Loss Ratio Dynamics

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Abstract

Most studies of the insurance profit cycle use industry-level annual data and focus on the existence of an AR(2) process. We take a different approach by adopting the idea of possible hard and soft markets, but that they are not necessarily cyclical in the classic sense. In addition to aggregated data, we use quarterly firm-level data to examine loss ratio behavior over time. This approach allows one to assess the degree of firm-level heterogeneity found in the insurance market. We further use a Markov switching model to assess the heterogeneity of response to economic variables. Using a K-means cluster approach, we examine the different clusters of firms and their different behavior over 2001q1-2020q4.

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Abstract

Most studies of the insurance profit cycle use industry-level annual data and focus on the existence of an AR(2) process. We take a different approach by adopting the idea of possible hard and soft markets, but that they are not necessarily cyclical in the classic sense. In addition to aggregated data, we use quarterly firm-level data to examine loss ratio behavior over time. This approach allows one to assess the degree of firm-level heterogeneity found in the insurance market. We further use a Markov switching model to assess the heterogeneity of response to economic variables. Using a K-means cluster approach, we examine the different clusters of firms and their different behavior over 2001q1-2020q4.

I. Introduction

Boyer, Jacquier, and Van Norden (2012) present the case for the non-existence of profit cycles in the property-liability insurance market. We usually think of cycles as something akin to a sinusoidal wave with a periodicity and a degree of predictability. Since Boyer, Jacquier, and Van Norden (2012), there have been no papers to argue these types of cycles exist.[1] Boyer and Owadally (2015) go further, and state "Insurance profitability cycles may, of course, exist in some lines, in some countries and for some time periods. However, the evidence is that they are not of the predictable linear autoregressive character that is ascribed to them." Other recent research (Barinov, Xu, and Pottier, 2020) examines various cycle-related economic variables to see whether they influence asset pricing for insurers. Barinov *et al.* find little evidence of cyclic-related variables influencing asset prices and argue the marginal investor is well diversified and can easily avoid any industry-specific risk. Thus, evidence suggests there are no predictable cycles, and even if they do exist, they do not influence investor behavior. Nonetheless the literature is full of papers talking about the existence of cycles.

[1] We did not find any—but it does not mean they do not exist.

Economic conditions or loss shocks are thought to influence the existence of hard markets (prices and profits increase abruptly and less coverage is available) or soft markets (prices and profits are stable or falling and coverage is readily available) (Harrington, Niehaus, and Yu 2013). Research exists (see Gron, 1994a, 1994b) and (Winter 1994)) that attempts to explain problems like the 1980s liability crises by examining sensitivity to loss shocks.

In terms of other economic conditions, Doherty and Garven (1995) examine the effect of interest rates, Grace and Hotchkiss (1995) look at the effect of GDP, short term interest rates, and inflation on profit cycles, Haley (1995) examines the effects of interest rates on individual lines of business. Boyer et al. (2012) use GDP growth, inflation, and stock returns to see if they influence the cycle and claim that the data follows a time series process that cannot develop a profitable investment strategy. Harrington, Niehaus, and Yu (2013) conclude after a thorough review of the literature that the perfect markets model does not explain variation in premiums and that additional work needs to be done to understand insurance price dynamics. Henriet, Klimenko, and Rochet (2016) model the dynamics of insurance prices using a competitive market with some fictions. Their results suggest there are no cycles but shifts in prices due to exposures to aggregate risks. Thus, there are hard markets and soft markets, but not cyclical changes in pricing or profitability over time.

From a time series perspective, the literature has focused on the existence of an AR(2) process in the annual measure of profitability. One strength (that may be a problem) with many of these papers is that they look at long series of annual data (perhaps over 50 years). From a historical perspective, that is interesting, but different market conditions exist that are essentially one-time events. We can learn from these temporal-institutional settings, but they often are not the types of events that repeat. For example, one of the rationales for the existence of cycles was regulatory delay (Venezian 1985). One can argue that the regulatory delay from the 1950-1970s in the U.S. is primarily gone as fewer American states regulate so strictly and that there have been process and deregulatory improvements (See, e.g., Klein (1996) and Harrington (2000)). This deregulatory change is especially true in auto insurance with accounts for nearly 40 percent of premiums written per year. Examining quarterly rather than annual data and looking at a period running two decades should allow one to see cycles if they exist within the typical period found in the literature. Further, we do not have to wait for changes in regulation or other events as we can use economic variables that reflect the state of the economy or the presence of market frictions to assess their influence on the potential cycle.

Aggregation bias is a well-known problem in macro-economic data (Blundell and Stoker 2005). Industry-level data has the potential to hide differences in firm opportunity sets that affect equilibrium prices and output. Using individual firm results could show heterogeneity among the firms in the industry. While not modeled as such here, it is an approach used to assess the cyclicality of macro business cycles (Kaplan and Violante 2018).

Instead of using annual data at the industry level, we use quarterly firm-level data spanning 80 quarters. This granularity may be preferred because we can examine effects within recent periods, and we can focus on economic or natural catastrophes that might arise during our recent past and *are likely to be like those* in the near future. Thus, looking at a relatively contemporaneous series might provide more helpful insight into *firm* behavior from a predictive standpoint. In addition, we can assess the extent to which the annual industry-level data is consistent with what is happening at the firm level.

A set of papers using the methods similar to those here are Higgins and Thistle (2000) and Feng et al. (2017), who use long annual periods but attempt to discern differences in hard or soft markets by using a Markov switching model to asses the possibility of different regimes existing over time. We use a Markov switching model for similar reasons to determine if there are different regimes and then look at the change from one regime to another. Since profitability is not predictable and not cyclical, we need to determine if different regimes are operating within the data and, to some extent, whether they are predictable.

As a preview, we find four states may exist between 2001 and 2020 in both industry-level and firm-level data. The four states are bounded by a low loss ratio state and a high loss ratio state. Two intermediate states exist within the boundaries, but while statistically significantly different from the low loss ratio state, they may not be discernible as being different from the loss ratio state. Looking specifically at a firm-level two-state model with switching variables related to economic conditions, we find that the two states are distinct. Further, changes in GDP, capacity (Surplus), exposure to catastrophes, the cost of liquidity, and the long-run interest rate premium are related to being in state 1. In contrast, the probability of being in state 2 is influenced by changes in capacity, loss adjustment expenses & Commissions, and the long-run interest rate premium.

Because we have individual data for each firm, we create a sample that looks at the two-state model with economic switching variables. These firms represent about 56 % of the premium volume over the period. We find a large amount of heterogeneity in the firms, as shown by a K-means cluster analysis of the mean loss ratios in each state. This heterogeneity may suggest that the macro loss ratio series aggregates different sets of incentives affecting individual firms. Further, the clusters are related to some firm characteristics.

The rest of the paper is organized as follows. The following section contains a brief overview of a Markov switching model. The data is describe in Section III and provides some insight into the quarterly time series we use, while section IV provides the estimation results and discusses their meaning. Section V concludes.

II. Markov Switching Model

A switching model supposes that there are a number of finite states with a structure like the following:

$$\begin{aligned} s_1 &: LR_t = \mu_1 + \varepsilon_t^1 \\ s_2 &: LR_t = \mu_2 + \varepsilon_t^2 \end{aligned} \qquad (1)$$

where μ_i are the intercept terms for each state *i* and ε_t^i are white noise terms with variance σ_i^2 , and s_i is state *i*. If we know the dates of a regime or a state change (due to introducing a new capital standard, for example), we could use dummy variables to separate the regimes and estimate this relationship by OLS. However, if we do not have any "date," the existence of a state becomes a latent variable and can be estimated using a Markov switching model where parameters may vary across a finite number of states. Because the likelihood of being in state *i* is probabilistic, we can obtain these probabilities and the transition probabilities (of moving from state 1 to state 2). We follow Hamilton (1990) and Frühwirth-Schnatter (2006), who use the E.M. algorithm to estimate starting values and then estimates a probability of being in state *i* by maximum likelihood. A general representation of the Markov switching regression is:

$$LR_t = \mu_s + \mathbf{X_t \alpha} + \varepsilon_s \qquad (2)$$

where L.R. is the industry (or firm) quarterly loss ratio at time t, μ_S is the state-dependent intercept, $\mathbf{X}_t$ is a vector of state-dependent variables (such as a change in GDP or a change in interest rates) with coefficients $\boldsymbol{\alpha}$ and ε_S is an iid normal error $\sim N(0, \sigma_S^2)$. First, we estimate a restricted model like that shown in equation (1), allowing only the mean level of the loss ratio to differ between the two states (hard-market with low loss ratio/high profits and soft-market with a high loss ratio/low prices). We estimate these models with a presumption that the variances differ between the two states. We then estimate a model like that shown in equation 2 with a set of economic variables that help predict the state. We do this for both the industry level and each firm in the sample.

