Asymmetric Information and Temporal Profitability in the Long-Term Care Insurance Market

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Introduction

Economists have long recognized that insurance buyers’ private knowledge of their risk confounds predictions based on equilibrium models of complete markets with full information (see, e.g., Pauly, 1968, 1974; Rothschild and Stiglitz, 1976). With asymmetric information and adverse selection, the paradigm of perfect competition either fails to produce market equilibrium or, if equilibrium is reached, it may not be efficient (Akerlof, 1970). Various market mechanisms arise to counteract adverse selection and to improve efficiency (see, e.g., Akerlof, 1970; Spence, 1973; Stiglitz and Weiss, 1981; Harris and Holmstrom, 1982). In insurance markets, for example, insurers offer menus of contracts with nonlinear pricing to induce self-selection by insurance buyers so that unobservable risk information is voluntarily revealed through contract choice (Rothschild and Stiglitz, 1976). In a dynamic setting, long-term contracts with \textit{ex post} price adjustment via experience rating also can induce buyers to reveal their true risk levels (Dionne, 1983; Dionne and Lasserre, 1985; Cooper and Hayes, 1987; Gal and Landsberger, 1988).

Cooper and Hayes (1987) specifically demonstrate that a menu of short-term contracts coupled with experienced-rated, long-term contracts can effectively sort insurance buyers according to their true risk. Insurers’ commitments to experience rating on long-term contracts provide disincentives to high risks for misclassifying themselves by choosing long-term policies and incentives to low risks for revealing themselves by selecting long-term policies. The Cooper-Hayes model indicate that low risks will tend to choose experienced-rated, long-term contracts, while high risks will choose short-term contracts without experience rating. A price highballing
pattern emerges that allows insurers to initially earn positive profits from their low-risk customers followed by periods of lower prices and profits. In a related study by Dionne and Doherty (1994), the authors also obtain such temporal pricing and profit outcome under more general assumptions about the extent of firm commitment to long-term contracts.

Alternatively, Kunreuther and Pauly (1985) and Nilssen (2000) show that in the absence of firm commitment, it becomes difficult to obtain a separating equilibrium using the contract menus suggested by Cooper and Hayes. Allowing insurers to observe private information about their existing customers’ risk characteristics, these studies show that the equilibrium outcome will be characterized by full pooling initially. In subsequent periods, experience rating occurs, but with price distortions because insurers’ private information makes it possible to lock in low risks and thereby capture informational rents. Consequently, the models developed by Kunreuther and Pauly (1985) and Nilssen (2000) imply a lowballing pricing pattern in which insurers initially incur losses on their new business but are able to extract quasi-rents from existing policyholders in future periods.

The contrasting predictions about the distribution of temporal pricing suggest that a direct examination of policy performance over time can be promising for purposes of discriminating between competing multi-period models of insurance pricing under adverse selection. Because policy-level pricing data are not publicly available, researchers have focused on the profitability of specific insurance lines with inconsistent results (D’Arcy and Doherty, 1990; Dionne and Doherty, 1994).

One problem with the previous empirical work is that the tested data are aggregated over policies written on a wide range of risk classes based upon observable risk characteristics. More valid empirical tests of adverse selection models can be devised using policy-specific experience
data on cohorts of policyholders with comparable, observable risk. In addition, estimation of adverse selection in a multiperiod setting requires data with both time-series and cross-sectional dimensions, i.e. panel data, for given cohorts of policies. A panel data model is necessary to produce reliable estimates. In this study, we are able to utilize unique data from health insurance markets that allow us to conduct a panel data analysis of cohort-specific experience while controlling for heterogeneity in observable risk.

In our study we examine the profitability of policy cohorts, which are initially written on relatively homogenous individuals, over the life these contracts. We specifically test cohort-specific data for virtually the universe of insurers issuing long-term care (LTC) insurance in the U.S. We find that loss ratios decline significantly with policy age, all else being constant. Our evidence is consistent with the lowballing pricing behavior implied by the Kunreuther-Pauly and Nilssen models, as well as the empirical evidence of D’Arcy and Doherty (1990).

