q}_k, \mathbb{C}_k)$ and the insurer

[16] From Figure 1 we know that the credit risk indeed increased during the recession.

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uses $L_k(CR'_k, \mathbb{Z}_k)$ to estimate the expected total loss, thus equation (2) becomes:

$$\frac{\partial \tilde{\pi}_k}{\partial CR'_k} = \frac{1}{L_k(CR_k, \mathbb{Z}_k)}\{f_k(\mathbb{Q}_k, \mathbb{C}_k)\frac{\partial L_k(CR'_k, \mathbb{Z}_k)}{\partial CR'_k}\}, \tag{3}$$

which is obviously positive according to Proposition 4.1.

On the other hand, if the insurance market is competitive, thereby forcing insurers to re-calibrate their pricing models to keep the expected total losses the same before and during the recession (i.e. $\tilde{L}_k(CR'_k, \mathbb{Z}_k) = L_k(CR_k, \mathbb{Z}_k)$), we have $\frac{\partial \tilde{L}_k(CR'_k, \mathbb{Z}_k)}{\partial CR'_k} = \frac{\partial L_k(CR_k, \mathbb{Z}_k)}{\partial CR'_k} = 0$, and equation (2) becomes:

$$\frac{\partial \tilde{\pi}_k}{\partial CR'_k} = \frac{\partial f_k}{\partial \mathbb{Q}'_k}\frac{\partial \mathbb{Q}'_k}{\partial CR'_k}, \tag{4}$$

which is negative according to Proposition 4.2.

The above findings lead to our first hypothesis (in null form):

$H1_0$: automobile insurance premiums increase in response to positive credit shocks.

If the market is not competitive, we have equation (3), and the relationship between credit risk and insurance price during the recession is positive. On the other hand, if the market is competitive, we have equation (4), and insurance companies cannot earn excess profit during an economic recession. They must re-calibrate their pricing models based on the new information gained from the credit shocks. Meanwhile, if the new information improves accuracy of insurance pricing, insurers will require less capital and less risk load, yielding positive $\frac{\partial \mathbb{Q}'_k}{\partial CR'_k}$ and negative $\frac{\partial f_k}{\partial \mathbb{Q}'_k}$. These forks in the road define our second hypothesis, again in null form:

$H2_0$: New information revealed during the Great Recession is not correlated with price uncertainty.

The following simplified example may help to clarify the concept of model calibration. Assume an insurance company insures 36 policyholders with the loss histories and credit variables in columns 1 and 2 of Table 1. Regressing CR on *Losses* fits the following model of expected losses $E(L)$.

$$Losses = \alpha + \beta CR + \epsilon. \tag{5}$$

$$E(L) = 2.06 + 106.8 \cdot CR. \tag{6}$$

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Table 1: Model Calibration Example

Driver	1 *Losses*	2 CR	3 CR'	4 $E(L)$	5 $E(\tilde{L})$	6 $E(L^{\$})$
1	5	3	4.5	3.41	3.53	5.01
2	4	3	4.5	3.41	3.53	5.01
3	3	3	4.5	3.41	3.53	5.01
4	3	2	3	2.34	2.36	3.41
5	3	2	3	2.34	2.36	3.41
6	3	2	3	2.34	2.36	3.41
7	2	2	3	2.34	2.36	3.41
8	2	2	3	2.34	2.36	3.41
9	2	2	3	2.34	2.36	3.41
10	2	2	3	2.34	2.36	3.41
11	2	2	3	2.34	2.36	3.41
12	2	2	3	2.34	2.36	3.41
13	1	1	1.5	1.27	1.19	1.81
14	1	1	1.5	1.27	1.19	1.81
15	1	1	1.5	1.27	1.19	1.81
16	1	1	1.5	1.27	1.19	1.81
17	1	1	1.5	1.27	1.19	1.81
18	1	1	1.5	1.27	1.19	1.81
19	1	2	3	2.34	2.36	3.41
20	1	1	1.5	1.27	1.19	1.81
21	1	1	1.5	1.27	1.19	1.81
22	1	1	1.5	1.27	1.19	1.81
23	1	0	0.5	0.21	0.41	0.74
24	1	0	0.5	0.21	0.41	0.74
25	1	0	0.5	0.21	0.41	0.74
26	1	0	0.5	0.21	0.41	0.74
27	1	0	0.5	0.21	0.41	0.74
28	0	0	0.5	0.21	0.41	0.74
29	0	0	0	0.21	0.02	0.21
30	0	0	0.25	0.21	0.22	0.47
31	0	0	0.25	0.21	0.22	0.47
32	0	0	0	0.21	0.02	0.21
33	0	0	0	0.21	0.02	0.21
34	0	0	0	0.21	0.02	0.21
35	0	0	0	0.21	0.02	0.21
36	0	0	0	0.21	0.02	0.21