III. Data

We have quarterly data from S&P Market Intelligence (S&P MI) for the loss ratio from 2001q1 – 2020q4.[2] In addition, we have several other series that we will use.[3] Our sample consists of all firms operating in each quarter from 2001q1-2020q4 with positive loss ratios (both direct premiums earned and direct losses incurred are positive). Table 1 shows the descriptive statistics. The data here represent about 58 percent of all direct premiums earned during this period. Firms that were eliminated were absent any time between 2001-2020, and those firms with negative premiums or negative losses in any quarter. This filter does create a potential survivor bias problem, but firms need to have data to estimate the likelihood of being in various states. We undertake a robustness test described below to see whether this potential bias assumption matters or how much it matters.

[2] The NAIC had published quarterly data back to 1993, but many firms are missing quarterly statements. S&Ps data since 2001 which are from the NAIC appear complete.

[3] The NAIC's quarterly statements collect a subset of the data collected by the annual statements. Premiums and losses are collected as well as expenses, total assets, surplus, and net income.

Table 1 Quarterly Summary Statistics, 2001q1-2020q4

	N	Mean	Min	Max	Std. Dev
Loss Ratio	46,960	.595	.002	61.839	.434
Direct Premiums Earned	46,960	128809.35	1	10247094	434071.99
Direct Losses Incurred	46,960	78749.417	.558	10649185	292358.51
Net Income	46,960	8715.261	-1774882.5	3969802.9	69734.517
Total Admitted Assets	46,960	1252538.5	469.511	1.939e+08	6275064.9
Capital & Surplus	46,960	522863.63	-3699.881	1.261e+08	3333301.9
LAE, Commissions & Other Expenses	46,960	105425.19	-10504.738	14053184	589555.11

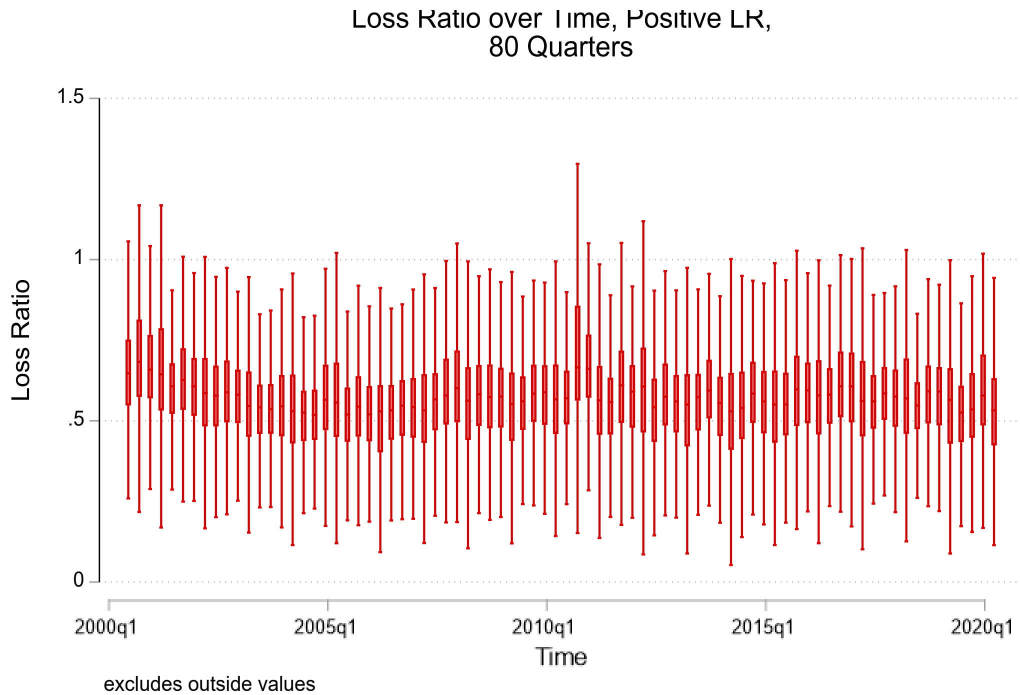
Figures are reported in $(000)s. The loss ratio is the ratio of direct losses incurred to direct premiums earned. Both are from the underwriting results exhibit in the NAIC quarterly statements. Net income is statutory net income from the NAIC quarterly income statement. Total Admitted Assets is from the asset page of the quarterly statement. LAE, commissions, and other expenses also come from the liabilities and surplus exhibit. These data were obtained from S&P Market Intelligence.

The summary statistics in Table 1 show the quarterly loss ratio, direct premiums earned, and direct losses incurred. These last two variables are the loss ratio components, calculated as the direct losses incurred/direct premiums earned. We also provide the quarterly statistics for net income, total assets, capital & surplus, and loss adjustment expenses (LAE), Commissions, and Other expenses. This last item is expenses and they may be unpaid or accrued and thus can have negative entries. One thing to note is that there is more volatility in the quarterly loss ratio series than is typically seen in annual loss ratio data. For example, the annual loss ratio volatility is .250 as measured by the standard deviation at the year firm level, while the minimum is .04 and the maximum is 15.27. In contrast, the quarterly loss ratio volatility is .434, with a maximum of 61.84.

Figure 1 shows a box chart over time of the loss ratio.[4] This figure summarizes the distribution of the loss ratio focusing on the density part of the distribution. Extreme outliers (outside the box range) are omitted from the chart so one can see how the distribution behaves near the median over time. This figure contains the firms with positive loss ratios in each

[4] A similar chart is in the appendix for the entire set of firms without any filters. It looks similar, but its range of loss ratio is greater.

Figure 1 Distribution of Loss Ratio over Time for Firms with a Positive Loss Ratio



quarter.[5] Figure 2, in contrast, shows the quarterly industry aggregate amounts for the Average Loss Ratio and the Median Loss Ratio over time. We focus on both the individual firms and the industry-level aggregated figures in the next section.

[5] The loss ratio is direct losses incurred over direct premiums earned. Direct losses incurred is an estimate of the losses or the amount due to policy owners. If the loss estimate decreases significantly or reserves are reduced to lower expected losses, it could make the direct losses in a given quarter negative.

Figure 2 Industry Aggregate Loss Ratio Distribution over Time

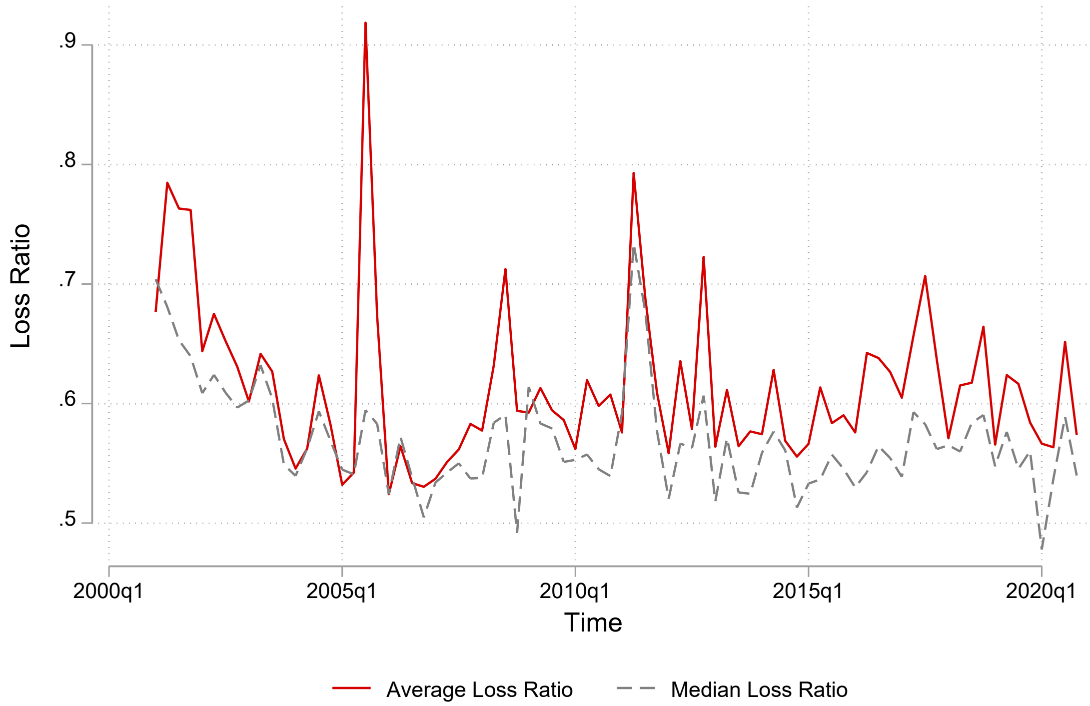


Figure 2 shows a spike in the average loss ratio in 2005q3, most likely due to Hurricane Katrina. Figure 1 and Figure 2 suggest one might be hard-pressed to see "cycles." Looking at the median Loss Ratio over time, one sees a decline from 2001q1 to 2005q1 and then a relatively flat period with occasional spikes following Katrina.