In the next section, we review the adverse selection literature, focusing on models of multiperiod insurance pricing under conditions of asymmetric information. We then describe our research design and, in the final two sections, present our empirical findings, a summary, and concluding remarks.

**Literature Review**

Since the seminal work of Akerlof (1970), the issue of adverse selection caused by private information has become one of the most heavily researched areas in information economics. Our understanding of the effects of informational inefficiencies can be traced to the works of Spence

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1 Chiappori and Salanié (2000) stress the importance of proper control of observable risks when estimating the impact of adverse selection.
Adverse Selection in Insurance Markets: Theory and Empirical Evidence

Akerlof’s “lemons” principal is applied to competitive insurance markets by Rothschild and Stiglitz (1976). Specifically they show that informationally disadvantaged insurers can design incentive-compatible schemes in their contracts so that observably similar buyers will separate themselves into distinct risk classes by choosing particular contracts consistent with their risk levels. One such self-selection mechanism is a menu of contracts with a convex pricing schedule. In equilibrium, risk separation occurs in which contracts with more comprehensive coverage are chosen by individuals with higher expected insurance costs at higher unit prices while low risks only can optimize by selecting partial insurance coverage.
Following Rothschild and Stiglitz’s original insight, researchers have devoted a great deal of effort identifying the existence of market equilibrium under adverse selection and characterizing the conditions and mechanisms allowing separation (Stiglitz, 1977; Miyazaki, 1977; Wilson, 1977; and Cho and Kreps, 1987). Collectively, their models generate important testable implications for insurance markets subject to imperfect information about buyers’ risks. Two primary implications emerge from the literature. One is that among the menu of contracts offered to indistinguishable buyers, those with greater insurance coverage will tend to be purchased by high-risk individuals and those with higher deductibles and less comprehensive coverage will be bought by low risks. A second prediction is that the marginal costs of insurance are increasing in the amount of coverage.

Empirical studies have provided somewhat ambiguous evidence about the impact of adverse selection in insurance markets. Evidence of significant adverse selection in automobile insurance markets is provided by Dahlby (1983) and Puelz and Snow (1994). Cawley and Philipson (1999) find no such impact in life insurance markets and neither do Chiappori and Salanié (2000) in automobile insurance markets, which directly rebuts Puelz and Snow.

**Multiperiod Insurance Markets with Adverse Selection**

In a multiperiod setting with repeated transactions between the contracting parties, Townsend (1982) demonstrates *ex ante* efficiency gains to multiperiod contracting in the presence of private information. Rubinstein and Yaari (1983) specifically show that using long-term contracts in which temporal prices depend on past experience can eliminate inefficiencies associated with moral hazard in insurance markets.

The subject of designing and pricing insurance contracts in a dynamic setting to overcome adverse selection and market inefficiencies has been explored in detail by Dionne (1983), Dionne and Lasserre (1985), Cooper and Hayes (1987), Hosios and Peters (1989), Dionne and Doherty
(1994), and Nilssen (2000). While these studies generally show an outcome of a separating equilibrium, they differ in many other ways including the timing of the separation, the specific design of incentive contracts, and the extent of allocative efficiency.

Dionne (1983) and Dionne and Lasserre (1985) show that a Pareto-optimal outcome with risk separation can occur in an infinite, repeated contracting relationship if long-term contracts are binding on both a monopolistic insurer and an insured who are committed to period-by-period ex post renegotiation. Cooper and Hayes (1987) explore finite-period adverse selection models under the assumption that long-term contracts are binding on both the insurer and policyholders. They show that a separating equilibrium occurs in the first period if the contract menu consists of a Rothschild-Stiglitz short-term contract designed for high risks and an experience-rated, long-term contract for low risks. This result holds for both monopolistic and competitive market conditions, with the difference being the impact on insurers’ expected long-run profits because, in the latter case, insurers’ long-run profits are constrained to zero.