Authors' calculations with hypothetical data.

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Estimates of $E(L)$ appear in column 4. The insurer would use these estimates to set its rates. Next, assume an economic recession changes the credit history for each driver from CR (column 2) to CR' (column 3) without affecting *Losses*. To re-calibrate the CBIS model, the insurer must fit a model of *Losses* and CR', calculating the new parameters for the new loss estimates, $E(\tilde{L})$, shown in column 5.

$$E(\tilde{L}) = 0.23 + 78 \cdot CR'. \tag{7}$$

Note that $\sum Losses = \sum E(L) = \sum E(\tilde{L}) = 48$; however, $E(\tilde{L})$ is a more accurate estimate of *Losses* than is $E(L)$. The square root of the sum of squared differences between *Losses* and $E(L)$ is 33.3, and that of *Losses* and $E(\tilde{L})$ is only 29.7. Intuitively, this improvement in accuracy happens because the standard deviation of credit information increased.

$$\sqrt{\sum [Losses - L_k(CR_k, \mathbb{Z}_k)]^2} = 33.3 > \sqrt{\sum [Losses - \tilde{L}_k(CR'_k, \mathbb{Z}_k)]^2} = 29.7. \tag{8}$$

Finally, $E(L^{\$})$ (column 6) is the result of applying the model parameters of $E(L)$ to the credit information collected after the economic recession begins (CR'). While the sum of actual losses does not change, the sum of $E(L^{\$})$ is 72, resulting in a 50% increase in expected losses predicted by the model.

The empirical analysis described in the next section tests two hypotheses. If we do not find a significant and positive relation between credit risk and the price of insurance, we reject $H1_0$, suggesting automobile insurance markets are sufficiently competitive to prevent tacit collusion in pricing. Assuming we find a negative relation between credit risk and price (we do), we reject $H2_0$, meaning new information revealed during the Great Recession improved the accuracy of insurance pricing and reduced required capital and risk load. It is then important to test for the cause of the negative relationship. A negative relation between credit information and measures of uncertainty in pricing would be consistent with improved accuracy in CBIS leading to decreases in capital costs.

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5 Data and Analysis

5.1 Data

We collect data from several sources. Automobile insurance data are from the National Association of Insurance Commissioners (NAIC) InfoPro database. We collect credit information from TransUnion's Trends database.[17] Trends data include measures of the average credit score, the standard deviation of credit scores, and the distribution of credit scores at the state level. We collect data on per capita income from the Bureau of Economic Analysis. We inflate per capita income to real 2011 dollars using the Consumer Price Index (CPI) from the Bureau of Labor Statistics. Finally, we collect miles driven and number of registered vehicles from the U.S. Department of Transportation's "Highway Statistics" publication series.[18]

Insurance firms are often organized as groups of companies. For example, in our sample the State Farm Insurance Group includes ten subsidiaries under common ownership and control. Cummins, Weiss, and Zi (1999) argue that groups of insurers make decisions at the group level. We analyze group-member firms at the group level and individual firms at the individual level. Thus, when we refer to "firms" we mean groups and unaffiliated insurers.