IV. Estimation of Switching Models

A. Introduction

Our approach here is to estimate a model at the industry level and then examine the underlying firm-level behavior by estimating a similar model for each firm. First, we examine a switching model based on Equation 1, where we look at whether there are any possible states excluding economic variables that might help separate loss ratio behavior into differing states. Table 2 shows the results of this exercise. Panel A in Table 2 shows the mean level of the Loss Ratio (μ_i) for state *i*. Models for various numbers of states are estimated. Several essential items come from Panel A. The switching model successfully estimated models with 2, 3, and 4 states. The four-state model has the lowest SBIC, which suggests that it is the proper model. Before going further, though, let us look at Column 2 of Panel A. The mean loss ratio for State 1 is .59, and the mean loss ratio for state 2 is 0.70. There is a statistical separation between a low loss ratio regime and a high loss ratio regime. [6]One can see that in column 3 that the mean for state 1 is statistically different from the mean for state 2 at the 95th confidence level as there is no overlap. This estimate suggests a high loss ratio regime and a low loss ratio regime, and they are different. This pattern could correspond to a cycle or an economically driven change from high to low loss ratios that are not smooth or necessarily forecastable.

Looking at Panel B of Table 2, we see the estimated duration of the high and low loss ratio periods. State 1 is estimated to be 8.96 quarters (approximately 2.25 years), and state 2 is estimated to be about 2.6 quarters which is just over half of a year.[7] These results are much less than the periodicity estimates from the literature (See, Venezian (1985), for example, and the papers cited in Boyer, Jacquier, and Van Norden (2012)) which typically suggest 4-10 years.

If we now examine the Markov switching model for a three-state model, we see that the mean for State 1 is 0.542. If we compare that to the Three-State model and look at the 95 percent confidence interval in the brackets below the coefficient estimate, it is easy to see that the coefficients are different between the Two-State model and the Three-State model. In addition, the coefficients among the three states in the three-state model are also statistically different. We do not see a difference if we compare the coefficient in the Three-State model for State 3 and the coefficient for the two-state model in State 2. We see a high loss ratio state in

[6] Below the coefficient in the brackets are the upper- and lower-95 percent confidence intervals (CI). We use the CI rather than a standard error to make it easier to see that the evidence suggests the coefficients are distinct.
[7] Duration is defined as $1/(1-p_{ii})$.

the Three-state model and two distinct lower loss ratio states. Going to the Four-state model, we see that the State 1 mean is about the same as the state 1 mean for the Three-state model. In addition, the high loss ratio states in each model have approximately the same mean (see the bolded coefficients on Table 2 Panel A, which are the high loss ratio states' means). Thus, the State 4 mean is similar to the State 3 mean in the Three-state model, which is about the same as the State 2 mean loss ratio in the Two-state model. Thus, the Four-state model has a high and low state with two intermediate states. What is possible is that the market can discern a high loss ratio state and a low loss ratio state but cannot discern intermediate states or does not believe that there is a difference except between the high and low loos ratio states.

Another item to note is that in Panel B of Table 2, we see the duration for the various states. As we estimate greater numbers of states, the length of the duration falls. This reduction induration is not necessarily a general rule, but it is true of this loss ratio data. Researchers do not expect to see multiple states with very low durations as evidence of cyclicality. This short duration is suggestive of the notion of shocks influencing the switch to a different state.

Table 2 A. Markov Switching Model for various States.

	(1) Four States	(2) Three States	(3) Two States
State1			
μ_1	0.539***	0.542***	0.590***
	[0.531,0.547]	[0.530,0.554]	[0.578,0.602]
State2			
μ_2	0.570***	0.597***	**0.703***
	[0.565,0.574]	[0.585,0.609]	[0.653,0.752]
State3			
μ_3	0.613***	**0.710***	
	[0.602,0.624]	[0.659,0.760]	
State4			
μ_4	**0.718***		
	[0.668,0.767]		
N	80	80	80
SBIC	-2.380	-2.556	-2.734

Note: 95% confidence intervals in brackets based on robust standard errors.
* $p < .1$, ** $p < .05$, *** $p < .01$ based on robust standard errors.

Table 2 B. Markov Switching Model Estimated Durations for various States (in Quarters)

	(1) Four States	(2) Three States	(3) Two States
State 1	1.91	3.97	8.96
State 2	1.00	8.21	2.58
State 3	2.15	2.52	
State 4	2.45		

We could theoretically estimate additional models with more than two states,[8] but it may be that economically there are only two states of the world that matter (high loss ratio/low prices and low loss ratio/ high prices). Figure 3 shows that the high state transition probabilities for each year are similar. This figure implies that there is a common high loss ratio state.

To see if other indicators help select the number of states, we create a simple counting index of the number of articles with the term "soft market" that appeared in either *A M Best's Review* or *Business Insurance* during the sample period 2001q1 - 2020q4. By counting the number

[8] With this data, a four-state model was the highest number of states where convergence is obtained in the maximum likelihood optimization.

of articles that mention the term "soft market" in each quarter, one can obtain evidence of how the press and commentators view the cycle of profits or losses.[9]

Figure 3. Estimated One Step Probabilities over Time for High Loss Ratio State for Two-state & Four-state Models.

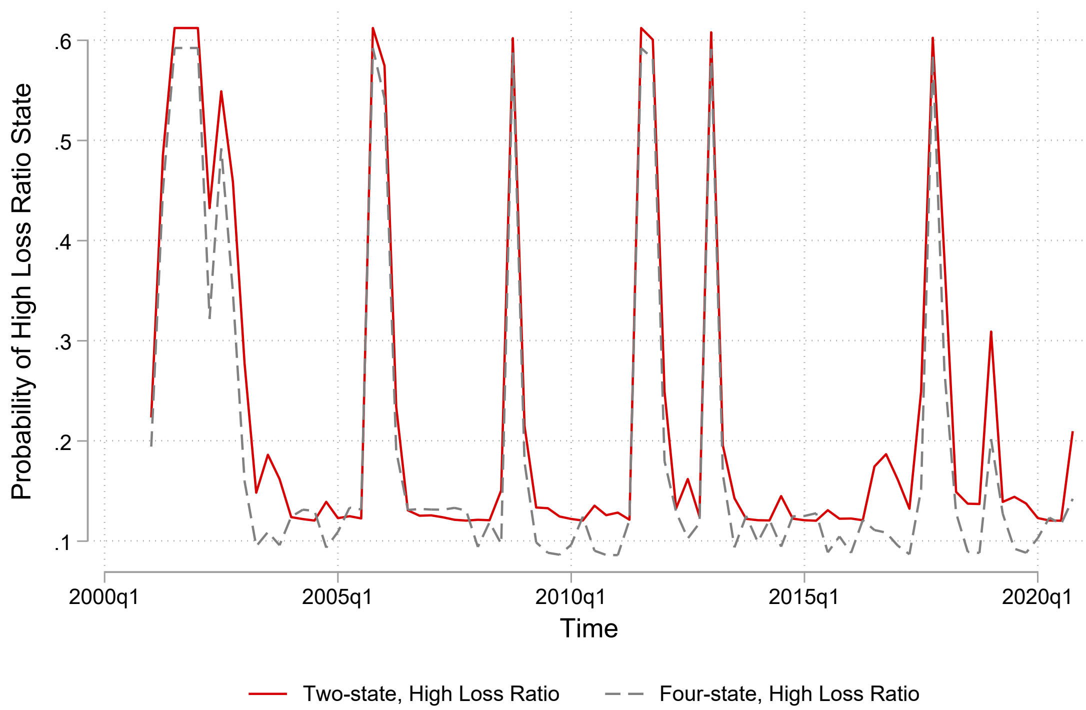


Figure 4 shows the number of mentions over time. We see a peak in the late decade of the 2000s and nearly zero mentions during 2015-2020. If we undertake a Markov switching model with the Log(#count of Articles with Mentions), we can see whether the market expects there to be 2 or more states of the "cycle."[10] Using this series, we could only estimate a two-state model as models with more states would not converge.