Although firm commitment between insurers and insureds is frequently assumed in multiperiod models, such a binding contract for the policyholder is generally considered too strong to impose (Dionne and Doherty, 1994). When firms are assumed to be bound to long-term contracts while policyholders are free to switch in any given period, second-period competition and the possibility of ex post renegotiation complicate the information mechanism in the multiperiod setting. Cooper and Hayes (1987) suggest that to counteract the incentive problem created by the presence of second-period competition -- i.e. high risks can pretend to be low risk in the first period and then switch to rival firms in the second period -- an additional incentive-compatible scheme needs to be built into Rothschild-Stiglitz contracts. They show that a multiperiod separating equilibrium can be obtained if contracts designed for low risks contain a premium that increases
the costs for high risks pretending to be low risks. In equilibrium, high risks choose short-term contracts with complete coverage and low risks purchase front-loaded, long-term contracts with partial coverage and experience rating. A multiperiod separating equilibrium occurs with additional costs imposed on low risks so that insurers initially realize profits on their long-term contracts. If long-run profits are constrained to zero by competition, losses should be realized in the second period. D’Arcy and Doherty (1990) use the term “price highballing” to describe the pricing pattern suggested by this model.

Dionne and Doherty (1994) relax the renegotiation prohibitions underlying the Cooper-Hayes model, allowing for ex post renegotiation if it is mutually beneficial to insurers and insureds. They show that a menu consisting of first-period, semi-pooling contracts with experience rating and second-period Rothschild-Stiglitz separating contracts makes the semi-pooling contracts renegotiation-proof so that the ex ante efficiency gains from commitment are retained. Consequently, the equilibrium outcome is characterized by semi-pooling of all the low risks and a proportion of the high risks, followed by second-period risk separation through self-selection. Although Dionne and Doherty (1994) extend the Cooper-Hayes model to allow for the possibility of renegotiation, they conclude that the temporal profit pattern of price highballing still applies.

Kunreuther and Pauly (1985) and Nilssen (2000) examine the effects of adverse selection in competitive insurance markets assuming no commitments by buyers or sellers to long-term contracts. Only single-period contracts are considered. Kunreuther and Pauly posit that pooling contracts will be offered in the first period, but then insurers will adjust prices in subsequent periods based on Bayesian updates of each insured’s loss experience. Nilssen suggests that risks can be separated in the second period by either a menu of Rothschild-Stiglitz contracts or a cross-subsidizing menu or both, depending on the information observed during the first period. With the
Kunreuther-Pauly model, prices will be adjusted upward for those who incur claims, while prices for the better risks will not fully reflect their favorable loss record as insurers extract quasi-rents. With the Nilssen model, this is a possible, but not absolutely necessary, conclusion.

The key result that differentiates these models from the previously discussed “commitment” models is the possibility of a virtually opposite pricing and profit pattern. In particular, losses are anticipated in the initial periods while profits are realized in subsequent periods as long-run profits are constrained to zero. This pattern of pricing adjustment is referenced as “price lowballing” (D’Arcy and Doherty, 1990).

**Empirical Evidence on Multiperiod Adverse Selection Models**

Because alternative models predict contrasting profit patterns over time, empirical examination of the financial performance for cohorts of insurance contracts can serve to discriminate between the models. Two previous studies explicitly test data from the automobile insurance markets to assess temporal pricing by insurers. Based upon survey data collected from a sample of seven insurers, D’Arcy and Doherty (1990) examine the average profitability of policies classified by policy age. They find that mean loss ratios decline steadily with policy age. In addition, the study shows that insurers’ aggregate loss ratios also decline over time and converge to the industry mean as the company ages. D’Arcy and Doherty conclude that their findings are consistent with the adverse selection model of Kunreuther and Pauly (1985), in which insurance buyers and sellers do not commit to long-term contracts and engage in price lowballing.