For the firm-level variables, random variation results in highly skewed observations in firms with few exposures. We address the variation by applying screens to our data prior to estimating the models. Empirical studies using insurer data employ similar screens to avoid companies that are entering or slowly exiting insurance markets (Grace and Leverty 2010; Choi and Weiss 2005). We limit the analysis to firms writing at least $1,000,000 of automobile insurance premium per year in each state and having a market share within the state of operation that is not less than 0.5%. Firms with missing data over our sample period are dropped, as are firms with less than the minimum level of capital ($2,000,000), or with a risk-based capital ratio less than 2. Observations from California, Hawaii, and Massachusetts are dropped because the use of credit-based insurance scores to determine the rate of private automobile insurance were banned in these states during the sample period. Finally, we winsorize the dependent variable *Price* at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles

[17] TransUnion no longer maintains or sells its Trends database. These data were commercially available for our sample period.

[18] See `https://www.fhwa.dot.gov/policyinformation/statistics.cfm`

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to reduce the potential influence of extreme observations.[19]

Because we are interested in the effects of the recession, we limit the sample to observations in years 2006 through 2011.[20] Our final sample for personal auto insurance includes 4,372 firm/state/year observations and our sample for commercial auto insurance has 4,099 firm/state/year observations.[21]

5.2 Analysis

We want to test for a causal relationship between the price of insurance and changes in credit risk, all else equal. Thus, the analysis requires measures of each, adequate control variables, and an identification strategy. Our proxy for the price of automobile insurance, *Price*, is premium divided by losses. Our measure of credit risk, *Credit CoV*, is the coefficient of variation of the TransUnion credit score in each state and year. We use the coefficient of variation because it captures changes in the distribution of credit scores, rather than only changes in the percentage of people with scores above or below some cutoff.

At the state level, we also control for market concentration, miles driven and per capita income. *Market Concentration* is the Herfindahl index of automobile insurance premium written by insurance groups in each state.[22] Bajtelsmit and Bouzouita (1998) find that market concentration is positively related to automobile insurance profit. While a concentrated market may reduce the expected cost of collusion among insurers, it may also occur because a small number of insurers has a competitive advantage over other insurers (Choi and Weiss 2005; Demsetz 1973). Therefore, the relation between price and concentration is left as an empirical question.

Hartwig, Lynch, and Weisbart (2016) find a strong relationship between miles driven and economic growth. Therefore, we expect a decrease in miles driven at the beginning of the recession and an increase as the economy rebounds. The number of miles driven can

[19] After screening the data but before winsorizing, we still found observations with personal insurance premium-to-loss ratios (*Price*) as high as 7.98, or 16.3 standard deviations above the sample mean. After winsorizing, the maximum price ratio is 2.82, which is 4.5 standard deviations above the winsorized sample mean.

[20] Observations in year 2005 are used to calculate lagged variables, but they are omitted in the panel regressions.

[21] We treat Washington DC as a state in the analysis.

[22] The Herfindahl index for each state is calculated as follows: $\sum_{i=1}^{n}(\frac{C_i}{S})^2$, 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.

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affect the price of automobile insurance because miles driven affects losses, but insurers cannot measure mileage with much precision. Therefore, changes in miles driven could cause short-term changes in the price of insurance. We control for miles driven at the state level with $\log(Travel)$, the natural logarithm of miles traveled per registered vehicle.

Next, we control for real per capita income with $\log(Income)$. Changes in income could potentially affect insurance prices in a few ways. First, Kamiya (2018) shows that changes in income are positively related to demand for insurance, which could cause changes in price. In addition, Harrington and Niehaus (1998) offer that income may be positively related to price if people with greater income choose higher-quality insurance products. They also note that the relation between price and income could be negative if wealthy people represent cross-selling opportunities for insurers (e.g., multiple cars, homeowners insurance, and life insurance).