Table 4 shows the results of this estimation. First, we see that the number of articles discussing soft markets is different between the two periods. Again, the bracketed numbers

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[9] There are other periodicals that also exist, but we need a complete series over the period and that was focused on P&C lines.

[10] We use the actual number of articles rather than the log and obtained qualitatively similar results. We use the log specification to account for the fact that the dependent variable is a count.

below the coefficient are the confidence intervals, and they do not overlap between the states.[11] The mean number of articles in state 1 is 3.09 = $e^{(1.130)}$, and for state 2, the mean is 14.76. State 2 discusses soft markets more often, and this would be associated with the high loss ratio periods. Thus, this is consistent with the Loss Ratio switching models shown in Table 2, where the distinct high loss ratio state is shared across all models. However, what is interesting is that the duration of the states is very high relative to the loss ratio models. For example, when the number of articles is low (hard market with a low loss ratio), the duration is estimated to be 70.5 quarters or over 17.5 years. In contrast, state 2 has a duration of just over 21 years. These estimates are both much higher than the estimated periodicity of cycles mentioned above.

Table 3. Markov Switching Model for Log of Number of Articles in *AM Best Review* or *Business Insurance* mentioning "Soft Market."

	Two-State
State1	
μ_1	1.130^{***}
	[0.943, 1.317]
State2	
μ_2	2.692^{***}
	[2.557, 2.826]
Duration State 1 (in quarters)	70.46
Duration State 2 (in quarters)	85.05
N	80.000
SBIC	1.729

95% confidence intervals in brackets using robust standard errors.
* $p < .1$, ** $p < .05$, *** $p < .01$ using robust standard errors.
Estimated variances are omitted but are significantly different from zero *and* each other. Estimated transition probabilities are omitted but are used to construct the duration measure shown.

[11] A standard test of a difference in the coefficients not being zero is significant at the 95% level.

B. Industry Level Switching Model

Our next step is to estimate a switching model with economic variables that hypothetically influence whether the loss ratio is in a high loss ratio state or a low one. We employ several variables related to the state of the economy, including those shown in Table 5. We are trying to discern the economic indicators that might be consistent with the capacity constraint theory, such as that a shock to the market might be the source of a price increase. We obtained the Actuarial Climate Index from a research project supported by the major actuarial societies, which measures several climate sub-indices, including wind, rain, drought temperature, and sea level, to account for natural disaster shocks.[12] GDP Scaled is the Real GDP (in $2012) from the Federal Reserve Economic Data (FRED) service and scaled by its mean. Capacity scaled is the premium to surplus ratio divided by its mean—the premiums and the surplus from the NAIC quarterly statements provided by S&P Market Intelligence. Scaled expenses are the loss adjustment expenses, commissions unpaid and accrued, and other expenses from the NAIC Quarterly statement and then scaled by its mean. The TED spread is the difference between the 3-month LIBOR rate in $ and the 3-month T bill rate obtained from FRED. The 10-year Treasury - 2-year Treasury is also obtained from FRED and measures the difference between long-term and short-term rates on a constant maturity basis.

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[12] See https://actuariesclimateindex.org/home/.

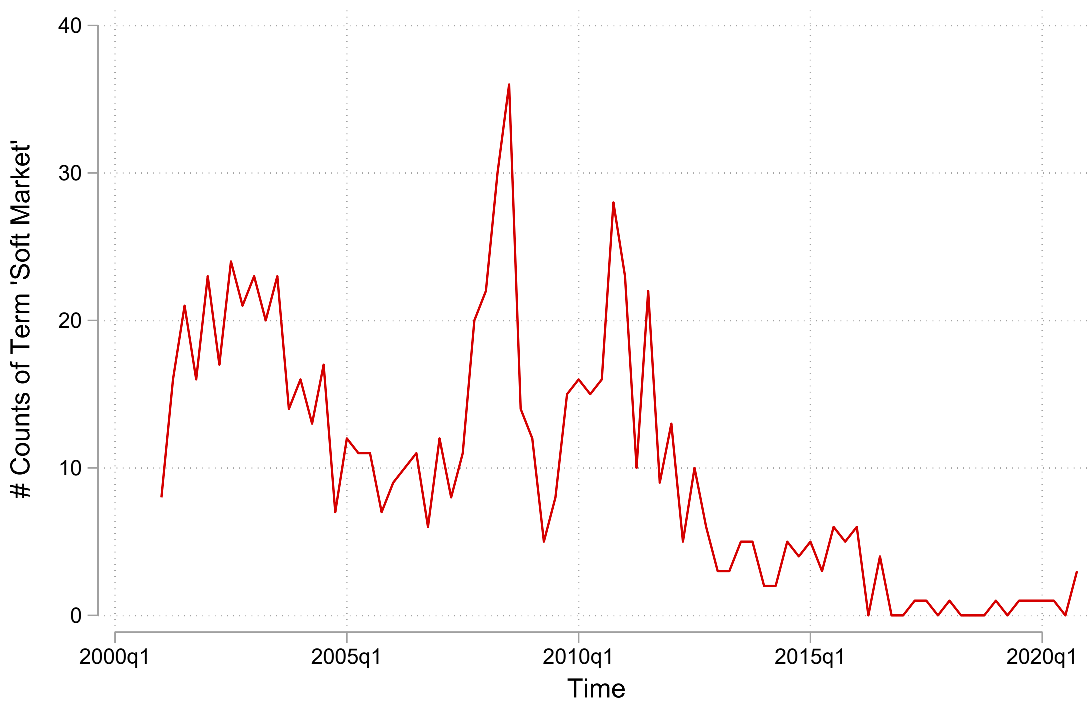
Table 4. Economic Variable Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Actuarial Climate Index	.811	.534	-0.6	1.910
GDP Scaled	1.000	.106	.821	1.195
Capacity (P/S) Scaled	1.000	.156	.815	1.376
Scaled Expenses	1.000	.198	.574	1.357
Unemployment Rate	6.088	1.971	3.6	13.067
TED Spread ~3 mo Libor - 3 mo T	.407	.366	.132	2.447
10 Yr Treas - 2 Yr Treas	1.35	.859	-0.107	2.80

N = 80 except for Actuarial Climate Index, where the N=79. GDP Scaled is the Real GDP ($2012) from FRED scaled by its mean. Scaled Capacity is direct premiums earned over surplus from the quarterly NAIC annual statement and scaled by its mean. The unemployment rate is the percentage of people unemployed divided by the number of people seeking work from FRED. The Actuaries Climate Index is a climate index for extreme temperatures, rainfall, drought, wind, and sea level obtained from actuariesclimateindex.org. Scaled expenses are loss adjustment expenses, commissions, and other expenses quarterly from the NAIC quarterly statement. The Ted spread is the difference between the 3-month LIBOR rate in $ U.S. and the 3-month T bill rate obtained from FRED. The 10-year Treasury - 2-year Treasury is obtained from FRED and measures the difference between long-term and short-term rates on a constant maturity basis.

The entire set of economic variables are designed to offer an empirical rationale for separating the loss ratio series into multiple states. A change in the Actuarial Climate Index may be related to a reduced supply which may increase prices. A positive change in real GDP may indicate an increase in demand for all goods and services, increasing prices. A change in capacity can also be related to the prices of insurance services, and as the supply of insurance increases in capacity, prices would fall. A change in unemployment can also be related to a change in demand for services. An increase in unemployment could be related to decreased working and a reduction in work-related activities. This change, in turn, might reduce losses (reduction in auto accidents or work-related injuries) or the cost of loss. A change in the TED spread would reflect a change in the price of liquidity, affecting profitability and the firm's ability to pay short-term obligations. The ten-year Treasury rate – the two-year Treasury rate reflects the term structure of interest rates. If negative, short rates are greater than long rates and may reflect a higher cost of providing insurance capital for short-tail lines.

Figure 4 Count of "Soft Market" Mentions in Articles by Quarter from Best's Review and Business Insurance



Our next Markov switching model is a two-state model with economic variables which influence the state (low loss ratio versus high loss ratio). We see that the mean (μ) differs between states. In addition, we see that nearly all the economic variables differ between the two states.

Table 5. Industry Level Markov Switching Model with Economic State-Dependent Explanatory variables. Dependent variable is the Quarterly Loss Ratio.