In contrast, the results obtained in Dionne and Doherty (1994) show a temporal profit pattern consistent with the price highballing implication of the firm commitment models (e.g.,

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2 As noted by D’Arcy and Doherty, their definition of policyholder cohort combines individuals of different classes of observable risk.
Cooper and Hayes, 1987; Dionne and Doherty, 1994). Dionne and Doherty examine a sample of more than eighty insurers writing auto insurance in California for the period 1985 through 1988. Using aggregate premium growth rate as the proxy for the average age of all existing policies issued by an insurer, the authors find a significantly negative relation between policy age and loss ratios for insurers who tend to select and insure lower risks. They observe no significant relation between policy age and loss ratios for those insurers with more mixed risk classes and a weak positive relation for those who insure higher risks. They conclude that their results are strongly consistent with their own semicommitment model as well as the Cooper-Hayes commitment model, both of which predict price highballing.

The studies of adverse selection in insurance markets generally have been hampered by limited data. Direct tests of alternative multiperiod adverse selection models require data for the contractual characteristics and pricing of insurance over time. Such data are not publicly available, however. Consequently, researchers have turned to indirect tests by examining the average profitability for groups of different contracts aggregated together. Such aggregation bundles together contracts designed for different risk classes based on observable risk characteristics. Adverse selection theory calls for performance measures to be applied to contracts observably similar insureds, however. Given the data problems, researchers should not be surprised that the limited empirical evidence gleaned from auto insurance markets presents a contrasting picture. In our study, we turn to the long-term care insurance markets, for which cohorts of profitability data are available for virtually the universe of U.S. insurers. In doing so, we are able to examine cleaner cohort data and generate results that will add insight into the debate about which adverse selection models best describe the temporal pricing behavior of insurers.
Research Design

In this study we investigate the financial performance for cohorts of LTC insurance contracts to test the implications of competing adverse selection models with respect to pricing. Our study differs from previous studies because we examine time-series variation as well as cross-sectional variation to draw inferences about the appropriate pricing mechanism. We also use a unique dataset that allows cohort-specific analysis of contract performance. Specifically, we are able to track a given cohort of policyholders insured under the same policy form for a number of years. By doing so, we can at least partially mitigate biases inherent in previous studies because of the aggregation of data for insureds with observably different risk characteristics.

Data

Our data are collected from the InfoPro database of Long-Term Care Insurance Reporting Forms, which is compiled by the National Association of Insurance Commission (NAIC). The NAIC’s long-term care (LTC) insurance database includes the annual reports filed by all insurers admitted to sell long-term insurance policies in the U.S. Insurers file direct experience reports, before reinsurance ceded or assumed, for each policy form. A policy form is defined by the NAIC as a type of policy issued to individuals with substantially similar risk classes and for which similar underwriting standards apply. All policy forms that meet the requirements of the NAIC Long-Term Care Insurance Model Act, or the similar laws and regulations of individual states, are included in the database. Policies sold to policyholders residing outside the United States are excluded.

For each policy form, the LTC data are further classified by the year in which a contract was first written. All contracts initially written in the same year are treated as a cohort and cohort-specific experience is reported. Calendar duration, defined as the year for which experience is reported for a particular contract less its year of initial issue, indicates how long a cohort of
policyholders have been insured under a particular policy form. For example, a cohort with a calendar duration of five in statement year 1995 first purchased these contracts in 1990. In addition, we know that because individuals were initially insured under the same policy form, they were considered to be in the same risk class at the time of initial issue.

In the NAIC database, the values of calendar duration increase by one each year through the first five years. Subsequently, the cohorts that have been with the current insurer for six to ten years are aggregated, and those in existence for over ten years are placed in a single classification. In each time period a new cohort is moved into the 6-10 calendar duration category and an existing cohort is moved out and into the 10+ category, so we combine all policyholders in these two calendar durations as well as the cohort falling under duration 5 category and treat them as one cohort for matching purposes. This practice allows us to track the results for all policyholders throughout the sample period.

Consider, for example, the cohort under calendar duration 5 category in 1995. By reporting year 1996, this group of policyholders no longer exists as a separate group in the database because their experience is reported together with other groups in duration 6-10 category. Likewise, those having an actual duration of 10 are moved out of category 6-10 and into the 10+ category by 1996. For tractability we need to merge these three different duration categories. Although any such aggregation unavoidably combines cohorts with some heterogeneous risk characteristics, it should not create serious limitations because the aggregation takes place within the same policy form.