We also control for three firm-specific factors. The first is *State Market Share*, the ratio of each firm's premium earned in a state divided by the total amount of premium earned in a state by all insurers. Similar to *Market Concentration* at the state level, *State Market Share* controls for market power at the firm level. Next, we control for financial strength with the insurers risk-based capital ratio (*RBC*)[23] and the natural logarithm of premium written in all states (*Company Size*)[24]. Sommer (1996) shows that insurers with greater financial strength can charge higher prices.

Table 2 presents the descriptive statistics for our sample of personal and commercial auto insurers.

5.2.1 Identification

Our identification strategy uses commercial auto insurance as a counterfactual for personal auto insurance. The important difference is that commercial auto insurance does not use credit information in pricing or underwriting.[25] More importantly, the similarities include

[23]Insurance companies do not compute RBC at the group level during our sample period. We calculate risk-based capital at the group level by dividing the sum of members' numerators by that of members' denominators. This is not a perfect measure of a group's financial strength, but it is not systematically biased and it has the advantages of being both granular and consistent across groups.

[24]Premium written by each firm in each state is controlled through its presence in the numerator of *State Market Share*.

[25]Several insurance agents confirmed that commercial automobile insurance carriers do not use CBIS for rating or underwriting. We also reviewed multiple applications for commercial automobile insurance. The

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Table 2: Descriptive Statistics

Variable	N	Mean	St. Dev.	Minimum	Maximum
Personal Auto Insurance					
Price	4,372	1.53	0.28	0.72	2.82
Credit CoV	4,372	0.24	0.02	0.21	0.28
Market Concentration	4,372	0.1	0.02	0.06	0.18
State Market Share	4,372	0.06	0.06	0.01	0.36
Risk Based Capital	4,372	8.82	3.74	2.69	33.81
Company Size (1,000,000s)	4,372	3,929	4,366	5	16,968
Travel	4,372	12,659	2,989	6,060	32,373
Income	4,372	42,145	6,963	31,695	68,628
Commercial Auto Insurance					
Price	4,099	1.68	0.67	0.48	5.82
Credit CoV	4,099	0.25	0.02	0.21	0.28
Market Concentration	4,099	0.05	0.01	0.03	0.11
State Market Share	4,099	0.05	0.04	0.01	0.26
Risk Based Capital	4,099	7.24	4.21	2.1	133.22
Company Size ($1,000,000s)	4,099	489	395	1	1,241
Travel	4,099	12,820	2,933	6,060	32,373
Income	4,099	41,994	6,785	31,695	68,628

Price is premium divided by losses measured at the state-firm level. *Credit CoV* is the coefficient of variation of the TransUnion credit score in each state. *Market Concentration* is a Herfindahl index of premium earned by company in each state. *State Market Share* is firm market share (by premium earned) in each state. *Risk Based Capital* is the regulatory risk-based capital ratio. *Company Size* is premium earned by each firm in all states divided by 1,000,000. *Travel* is miles driven divided by number of registered vehicles. *Income* is real per capita income inflated to 2011 dollars using the Consumer Price Index. *Price* is winsorized at the 1st and 99th percentiles.

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driving on the same roads in the same states and during the same period as the drivers in our primary analysis. We undertake the same analysis described above, except we substitute commercial automobile insurance premiums and losses for those of personal automobile insurance.

We test our first hypothesis by estimating Equation (9).

$$Price_{i,t} = \alpha_i + \beta_1 Credit\, CoV_{i,t-1} + \beta X_{i,t-1} + \delta_t + \gamma_s + \epsilon_{i,t}, \tag{9}$$

where $Price_{i,t}$ denotes insurance price for state-firm i at year t, $X_{i,t-1}$ is a vector of state/firm characteristics. We estimate the model with year, state, and firm fixed-effects and errors clustered at the firm level.[26]

5.3 Results

Table 3 presents the results from our regression analysis. Results from estimating Equation (9) lead us to reject our first hypothesis and are consistent with sufficient competition in automobile insurance markets. First, the coefficient estimate for the credit risk variable is not positive, indicating competition prevents excess profit from (even tacit) collusion. Furthermore, the coefficient estimates on the credit risk variable are negative, suggesting insurers may use the new information to decrease prices.[27]