Variable Name	State 1	State 2
Δ.GDP Scaled	1.616***	0.996
	[0.640,2.592]	[-2.867,4.859]
Δ.Capacity (P/S) Scaled	1.085***	0.659**
	[0.959,1.210]	[0.140,1.178]
Δ.Unemployment Rate	0.005	0.007
	[-0.013,0.023]	[-0.039,0.054]
Δ.Scaled Expenses	0.136	0.681***
	[-0.064,0.337]	[0.175,1.187]
Δ.Actuarial Index	-0.020***	0.026
	[-0.029,-0.011]	[-0.012,0.065]
Δ.TED Spread	-0.011*	-0.003
	[-0.022,0.000]	[-0.068,0.062]
Δ.(10Yr Treas - 2Yr Treas)	0.029***	0.067*
	[0.012,0.045]	[-0.010,0.143]
μ	0.563***	0.622***
	[0.554,0.572]	[0.598,0.646]
Sigma σ^2 for State	0.009	0.058
	[0.007,0.013]	[0.037,0.091]
P_{11} | {State 1's Duration in Qtrs}	0.666	{2.996}
	[0.393,0.860]	
P_{12} | { State 2's Duration in Qtrs}	0.140	{7.139}
	[0.050,0.334]	
N	78.000	
SBIC	-2.163	

95% confidence intervals in brackets estimated with robust standard errors.

* $p < .1$, ** $p < .05$, *** $p < .01$ based upon robust standard errors. μ is the mean loss ratio for the state. Scaled GDP is the Real GDP ($2012) from FRED scaled by its mean. Scaled Capacity is direct premiums earned over surplus from the quarterly NAIC annual statement and scaled by its mean. The unemployment rate is the percentage of people unemployed divided by the number of people seeking work from FRED. The Actuaries Climate Index is a climate index for extreme temperatures, rainfall, drought, wind, and sea level obtained from actuariesclimateindex.org. Scaled expenses are loss adjustment expenses, commissions, and other expenses every quarter from the NAIC statement. The Ted spread is the difference between the 3-month LIBOR rate in $ and the 3-month T bill rate obtained from FRED. The 10-year Treasury – 2-year Treasury is obtained from FRED and measures the difference between long-term and short-term rates on a constant maturity basis. Duration for state i is $1/p_{ii}$. For state 1 this is $1/(1-P_{11})$ and for state 2 this is $1/p_{12} = 1/p_{21}=1/(1-p_{22})$.

C. Two State Switching Model for Each Firm

Using the approach shown in Table 6, we now estimate a Two-state model for each firm in the sample. Of the 587 firms in our sample, which account for approximately 60 percent of direct premiums written, 528 have estimated two-state switching models and account for 50 percent of the total market's direct premiums earned. We show summary results in the following table and figures. Table 6 shows a table of the descriptive statistics from the set of coefficients produced by a 2-State Markov switching model for each sample firm. The mean loss ratio in state 1 is less than the mean loss ratio in State 2, consistent with the industry results, but there is heterogeneity in the results. Looking at Δ.Scaled GDP, for example, in State 1, it has a negative mean implying that if the change in Scaled GDP increases, the loss ratio decreases. However, the distribution of the coefficient on Δ.Scaled GDP ranges from negative to positive, so even within State 1, a change in GDP affects firms differently. If we focus on two specific results, we can see this heterogeneity in more detail.

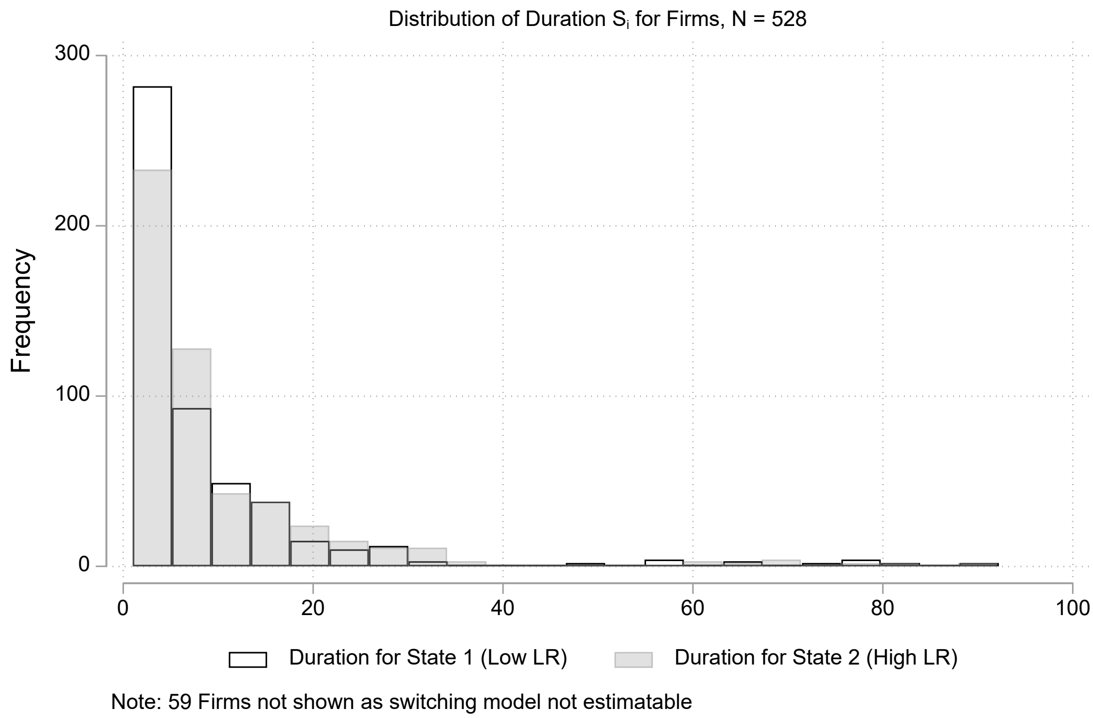
Table 6 Firm-Level Summary Statistics of 528 Firms Markov Switching Model Coefficients for a Two-State Model with Economic State Predictor Variables.

	Mean	Min	Max	SD
State 1				
Δ.Scaled GDP	-1.871	-41.339	21.835	6.847
Δ.Scaled Capacity	1.952	-25.66	56.676	5.36
Δ.Unemployment Rate	-.024	-.636	.39	.112
Δ.Scaled Expenses	-3324.084	-1886506.1	181723	82510.355
Δ.Actuarial Climate Index	.005	-.291	.386	.064
Δ.TED Spread	-.049	-1.193	.885	.175
Δ.10-year T rate – 2-year T rate	-.005	-.651	.534	.127
μ_1	.497	.049	.849	.106
State 2				
Δ.Scaled GDP	2.965	-491.32	809.673	50.127
Δ.Scaled Capacity	5.778	-255.628	744.362	38.669
Δ.Unemployment Rate	.036	-6.417	13.09	.814
Δ.Scaled Expenses	7021.402	-752900.81	4406784	194629.64
Δ.Actuarial Climate Index	.025	-3.318	3.624	.314
Δ.TED Spread	.092	-7.418	29.056	1.613
Δ.10-year T rate – 2-year T rate	.012	-5.794	6.954	.766
μ_2	.697	-1.738	8.633	.427
Duration State 1	9.725	1	92.217	14.717
Duration State 2	10.709	1	92.062	14.290

N = 528. Scaled GDP is the Real GDP ($2012) from FRED scaled by its mean. Scaled Capacity is direct premiums earned over surplus from the quarterly NAIC annual statement and scaled by its mean. The unemployment rate is the percentage of people unemployed divided by the number of people seeking work from FRED. The Actuaries Climate Index is a climate index for extreme temperatures, rainfall, drought, wind, and sea level obtained from actuariesclimateindex.org. Scaled expenses are loss adjustment expenses, commissions, and other expenses quarterly from the NAIC quarterly statement. The Ted spread is the difference between the 3-month LIBOR rate in $ and the 3-month T bill rate obtained from FRED. The 10-year Treasury – 2-year Treasury is obtained from FRED and measures the difference between long-term and short-term rates on a constant maturity basis. Duration for state i is $1/p_{ii}$. For state 1 this is $1/(1-p_{11})$ and for state 2 this is $1/p_{12} = 1/p_{21} = 1/(1-p_{22})$. μ_i is the constant intercept (the mean Loss Ratio) in state *i*.

First, Figure 5 shows the distribution of duration for each state. Just over 50 percent of the firms have a State 1 duration of 4 quarters. Just over 11 percent have durations longer than 5 years or longer (20+ quarters). For State 2, approximately 43 percent have durations of 1 year or less, and 12.5 percent have durations of 5 years or longer. For direct premiums earned, those with durations of less than 1 year (for both states) account for 11.5 percent of premiums, while those with durations for both states greater than 5 years account for almost 7 percent of the premiums earned. This is not evidence of an "insurance cycle" as there is significant heterogeneity among the firms.