The sample data encompass the period 1995 through 2000 because these currently are the first and last years for which the data from LTC reporting forms are available from the NAIC. Our raw sample contains all life and health insurers that submitted information required by the state
insurance commissions and departments. Financial data, such as measures of risk-based capital, are collected from the NAIC Annual Statement Report, also available from the NAIC.

The Empirical Model

In previous studies of auto insurance markets an insured’s probability distribution of losses is implicitly assumed to be constant over time (D’Arcy and Doherty, 1990; Dionne and Doherty, 1994). Temporal variations in the financial performance of policy cohorts consequently are deemed attributable to price adjustments made by insurers as they gain new information from their insureds’ loss experience. For LTC insurance, however, such a probabilistic scenario is unlikely. Over time, as both the insured and the contracts age, the probability distribution should shift to the right. Losses should rise as policy cohorts age. Therefore, to isolate adverse selection effects, we must carefully control for time effects on insurer prices and profitability.

Following D’Arcy and Doherty (1990) and Dionne and Doherty (1994), we use loss ratios, defined as incurred losses to total premiums, to estimate profitability for a given cohort of contracts. Direct estimates of cohort-specific underwriting profits are not available for LTC insurance because underwriting expenses are not published by the NAIC. Using $i = 1, 2, \ldots, n$ to denote policy cohort $i$, $t = 1, 2, \ldots, T$ for time period $t$, and subscript $j$ for the $j$th insurer, we model contract profitability for each insurer as follows:

$$
\frac{L}{P}_{it} = \alpha_1 Age_{it} + \alpha_2 Age^2_{it} + \beta X_{it} + \gamma W_{it} + c_i + \epsilon_{it}
$$

where $\frac{L}{P}$ is the loss ratio, $Age$ is the time period for which the cohort of contracts has been in effect, $X$ is a vector of contract characteristics including the expected loss ratio and lagged actual

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3 See D’Arcy and Doherty (1990) and Dionne and Doherty (1994) for a discussion on the advantage of loss ratios over underwriting profits.
loss ratio, \( \left( \frac{L}{P} \right)_{i,t-1} \), \( W \) is a vector of firm-specific characteristics, such as firm size and organizational structure, \( c \) is the contract-specific individual effect, and the error term \( \varepsilon \) is assumed to have a mean of zero.

We particularly focus upon the estimated coefficient for the quadratic form of the policy age variable. A significant and positive coefficient \( \alpha_2 \) is consistent with the price highballing implication of the models proposed by Cooper and Hayes (1987) and Dionne and Doherty (1994), while a negative and significant \( \alpha_2 \) is consistent with price lowballing behavior suggested by the models developed by Kunreuther and Pauly (1985) and Nilssen (2000).

To see why, recall that our discriminating test must answer the question: How does the profitability for a given cohort of policies issued to observably similar individuals change over time? In statistical terms, the price highballing hypothesis implies a negative relation between profitability and policy age, while price lowballing indicates that profits should rise with policy age. If we were examining an insurance product market in which the probability distribution of losses does not change over time, as is reasonable for auto insurance markets, we would primarily focus on the sign of the coefficient, \( \alpha_1 \), in Eq. (1). Given the nature of LTC insurance, first-order correlation between loss ratios and policy age, as measured by \( \alpha_1 \), primarily reflects the inherent time effect on losses, however. The second-order correlation captured by \( \alpha_2 \) reflects the effects of adverse selection on the temporal relation between losses and policy age. With price highballing, the rate of change in insurer profitability, i.e. the rise in loss ratios, with respect to policy age should increase as a given cohort of LTC insurance buyers ages, because a price highballing strategy magnifies the positive time effect on insurer loss. The opposite is true with price
lowballing as the marginal effect of policy age on loss ratios should be a declining function of policy age because price lowballing mitigates the positive time effect on insurer loss.

