COMMENT ON CHAPTER 7

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In chapter 7 Scott Harrington analyzes the effects of insurance rate regulation on the automobile insurance market. He offers an econometric estimate of the effects of prior approval rate regulation on three variables: the level of automobile insurance loss ratio; the volatility of two variables—loss ratios and growth rates in average spending on automobile insurance—that are used as proxies for the volatility of insurance rates; and the level of residual market share for automobile insurance. The insurance loss ratio is a proxy for the inverse insurance price. Rate volatility is a concern for risk-averse participants in the market, and lower residual market share is an indirect measurement of the availability of insurance. The analysis uses cross-state data from all fifty states over the period 1972–98.

My comments are divided into two parts. I first discuss the author's methodology and argue that he has not emphasized the most appropriate estimation method to reach his study's objectives. I then discuss alternative ways of measuring welfare effects and the possibility of assessing the effects of rate regulation without reference to the strategic behavior of the different states.

The main findings of the study can be summarized as follows:

—Prior approval rate regulation is found to have a slightly positive effect on loss ratios over time, but the estimated effect is negligible and at best only weakly significant during the 1972–98 period. The significant findings also reflect the market experience of the 1970s. This positive effect is indeed quite weak.

—Prior approval rate regulation is associated with more highly volatile loss ratios and expenditure growth rates. This finding can be interpreted as a welfare loss to both risk-averse insurers and risk-averse consumers.

—Prior approval regulation is persistently and reliably associated with larger residual market shares, which can also represent a welfare loss.

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These results can be interpreted as a net welfare loss, since the prior approval has little or no effect on insurance rates but increases both volatility and residual market shares.

Methodology

My discussion focuses on loss ratios, although its general thrust applies to all three estimations. To obtain his first finding, the author constructed a data set containing information on all fifty states in the United States for twenty-seven periods: a total of 1,350 observations. This type of data set is a complete panel, in the sense that there are no entries into (nor exits from) the sample: in other words, all fifty states are present over the twenty-seven periods. The sample is thus free from potential bias due to entries or exits. This sort of bias is often present in models that infer technological parameters from incomplete panel data. An example is the case where efficient firms enter and no efficient ones exit.[1] When a firm is absent for a number of periods, all the information relevant to this firm is missing for these periods. The major problem is to know whether the absence is explained by randomness (incomplete surveys) or by numerous factors that may affect the technological parameters (mergers, bankruptcies, and so forth). Usually a test for selectivity bias must be applied.

Panel data sets cannot be properly treated without an appropriate methodology. In his chapter Harrington uses a method that allows the parameters to vary over time (the Fama-French method). While he notes that the main results are robust to using fixed effects estimation, he almost exclusively emphasizes the time-varying parameter results. He claims that the panel method with state fixed effects is less appropriate because it does not take into account the regulation effects in states where regulation did not change. This is not necessarily true. Panel data can be used to control for both fixed or state effects and regulation effects.

There are currently two schools of thought about the effects of regulation. The first believes that regulation is necessary to reduce the effects of imperfect competition between insurers, particularly in states where only a few insurance firms operate. This school also believes that the existence of regulation in some states will affect the behavior of insurers in unregulated

1. See Baltagi (1995); Dionne, Gagné, and Vanasse (1998).

states, as there is always a probability that regulation will be extended to all states if the differences between insurance rates become too large. The second school believes that regulation has no effect: the variations observed are explained by differences in the markets before regulation and after deregulation. Insurance rates are said to be lower in unregulated markets because the insurers in these markets are more efficient, for example, and life is said to be easier for inefficient insurers in regulated markets.

If one thinks that the second interpretation is correct, a significant dummy variable might act as a proxy for insurer efficiency and not necessarily for any regulation effect. Cross-sectional analysis (or an average of cross-sectional analyses) cannot discriminate between the two stories. Panel data analysis, however, can distinguish between the two hypotheses by analyzing the loss ratios of states moving from a regulated to an unregulated status (and vice versa).

Another advantage of panel data analysis is that it lessens the problems associated with omitted variables.[2] What seem to be regulation effects may be obtained because some other real effects (potentially correlated with other explanatory variables) are not observable. Using information on many periods in a dynamic way can introduce control over unobservable variables. When omitted variables are correlated with the included variables, cross-sectional analysis will not provide adequate means of obtaining consistent coefficients for the effect of regulation. This is particularly true when coefficients vary over time, as can be seen in Harrington's table 7-5. Nor is it clear to me that one can take the average of coefficients when some are significantly different from zero and many others are not.