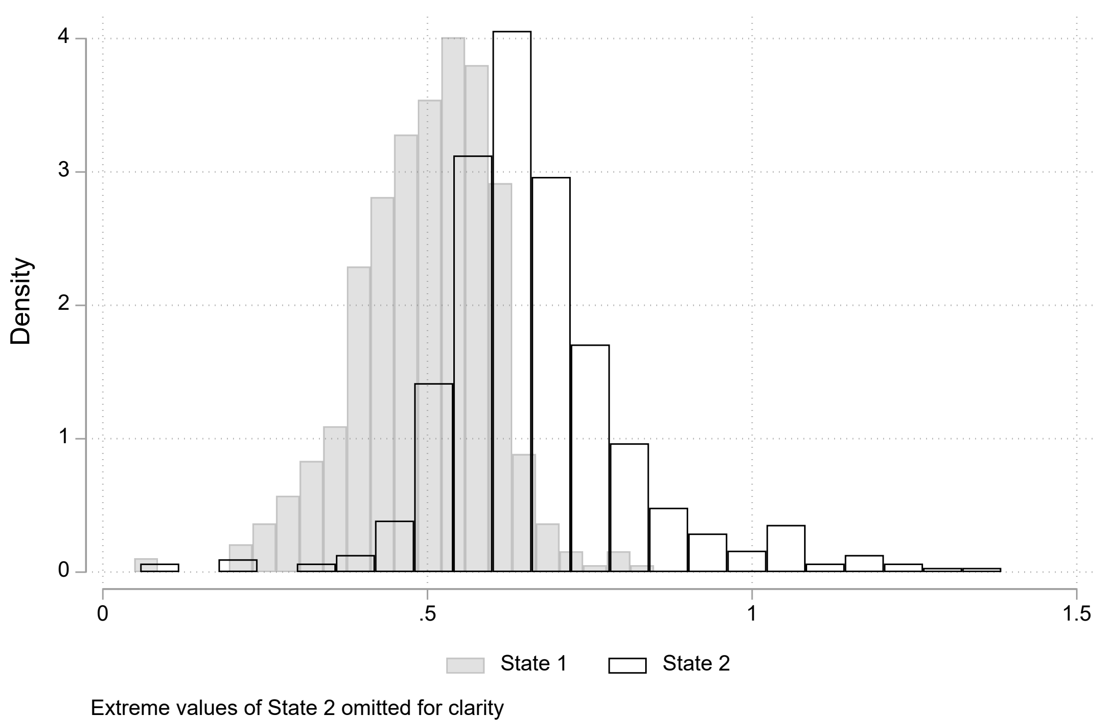
Figure 5 Histogram of Duration by State



Second, we can look at the distribution of the means (intercepts) for each state, reflecting the mean loss ratio. These distributions are shown in Figure 6. The mean loss ratio for state 1 is 0.497, and the mean for state 2 is .697. These are statically state-specific loss ratios are different at the 0.001 level (with 10,000 bootstrap replications). In addition, they strongly suggest the existence of a high loss ratio state and a low loss ratio state.

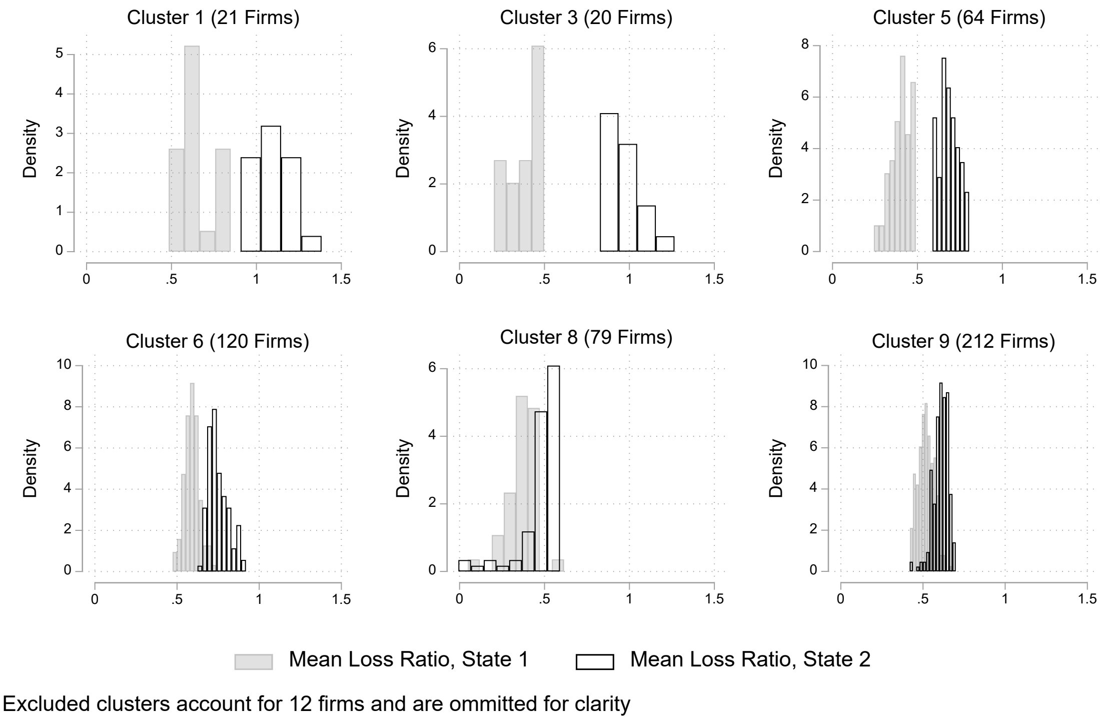
Given this distribution of low and high loss ratios, one might ask whether we can separate different types of firms. Using a K-means cluster analysis, we find different sets of firms with a pair(m1,m2) distinct from other pairs. While the researcher sets the number of clusters, it is possible to get the suggested number of clusters *a priori* by looking at various numbers of clusters from say 1-10 and then choosing one based upon a criterion such as Caliñski and Harabasz's (1974) pseudo- F index. This method suggests nine clusters. Figure 7 shows the histograms for each cluster (cluster 2 and cluster 7 are omitted for clarity as together they only had two firms). One thing to note is that each pair(m_1,m_2) is visually distinct (note that the y-axis is different for each graph). These clusters make it appear that the underlying firms behave differently across states and that aggregation (Figure 6) shows a much different distribution of the overall mean(m_1,m_2) compared to the clusters.

Figure 6 Histogram of Estimated Mean Loss Ratios for Each State



With cluster identification, it is possible to see if structural variables (organizational form, marketing, or business mix) might influence the likelihood of being in a particular cluster or the duration of being in a particular state. Table 7 shows some descriptive statistics of structural or institutional indices that might influence cluster membership.

Figure 7 Histograms of Estimated Mean Loss Ratio by Cluster



We present two ways to look at the classification by cluster. The first is to look at the descriptive statistics of the cluster. Thus, Table 7 (various panels) shows that:

- Cluster 9 (46 percent of premiums) is nationally oriented, mostly stock companies operating in personal lines with brokers or independent marketing channels. The duration for the low loss ratio state has a mean of 8 quarters, while the high loss ratio state has a mean of nearly 13 quarters.
- Cluster 6 (38 percent of premiums) is and is a mix of stocks and mutuals, has a personal lines focus, uses independent and captive agents, and has a national market focus, predominantly using brokers. The duration for the low loss ratio state has a mean of 10 and quarters, while the high loss ratio state has a mean of 9 quarters.
- Cluster 8 (6.2 percent of premiums), mostly mutual companies, writes predominantly in commercial property in the run-off lines (Geographically Minimum NPW) and uses a mixture of broker and independent agent distribution channels. The duration for the low loss ratio state has a mean of 5.6 quarters, while the high loss ratio state has a mean of 11.6 quarters.
- Cluster 5 (5.8% percent of premiums) comprises mainly stock companies with a Southeastern regional focus in personal lines with brokers as their distribution method. The duration for the low loss ratio state has a mean of 17.9 quarters (4.5 years), while the high loss ratio state has a mean of 14.9 quarters (3.6 years). This cluster is the only one that appears to have a periodicity in the range found using annual data aggregated to the national level.