**Contract-Specific Variables**

We include two contract-specific variables to allow for other factors that systematically affect policy loss ratios. They are the expected loss ratio, \( \text{ExpLoss}_{it} \), and the lagged actual loss ratio, \( \frac{L}{P_{i,t-1}} \). The data for expected loss ratios are reported by insurers for each policyholder cohort insured under a given policy form. The ratio is the anticipated policy losses as a percentage of earned premiums without adjustment for changes in policy reserves. Variations in loss ratios across cohorts are likely to reflect differences in observable risk characteristics. We therefore assume that cohort-specific expected loss ratios impound the risks of individual policyholders in the cohort that are observable to the insurer. We expect a positive relation between expected losses and actual losses.

The lagged dependent variable, \( \frac{L}{P_{i,t-1}} \), is included in our model to capture short-run departures from equilibrium. It can capture temporary effects such as those arising from slow price adjustments, possibly because of adjustment costs or regulatory delay.\(^4\) Consequently, we anticipate that any costs or delays, as captured by the lagged loss ratio, will be positively related to the current-period loss ratio.

**Firm-Specific Variables**

In order to produce reliable measures of the relation between policy age and profitability, we must control for differences in policy risk characteristics across insurers’ portfolios. These

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\(^4\) See, e.g., Dahlby (1992), for a test of auto insurance price rigidity when price adjustments are costly.
differences can be captured by incorporating firm characteristics that reflect the propensity of insurer managers to accept risk. More aggressive managers will tend to underwrite policies for customers with observably higher risk. Two firm-specific characteristics are considered here: organizational structure (\textit{Stock}) and risk-based capital (\textit{RBC}). Agency theory suggests that managers of stock firms are less averse to risk. Risk-based capital reflects managerial willingness to accept financial risk. We expect positive relations between loss ratios and both of these measures of risk preference. Likewise, firm size can be associated with greater expertise and resources in screening and sorting risks (Kroner and West, 1995). We therefore expect a negative relation between firm size and loss ratios. To fully describe our test model, we rewrite equation (1) as follows:

\[
\begin{align*}
\frac{L}{P}_{it} = \alpha_1 & \text{Age}_{it} + \alpha_2 \text{Age}^2_{it} + \beta_1 \text{ExpLoss}_{it} + \beta_2 \bigg( \frac{L}{P} \bigg)_{h,t-1} \\
& + \phi_1 \text{Stock}_j + \phi_2 \text{RBC}_j + \phi_3 \text{Size}_j + c_i + \epsilon_{it}
\end{align*}
\]

We apply equation (1’) using four different model specifications and estimation procedures, as shown in Table 1. Detailed descriptions are provided subsequently as we present the estimates for each model.

[Table 1 about here]

**Results**

The model is fitted to 1995-2000 data. Standard screens for missing observations and outliers are applied to our raw sample data. Considering that in any given time period a large proportion of newly issued and younger policies do not incur losses during the first few years because of initial underwriting effects and the long-term nature of LTC insurance claims, we
exclude policy cohorts with calendar durations less than four years. This sample selection procedure creates *a priori* bias against price lowballing effects. Our final sample consists of a panel of 100 insurers for which there are a total of 359 policyholder cohorts that are insured under different policy forms for the sample period. A total of 1035 cohort-year observations remain.

Table 2 contains summary statistics of the variables used in the regression analysis. To give a feel of the data we report the mean values and standard deviations as well as pairwise correlation coefficients, all computed using 1035 cohort-year observations contained in the final sample. The mean cohort age is nine years and the maximum is twenty-one, with a standard deviation equal to 2.64. We also observe a wide range of actual loss ratios, varying from zero to as high as 670 percent with a standard deviation at about 70 percent. Also note that while the coefficient of correlation between expected loss ratios and cohort age is .397, the contemporaneous correlation between actual losses and cohort age is .167 (.137 is shown in the table for that between cohort age and lagged losses).