Next, we notice that the coefficient estimate for *Market Concentration* is negative while that for *State Market Share* is not statistically significant. This result is not consistent with Bajtelsmit and Bouzouita (1998) findings from the mid-1980s and early 1990s, suggesting technological advances may have improved competition in automobile insurance markets.[28] The coefficient estimate for *Travel* is positive and statistically significant, indicating a positive relation between driving and price. The coefficient estimate for real per capita income is not statistically significant. Thus, the change in demand for insurance appears to statistically outweigh any potential change in damages.

applications neither ask for drivers' social security numbers, nor provide notice that credit information will be collected, both of which would be required for insurers to use CBIS.

[26] An F-test rejects the null hypothesis of no fixed-effects at less than the 1% level. Clustered errors are appropriate given the panel structure of our data. Clustering also mitigates potential serial correlation, which we detect using a Durbin-Watson test. Results are qualitatively the same if we use a correction process (e.g. Yule-Walker) to address serial correlation.

[27] We explore this finding further in Section 5.4.

[28] This finding is similar to that of the Brown and Goolsbee (2002) study of life insurance markets.

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Table 3: Panel Regression of Credit on Auto Insurance Price

	Personal Insurance	Commercial Insurance
Credit CoV	-2.60**	-0.96
	(1.31)	(3.32)
Market Concentration	-4.41***	-0.85
	(1.25)	(2.45)
Log(Travel)	0.11***	0.02
	(0.03)	(0.10)
Log(income)	-0.22	-0.07
	(0.22)	(0.56)
Company-State Market Share	0.22	1.34***
	(0.14)	(0.39)
Risk Based Capital	-0.01**	0.002***
	(0.00)	(0.00)
Company Size	0.01	-0.12**
	(0.04)	(0.05)
Constant	4.22	5.36
	(2.62)	(6.58)
Observations	4,372	4,099
Adj. R^2	0.310	0.136

The dependent variable, *Price*, is premium divided by losses. *Credit CoV* is the coefficient of variation of TransUnion credit scores at the state level. *Market Concentration* is a Herfindahl index of premium written by company in each state. *Travel* is miles driven divided by number of licensed drivers. *Income* is per capita income inflated to 2011 dollars using the Consumer Price Index. *Company Size* is premium earned by each firm in all states. *State Market Share* is firm market share (by premium earned) in each state. *Risk Based Capital* is the regulatory risk-based capital ratio. *Log()* indicates the natural logarithm of the variable inside parentheses. The model is estimated with year, state, and firm fixed-effects, errors are clustered at the firm-state level. *Credit CoV*, *Market Concentration*, and all firm-level independent variables are measured at time $t-1$. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

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Finally, the coefficient estimate for *Company Size* is not statistically significant, suggesting larger companies cannot charge a higher price for insurance. Also, the coefficient estimate for *Risk Based Capital* is negative and significant.

5.4 Effect of New Credit Information on Price Uncertainty

We are confident that the correlation between credit risk and the price of automobile insurance is not positive, hence our first hypothesis is settled. However, we want to determine why the coefficient is negative to further examine the issue and support identification of the model. If changing credit risk makes insurance prices more accurate, we should observe a negative relation between *Credit CoV* and price uncertainty. In this section, we estimate the relation between credit risk and a measure of accuracy in pricing. Our measure of accuracy is the absolute value of the difference between the realized price and a target price estimated for each insurance company in each state.[29]

We estimate target price using a partial adjustment regression model. First introduced by Koyck (1954) to analyze investments, recent applications of the partial adjustment model in economics address target financial structure (Flannery and Rangan 2006; Fier, McCullough, and Carson 2013; Huang and Ritter 2009). However, the broader literature employs this framework to assess a range of outcomes from gasoline prices (Bacon 1991), board structure (Cicero, Wintoki, and Yang 2008), and inventory levels (Krane 1994), to the milk production of dairy cows (Dhanoa and Le Du 1982).