- Cluster 1 (4 % of premiums) is primarily nationally focused stock companies in commercial lines with brokers as their predominant distribution channel. The duration for the low loss ratio state has a mean of 10 and quarters, while the high loss ratio state has a mean of 3 quarters.
- Cluster 3 (3.6 %) of the premiums and is commercial lines focus cluster with national market focus and stock companies as the predominant focus. It predominantly uses an Affiliate marketing system. The duration for the low loss ratio state has a mean of 9.9 and quarters, while the high loss ratio state has a mean of 2.8 quarters.
- Cluster 4 (0.53% of premiums) comprises stock companies, writing nationally or with run-offs and using brokers as a distribution network. The duration for the low loss ratio state has a mean of 12.5 and quarters, while the high loss ratio state has a mean of 2.1 quarters.

A second way to examine the cluster classification is to examine the probability of being assigned to a particular cluster. It would be nice to employ all the variables in Table 7 to help determine the variables associated with cluster assignment, but there is a large degree of sparsity among the descriptors. Many clusters only have stocks or mutual companies and no syndicates, for example.

We estimate a multinomial probit model to predict which variables are associated with a cluster. Thus we estimate

$$mProbit(Y = Y_i) = \mathbf{Z}'\mathbf{b} + e \text{ for cluster } i \quad (3)$$

where **Z'** is a matrix of explanatory variables and **b** is a vector of coefficients. Table 8 provides the marginal effects of this estimation. We employ a subset of the variables described in Table 7, the coefficient of variation of the loss ratio from 2001q1 – 2020q4, and the estimated duration for each state.

Table 7 Cross Tabulations by Cluster.

Panel A. Percent Distribution of Ownership Structure by Cluster

Ownership Structure	1	2	3	4	5	6	7	8	9	Total
Mutual Company	0.11		0.07	0.01	0.93	15.12		1.11	8.81	26.15
Reciprocal Exchange					0.01	2.89			2.51	5.41
Stock Company	3.92	0.07	3.51	0.52	4.18	20.03	0.04	5.07	30.28	67.60
Syndicate			0.11	0.01	0.72					0.84
Total	4.02	0.07	3.68	0.53	5.84	38.03	0.04	6.18	41.60	100.00

Panel B. Percent of Business Focus by Cluster

Business Focus	1	2	3	4	5	6	7	8	9	Total
Commercial Financial Lines Focus								0.03		0.03
Commercial General Liability Focus	0.18		0.09		0.03			0.58	1.05	1.92
Commercial Lines Focus	2.60		2.21		1.12	1.82		1.35	5.84	14.94
Commercial Medical Malpractice Focus	0.02									0.02
Commercial Property Focus	0.10		0.02	0.02	1.39	2.79		2.49	5.20	12.00
Commercial Workers Compensation	0.04				0.28	0.33		0.05	0.47	1.16
Large Reinsurance Focus			0.04							0.04
P&C Minimum NPW	0.53		0.65	0.24	0.62	4.68		1.07	5.55	13.34
Personal Lines Focus	0.58	0.07	0.67	0.27	2.40	28.41	0.04	0.62	23.49	56.55
Total	4.02	0.07	3.68	0.53	5.84	38.03	0.04	6.18	41.60	100.00

Panel C. Percent of Firms by Size (by Decile of DPE) and Cluster

Dir Premiums Earned Decile	1	2	3	4	5	6	7	8	9	Total
1	0.19		0.38	0.76	1.70	1.33		3.03	2.46	9.85
2	0.38		0.95	0.19	2.46	1.70		1.89	2.84	10.42
3	0.95		0.38	0.38	0.76	3.03		2.08	2.27	9.85
4	0.19			0.38	1.33	3.41	0.19	1.70	3.60	10.80
5	0.95			0.38	0.95	2.27		1.14	4.55	10.23
6	0.19	0.19		0.19	1.52	2.27				
7	0.19		0.38	0.38	1.14	2.08		1.70	3.60	9.66
8	0.19			0.19	1.14	2.27		1.14	4.92	10.23
9	0.38		0.19	0.19	0.57	1.70		0.57	6.44	10.04
10	0.38		0.38		0.57	2.65		0.57	4.73	9.28
Total	3.99	0.19	3.79	1.89	12.12	22.73	0.19	14.96	40.15	100.00

Panel D. Percent of Firms by Marketing Focus and Cluster

Marketing Focus	1	2	3	4	5	6	7	8	9	Total
Broker	0.97	0.00	0.97	1.36	3.69	7.38	0.19	3.69	12.43	30.49
Captive Agent	0.39	0.00	0.19	0.19	0.39	3.50	0.00	0.39	2.72	7.77
Managing Gen Agent	0.39	0.00	0.39	0.00	1.36	1.36	0.00	2.14	3.11	8.74
Independent	1.17	0.19	1.17	0.39	6.02	6.60	0.00	6.21	14.56	36.31
Direct Marketing	0.39	0.00	0.39	0.00	1.17	0.00	0.00	0.97	1.75	5.24
Affinity Marketing	0.58	0.00	0.78	0.00	0.00	2.72	0.19	0.97	6.02	11.46
Total	3.88	0.19	3.88	1.94	12.62	21.55	0.39	14.37	40.58	100.00

Panel E. Statistics for Duration for States 1 and 2 by Cluster

		Duration State 1					Duration Sate 2				
Cluster	N	Mean	Median	Min	Max	SD	Mean	Median	Min	Max	SD
1	21	10.816	11.941	1.367	81.136	9.381	2.972	2.106	1.000	72.104	7.807
2	1	9.524	9.524	9.524	9.524	-	1.537	1.537	1.537	1.537	-
3	20	9.905	10.970	2.375	72.998	4.384	2.881	2.834	1.000	13.874	1.268
4	10	12.570	10.890	5.264	29.179	5.983	2.101	1.678	1.000	5.624	1.266
5	64	17.868	7.306	1.000	85.451	22.170	14.190	8.372	1.000	87.930	16.691
6	120	10.679	5.855	1.000	88.318	14.814	9.302	6.257	1.000	80.501	12.348
7	1	12.060	12.060	12.060	12.060	-	2.120	2.120	2.120	2.120	-
8	79	5.584	3.982	1.000	92.217	7.310	11.649	8.179	1.000	92.062	9.116
9	212	8.104	4.342	1.000	78.812	10.446	12.903	8.465	1.000	85.621	13.769
Total	528	9.700	5.855	1.000	92.217	13.057	10.692	6.257	1.000	92.062	12.980

All tables' percentages are weighted by Direct Premiums Earned by firm except for Panel C, which is size as measured by Direct Premiums Earned. Ownership structure, Business Focus are from the S&P MI database are from its classification of firms from the NAIC data. Duration is estimated from the two-state model shown in Table _, and Direct Premiums Earned are the direct premium earned from the NAIC quarterly statement.

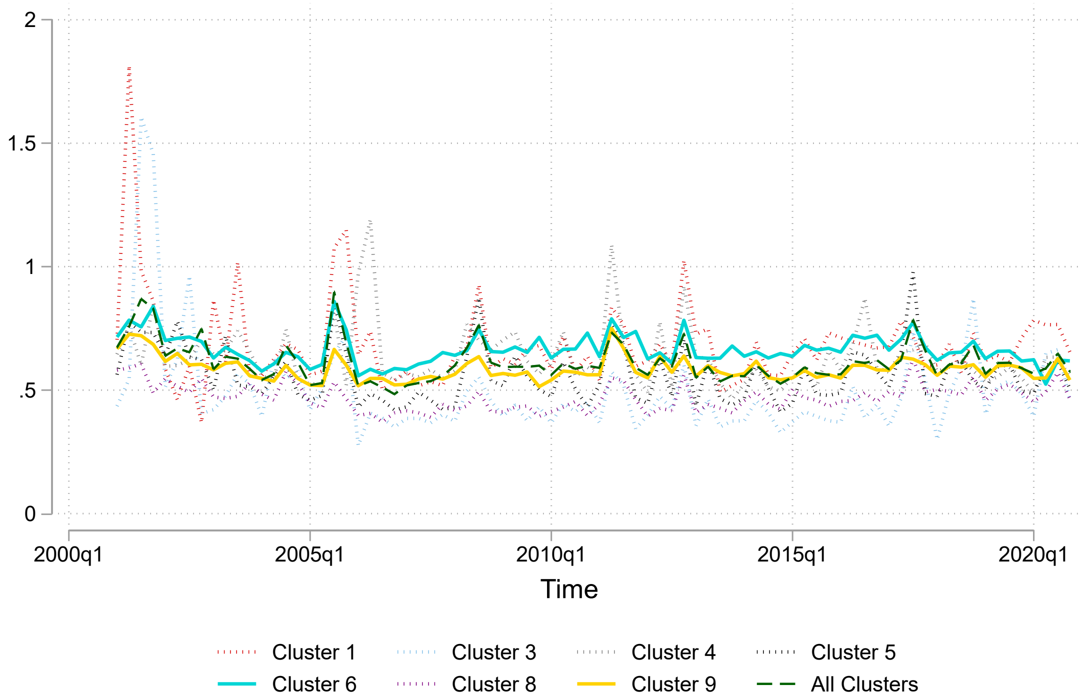
Table 8 Marginal Effects from Multinomial Probit Model by Cluster