Table 3 contains regression results for the empirical models specified in Table 1. Using generalized least squares (GLS), we first estimate equation (1') without including the lagged loss ratio as a control variable. We obtain an estimated autocorrelation coefficient of .444. The first-order autoregressive form, AR(1), is thus specified for the disturbance process. Subsequently, the estimates are corrected for serial correlation as well as heteroscedasticity using White’s robust covariance estimators. In regression (2), which corresponds to specification (B) in Table 1, we specify an autoregressive model by including the lagged dependent variable. As discussed earlier, the lagged dependent variable is expected to capture temporary departure from long-run equilibrium when adjustment costs or regulatory factors lead to slow price adjustment. Hatanaka’s
two-step instrumental method is used to obtain the estimates for regression (2).\textsuperscript{5} In regression (1) and (2) we assume no individual effects in our panel data.

Column (3) contains the estimates of a random effects model (REM) because Hausman’s test fails to reject the null hypothesis that individual effects are uncorrelated with other regressors. In column (4), we report the results obtained with a dynamic panel model method. As is well known, the standard transformation to eliminate individual effects is insufficient to obtain consistent estimators in a dynamic panel model. Instrumental variable (IV) methods can be used to obtain consistent estimators (Greene, 2000). Because of the relatively short time series for our unbalanced panel, we obtain our estimators with a two-step IV approach as developed in Ge and Cox (2002).

[Table 3 about here]

As expected, the coefficients for the \textit{Age} variable indicate a consistent and significantly positive time effect on incurred losses for LTC insurance policies. Under the four different model specifications, the estimated coefficients for the key variable, \textit{Age}^2, is consistently negative and statistically significant. This evidence of a decreasing marginal effect of policy age on loss ratios is consistent with the price lowballing hypothesis. That is, while loss ratios rise over time because of the nature of long-tailed claims for LTC insurance, they do so at a decreasing rate, which suggests that insurers use lowballing pricing strategies.

Among the other control variables, the estimated coefficients for the expected loss ratio (\textit{ExpLoss}) and the lagged actual loss ratio \(\frac{L}{P_{t-1}}\) have the expected positive sign and are consistently significant. This means that actual losses generally are higher for policies written on

\textsuperscript{5} See Greene (2000) on the efficiency of Hatanaka’s estimators relative to standard IV methods in an autoregressive model.
groups of individuals with greater observable risk. The coefficients for the lagged dependent variable obtained using Hatanaka’s IV approach and random effects estimation are comparable, while the dynamic panel model method yields a substantially smaller adjustment coefficient. Firm size (Size) and organizational structure (Stock) effects, though not significant, are in the expected direction. If stock firms tend to take more risks than mutual insurers, higher losses are expected across their polices. Similarly, a negative relation between size and loss ratio is expected if larger firms are better at screening and sorting risks due to their experience and expertise. We measure firm size alternatively by the log of insurer’s total admitted assets and by LTC market share, but the results are quite similar. The estimates reported in Table 3 are obtained using insurers’ LTC market share as the size measure. The estimated coefficients for risk-based capital (RBC) do not indicate any specific explanatory power and they appear to be somewhat unstable over different model specifications. When we drop RBC in all specifications, we obtain very similar results for the other variables.

**Summary and Conclusions**

Multiperiod adverse selection models applied to insurance markets have produced very different implications. Models built on assumptions of firm commitment to long-term contracts indicate that equilibrium can be characterized as full separation or semipooling followed by separation. Consistent with temporal price movement described as “price highballing,” these models imply that insurer profitability for a given cohort of observably similar insureds will fall over time because of temporal rent redistribution. Alternatively, models built on assumptions of no long-term commitments between buyers and sellers and insurer retention of private information
indicate price lowballing as insurers extract informational rents from existing policyholders. Consequently, insurer profitability for a given cohort of policyholders should rise over time.