Three steps characterize this analysis. First, we test for the existence of target prices in automobile insurance. Second, we estimate the difference between target price and realized price. Third, we estimate the relation between this difference at the firm-state level and *Credit CoV* at the state level.

Following Flannery and Rangan (2006) and Fier, McCullough, and Carson (2013), we specify the target price structure as:

$$Price^*_{i,t} = \beta X_{i,t-1}, \tag{10}$$

where $Price^*_{i,t}$ is the (unobserved) target price for firm i in year t and $X_{i,t-1}$ is a vector of firm characteristics related to target price in the prior year, and β is a vector of coefficients

[29] We first considered a measure of loss reserve development (see Grace and Leverty (2010)) to estimate accuracy in pricing; however, a large literature describes many reasons for reserve development other than ability to accurately forecast losses (see Grace and Leverty (2010, 2012)).

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describing the relations between target price and predictive factors. With the existence of adjustment costs,[30] we assume an insurance firm partially adjusts its price toward its target within each time period. The standard partial adjustment model is given as:

$$Price_{i,t} - Price_{i,t-1} = \lambda(Price^*_{i,t} - Price_{i,t-1}) + \delta_{i,t}, \tag{11}$$

where λ is the proportion by which the firm is able to close the gap between its actual price and target price. Substituting Equation (10) into Equation (11) makes Equation (12), which we can observe and estimate.

$$Price_{i,t} = \lambda\beta X_{i,t-1} + (1-\lambda)Price_{i,t-1} + \delta_{i,t}. \tag{12}$$

Given the dynamic panel structure of this analysis, a standard firm fixed-effects regression model can produce biased results. Thus, we use the system generalized method of moments (GMM) approach proposed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach is common in the literature assessing target leverage (Fier, McCullough, and Carson 2013; Antoniou, Guney, and Paudyal 2008; Lemmon, Roberts, and Zender 2008). Moreover, Roodman (2009) notes that the GMM methodology is most appropriate for analysis of panels like ours with small T and large N. Finally, Roodman (2009) indicates that coefficient estimates from a well-specified GMM model will fall between those found via OLS with year fixed-effects and estimates from a two-way firm-year fixed-effects model. Therefore, to examine the validity of our GMM model, we estimate equation (12) with all three models and compare the coefficient estimates. We estimate the one-step system GMM model with *Lag Prices* as the instruments for the first differences equation and other control variables, $X_{i,t-1}$, as the instruments for the levels equation. Results from estimating each of these three specifications appear in Table 4.

Results in Table 4 indicate that insurance companies have target prices. The coefficient estimate for the lagged price from the two-way fixed-effects model is 0.176, which serves as the lower bound for an appropriate estimate. The coefficient estimate from the year fixed-effects model is 0.517, which represents the upper bound. The estimate obtained from the system GMM model is 0.365, which falls between the bounds.

Next, we calculate target price using the coefficient estimate from the system GMM model. Rearranging Equation (11) gives us the expression of estimated target price as:

[30] Adjustment costs represent investments in information and underwriting.

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Table 4: Partial Adjustment Model Results

Variable	Year FE	Year-Firm FE	**System GMM**
Lag Price	0.517***	0.176***	0.365***
	(0.016)	(0.020)	(0.031)
Company-State Size	−0.021***	0.033	−0.025***
	(0.004)	(0.031)	(0.005)
Company Size	0.003	0.031	0.003
	(0.003)	(0.038)	(0.003)
State Market Share	0.272***	−1.143**	0.342***
	(0.073)	(0.534)	(0.095)
Constant	1.094***	0.170	1.403***
	(0.081)	(0.875)	(0.115)
N	4,372	4,372	4,372
Adj. R^2	0.303	0.400	
AR(1)			−14.27 ***
AR(2)			1.03
Sargan			28.47
Hansen			19.83