With panel data it is often assumed that the true model is one with constant parameters but variable intercepts over time and cross-sectional units. Harrington's method allows the intercept and the slopes to vary over time but does not allow for intercepts that vary across states. The variable intercepts approach in conventional panel data estimation methods can account for the unobservable features that distinguish states within any given period or over time. Consider the following simple example:

$$L_{it} = \alpha + \beta x_{it} + \mu_{it},$$

where L_{it} is the loss ratio in state i for period t, x_{it} is a dummy variable for regulation in state i for period t, and μ_{it} is a random term.

2. Hsiao (1986).

This random term is not necessarily independent from x_{it} and can be written as

$$\mu_{it} = \delta S_i + \lambda M_t + \nu_{it},$$

where S_i is an unobservable variable in state *i*, M_t is an unobservable market variable in period *t*, and ν_{it} is a random term. Here μ_{it} is correlated with one unobservable state variable, S_i, and with a market variable, M_t, that varies over time. This correlation may affect the conclusions about the estimated parameter $\hat{\beta}$. Panel data methods are capable of obtaining a consistent estimate of β even if M_t and S_i are not observable. This correlation will introduce a variable intercept model (α_{it}) that will yield an appropriate $\hat{\beta}$ by eliminating the omitted-variable bias.

There are two standard methods of estimating models with panel data: the fixed effects model, where both the time and the state effect are controlled, and the random effects model. Because both the number of periods and the number of states being considered here are quite low, the fixed effects model can be applied by simply using twenty-seven dummies for the years (dates) and fifty dummies for the states and checking whether the coefficients and the *t*-student values are appropriate. Seventy-seven dummies with 1,350 observations is a manageable proposition. When the number of observations is very high—say, 30,000 individuals over ten years—one cannot use dummies for the individuals. In that case, one can turn to the random effects model, where the distribution of the random term must be analyzed.

Of course, matters are much more complicated when the endogenous aspects of regulation also enter into the equation. But here regulation is treated as only exogenous.

Macroeffects

On the aggregate level, it is interesting to observe (from Harrington's figures 7-1 and 7-2) that there is a strong relationship between variations in the number of rate-regulating states and variations in the mean loss ratios for both types of states (competitive rating and prior approval). This observation suggests a number of interesting areas for further research. Is there any causal connection between the two distributions at the macrolevel? In other words, is there any relationship between average loss ratios for auto

Table 1. *Deaths in Motor Vehicle Accidents per 100,000 Persons, 1994 and 1997*

Geographical area	*1994*	*1997*
United States	16.3	15.8
California	14.3	10.5
Illinois	15.0	11.7
Massachusetts	8.0	7.2
New Jersey	9.8	9.3[a]
South Carolina	22.6	23.8
Canada	10.9	9.6
Quebec	11.3	10.4
France	13.8	14.1

Sources: *Statistical Abstract of the United States, 1998;* Statistics Canada (1998); and data from the Organisation Nationale Interministérielle de la Sécurité Routière, France, 1998.

a. 1998.

insurance and the number of states that regulate? Or are these relationships to be explained only by the liability insurance crisis?

Can one test to see whether average rates (in both regulated and unregulated states) started to rise when the number of states with regulation started to decrease, and vice versa? Who are the leaders, the states that regulate or those that do not? Do regulators follow the market in the other states, or are insurers in unregulated states influenced by the behavior of regulators in states that do regulate?

Finding answers to such questions might help in predicting what effect complete deregulation in all fifty states might have on the auto insurance market. More generally, are there any strategic differences between states that regulate and those that do not? Furthermore, are market structures the same in regulated and unregulated states? Is the market less competitive in the regulated states (fewer insurers, more market power)?

Finally, I would like to point out a possible link between regulation and automobile accident fatality rates. Table 1 reproduces the number of deaths per 100,000 individuals in the states, provinces, and countries analyzed in this conference. Although many factors could cause differences in automobile accident fatality rates across regions, it is nonetheless interesting to observe that the number of deaths per 100,000 individuals is much lower in regulated states than in unregulated states. Rates in Canada and France are also lower than in the United States, where many states are not regulated. A recent article in *Insurance Day* reports that bodily injury claims are increasing in the United Kingdom.[3] According to some specialists, the driving force behind this finding is the pricing by insurers.[4]

As I show in chapter 9 of this book, deregulation should not be brought in too rapidly, and appropriate substitutes must be introduced to replace certain beneficial properties of regulation. In particular, I consider the commitment value of regulation.

Conclusion

I very much enjoyed reading Harrington's chapter. It reports interesting results that will likely influence the way the regulation of automobile insurance rates will be discussed in the United States over the coming years. However, the findings reported are not necessarily independent of the methodology used. I would therefore suggest that different methodologies be applied to the data set before any political decisions are based on this information.

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3. N. Munns, "Bodily Injury Claims on Increase," *Insurance Day*, March 20, 2001, p. 8.

4. See Danzon and Harrington (2001) and Harrington and Danzon (2000) for similar analyses of workers' compensation insurance.