	Log of Direct Premiums Earned	National Market Firm	Stock Company	C V Loss Ratio	Log of Duration 1	Log of Duration 2
Cluster 1	-0.007	0.023	0.037	0.003	0.032**	-0.033***
	(0.006)	(0.020)	(0.021)	(0.006)	(0.010)	(0.010)
Cluster 3	0.001	0.023	-0.025	-0.032***	0.018*	-0.024*
	(0.006)	(0.025)	(0.016)	(0.010)	(0.009)	(0.009)
Cluster 4	-0.006	-0.001	0.012	-0.007*	0.034**	-0.031**
	(0.004)	(0.016)	(0.012)	(0.004)	(0.012)	(0.011)
Cluster 5	0.002	0.022	-0.020	-0.068***	-0.020	0.064***
	(0.009)	(0.038)	(0.028)	(0.017)	(0.012)	(0.016)
Cluster 6	0.013	-0.157**	0.023	0.052***	0.074***	-0.078***
	(0.013)	(0.051)	(0.039)	(0.009)	(0.016)	(0.018)
Cluster 8	-0.031*	0.054	0.010	-0.042*	-0.052**	0.061***
	(0.013)	(0.040)	(0.032)	(0.017)	(0.017)	(0.017)
Cluster 9	0.027	0.037	-0.037	0.094***	-0.087***	0.041
	(0.015)	(0.053)	(0.042)	(0.012)	(0.019)	(0.022)
Observations	526					

Robust Standard errors in parentheses. Clusters 2 and 7 are omitted due to too few observations.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Log of direct premiums written is the log of direct premiums written from the NIAC quarterly statement from S&P MI. National Market firm denotes the category given by S&P MI for the companies' geographic focus. Stock Company is the NIAC's ownership category for the firm. CV Loss Ratio is the coefficient of variance of the loss ratio over the period 2001q1-2020q4. Duration for state i is the duration calculation from the Switching Models estimated and shown in Table 6.

Figure 8 Loss Ratio by Cluster and Overall Loss Ratio over Time



The marginal effects show that duration in state 1 is positively related to the probability of being in clusters 1, 2, 3, and 6, while duration in state 1 is negatively associated with being in Clusters 8 and 9. Interestingly, most of the duration marginal effects coefficients have opposite signs from state 1 and state 2, and the coefficients are nearly the same size. This shows a symmetric response to the length of the duration and the probability of being in a particular cluster. The main exception is Cluster 5, where the marginal effect for the duration of state 2 is approximately 3 times greater in absolute value.

The marginal effect for the coefficient of variation of the loss ratio is primarily negative but positive for clusters 6 and 9. These two clusters make up the majority of firms in the sample, and from the descriptive statistics from table 7 seem to be very close. The organizational form seems to have no marginal effect on the probability of being in any cluster. However, the national market firm is negatively related to being in cluster 6, and size in terms of the log of direct premiums written is negatively and significantly related to being in cluster 8.

Finally, we show the loss ratios over time for each cluster and all sample firms in Figure 8. The dashed line is all the firms together. Clusters 9 and 6 (the solid-colored lines) seem to follow the same pattern as the all-cluster sample. The dotted lines represent the various other clusters and, while similar, have some notable differences. For example, cluster 8 is always below the All-Clusters loss ratio, and Cluster 3 is nearly always below the All-Cluster's loss ratio except at the beginning of the period. This graph suggests that these firm's high and low loss ratio states are different from the aggregate.

D. Robustness

We have undertaken one full robustness test so far. This test examines the number of states in the switching model. We have found that it is possible to estimate up to 4 states in the model and that using a four-state model rather than a two-state model, our overall conclusion that there are many loss ratios different patterns in the data remains true. A second robustness test will examine the effects of survivor bias. Our sample consists of all firms in operation for the entire period. We can shorten the series, and more firms will be in the sample. We can also look at the first x quarters and the last y quarters to assess the conclusions. Early indicators using the national sample indicate that the main switching model results still hold. We need to examine the effect on the individual firms and undertake a K-means analysis on them. Finally, we can assess the effect of including past values of the loss ratio in the switching model. The traditional cycle literature focuses on an annual AR(2) process. We can account for past loss ratio behavior as a predictor of the loss ratio state. Early indicators suggest that adding the previous period's loss ratios reduces the power of the switching model at the aggregate level. This result still needs to be confirmed for the individual companies.

V. Conclusions

The ubiquity of discussions of cycles in property-liability property/casualty business in the business press and the academic literature is astounding especially given Boyer, Jacquier, and Van Norden's (2012) conclusion that they do not generally exist. In this paper, we look at the phenomenon differently. We accept the possibility that there is a high loss ratio state and a low loss ratio state but that they are not predictable. Unlike previous literature, we focus on firms. We find that significant economic events influence whether the firm is in a high or low loss ratio state using a Markov switching model. In addition, we find that there are different patterns in the data and that the variation between high and low loss ratio states (and the absolute difference between the two states) is not uniform. Using a K-means cluster analysis, we find nine clusters suggesting that examining aggregate data on "cycles" might be misleading.

We find that only one cluster has "cycle" durations of the length found in the literature. This result is consistent with the predictions of Henriet, Klimenko, and Rochet (2016), who suggest there are no cycles but shifts in prices due to exposures to aggregate risks. So we see distinct evidence of both hard and soft markets, but not cyclical changes in pricing or profitability over time.

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VII. Appendix

Graph of the entire sample

Figure A1 Box Chart of NAIC Quarterly Universe of Loss Ratios over Time.

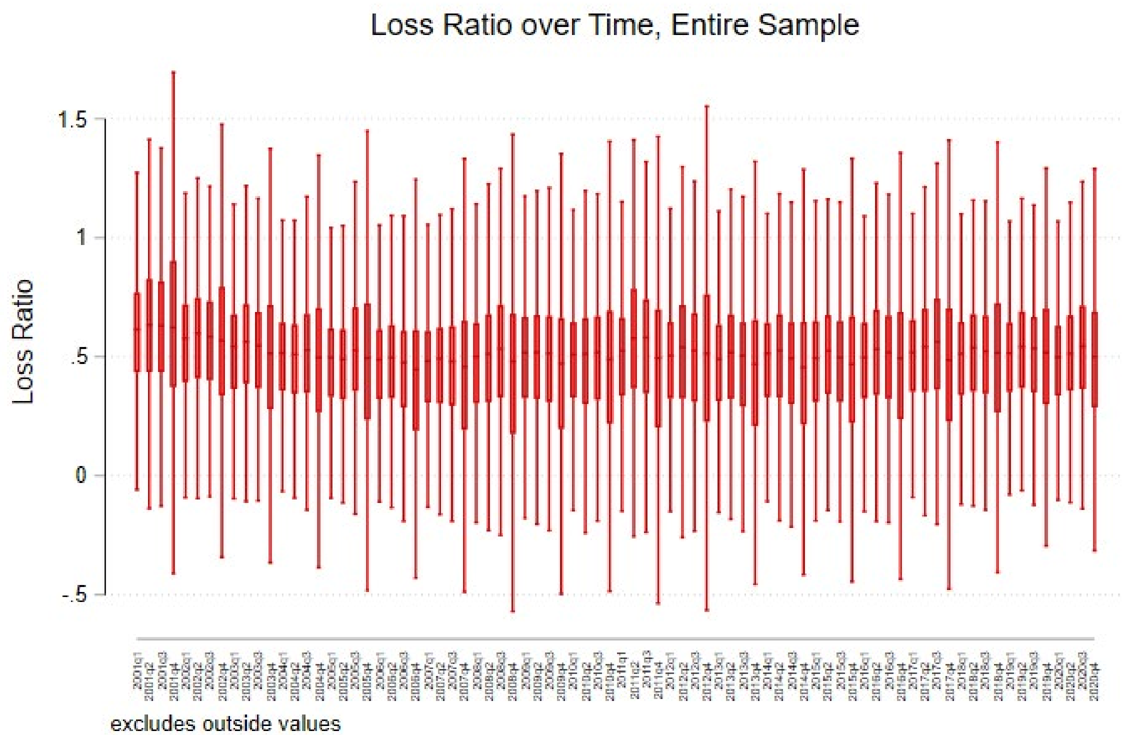

Figure A1 All Loss Ratios over time.