The system GMM model includes year fixed-effects. All variables are taken at time $t-1$. Standard errors are shown in parentheses. The Arellano-Bond tests for autocorrelation suggest the existence of first order serial correlation and the lack of second-order serial correlation in the system GMM model. Neither the Sargan nor the Hansen are statistically significant at the 10% level, suggesting the instrumental variables are identified and valid. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

$$Price^*_{i,t} = \frac{1}{\lambda}(Price_{i,t} - Price_{i,t-1} - \delta_{i,t}) + Price_{i,t-1}. \tag{13}$$

We then calculate *Target Deviation*, the absolute value of the difference between target price and realized price as:

$$Target\ Deviation_{i,t} = |Price_{i,t} - Price^*_{i,t}|. \tag{14}$$

Next, we examine whether new credit information improves the accuracy of insurance pricing. We examine the relation between credit risk and the absolute value of deviation from target price by estimating the following model:

$$Target\ Deviation_{i,t} = \alpha_i + \beta_1 Credit\,Cov_{i,t-1} + \beta X_{i,t-1} + \delta_t + \gamma_s + \epsilon_{i,t}, \tag{15}$$

where X includes *Company-State Size*, the natural log of premium earned by company i in state s, and *Company Size*, the natural log of premium earned by company i in all states. X controls for each company's ability to set insurance prices.

We estimate Equation (15) in a regression model with year-firm-state fixed-effects. The results appear in Table 5.

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Table 5: Effects of New Credit Information on Price Uncertainty

Variable	Coefficient Estimate	Standard Error
Credit CoV	−1.660**	0.732
Company-State Size	−0.012***	0.005
Company Size	0.011	0.022
Constant	0.639	0.494
N	4,372	
Adj. R^2	0.121	

The bootstrapped results are estimated with 5,000 iterations. The dependent variable is the absolute value of the difference between estimated target price and the price charged by each firm. The model is estimated with year-firm-state fixed-effects. Standard errors are shown in parentheses. All independent variables are measured at time $t-1$. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The results presented in Table 5 support rejection of our second hypothesis and imply that improved accuracy of CBIS models during the economic recession allowed insurers to decrease the price of automobile insurance. The parameter estimate for *Credit CoV* is negative and significant at the 5% level, suggesting increased accuracy of credit information decreases price uncertainty.

6 Conclusions

Automobile insurance is the largest line of insurance by premium volume. In 2019, U.S. drivers spent more than $299 billion to insure approximately 250 million vehicles. Therefore, it is economically important to understand the marketplace for automobile insurance.

Industry critics, consumer advocates, and some regulators voice concerns that market competition in automobile insurance is not adequate to protect consumers. Moreover, some assert that CBIS exacerbate market problems, especially during hard economic times. As the COVID-19 pandemic retards economic activity, the same questions and comments emerge, increasing the relevance and timeliness of our research.

We address these concerns by measuring insurer reactions to an exogenous shock to credit information caused by the economic recession that occurred from 2007 through 2011. We demonstrate that, in a noncompetitive market, insurers could have increased profits beyond efficient equilibrium levels during this period via tacit collusion. They only had to maintain their existing pricing coefficients to increase profits.

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Evidence is not consistent with insurers participating in tacit collusion. In fact, we estimate a *negative* correlation between credit risk and the price of automobile insurance, suggesting not only do insurers recalibrate models to incorporate new information, but increased accuracy from new information allows them to decrease price. In support of this hypothesis, we find a negative relation between variation in credit risk and a measure of pricing accuracy at the firm-state level.

Our results and conclusions differ from those of extant literature. Previous papers find evidence of price dispersion in personal automobile insurance markets, which they attribute to search costs that dampen competition. Others find a positive correlation between market concentration and profit, suggesting collusion in these markets drives prices above a fair market equilibrium. In contrast, we find that automobile insurance markets are highly competitive. In addition, we find negative correlation between market concentration and price. We attribute the differences between our findings and those of prior studies to advances in technology that decrease search costs for automobile insurance consumers and information costs for insurance companies.

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