In this study we use cohort-specific data for long-term care (LTC) insurance to test the two competing propositions concerning insurers’ temporal profit patterns. Our results show that while the loss ratio on a given cohort of policyholders rises over time in a pattern consistent with the nature of long-tail claims for LTC insurance, the rate at which loss ratios increase with policy age declines significantly over time. This decreasing marginal effect of policy age is consistent with the rising temporal profit pattern characterized as price lowballing. Our evidence from the LTC insurance markets therefore is more supportive of the Kunreuther-Pauly and Nilssen models, which indicate that multiperiod equilibria in markets with asymmetric information involve risk pooling and subsequent price distortions. Our findings are also in line with the empirical results of D’Arcy and Doherty (1990). Considering that a potential upward bias in the estimated coefficient for cohort age is likely given our sample selection procedure, our results probably underestimate the positive relation between policy age and loss ratios, which implies even stronger support for price lowballing.

As in previous studies, our research design focuses on the temporal profit implications of multiperiod adverse selection models. Hopefully, researchers will be able to more directly examine insurance prices, as well as firm- and contract-specific risk characteristics, to test temporal price adjustment issues in the future. Another possible issue relates to the maturity of the markets tested. While the automobile insurance markets tested by other researchers presumably are well-established and mature, we examine the relatively young, dynamically changing LTC insurance market. The impact of financial innovation on temporal pricing patterns strikes us as an issue worthy of further investigation by researchers.
References


Table 1

Regression Models of the Effects of Cohort Age and Observable Risk Characteristics on Cohort Loss Ratios

This table shows four model variations. In specifications (A) and (B), we assume no individual effects in our panel data. Specifications (C) and (D) are unrestricted panel data models. We include the lagged dependent variable in (B) and (D) to impound dynamics in price adjustment. The dependent variable is the ratio of losses to premiums. Age is the number of years a given cohort of policyholders has been with the current insurer. ExpLoss is the policy-specific expected loss ratio. Stock is a binary indicator equal to one if an insurer is a mutual firm and four if it is a stock firm. RBC is the ratio of adjusted capital to risk-based capital. Size is, alternatively, a measure of firm asset size or its LTC insurance market share.

<table>
<thead>
<tr>
<th>Model</th>
<th>Model Specification</th>
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<tbody>
<tr>
<td>A</td>
<td>Restricted Panel Model (no lagged dependent variable)</td>
</tr>
<tr>
<td></td>
<td>[ \frac{L}{P_{it}} = \alpha_0 + \alpha_1 \text{Age}<em>{it} + \alpha_2 \text{Age}</em>{it}^2 + \beta_1 \text{ExpLoss}<em>{it} + \phi_1 \text{Stock}<em>j + \phi_2 \text{RBC}</em>{jt} + \phi_3 \text{Size}</em>{jt} + \epsilon_{it} ]</td>
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<tr>
<td>B</td>
<td>Restricted Panel Model (with lagged dependent variable)</td>
</tr>
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<td></td>
<td>[ \frac{L}{P_{it}} = \alpha_0 + \alpha_1 \text{Age}<em>{it} + \alpha_2 \text{Age}</em>{it}^2 + \beta_1 \text{ExpLoss}<em>{it} + \beta_2 \frac{L}{P</em>{it-1}} + \phi_1 \text{Stock}<em>j + \phi_2 \text{RBC}</em>{jt} + \phi_3 \text{Size}<em>{jt} + \epsilon</em>{it} ]</td>
</tr>
<tr>
<td>C</td>
<td>Unrestricted Panel Model (no dynamic effects)</td>
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<tr>
<td></td>
<td>[ \frac{L}{P_{it}} = \alpha_1 \text{Age}<em>{it} + \alpha_2 \text{Age}</em>{it}^2 + \beta_1 \text{ExpLoss}<em>{it} + \phi_1 \text{Stock}<em>j + \phi_2 \text{RBC}</em>{jt} + \phi_3 \text{Size}</em>{jt} + c_i + \epsilon_{it} ]</td>
</tr>
<tr>
<td>D</td>
<td>Dynamic Panel Model</td>
</tr>
<tr>
<td></td>
<td>[ \frac{L}{P_{it}} = \alpha_1 \text{Age}<em>{it} + \alpha_2 \text{Age}</em>{it}^2 + \beta_1 \text{ExpLoss}<em>{it} + \beta_2 \frac{L}{P</em>{it-1}} + \phi_1 \text{Stock}<em>j + \phi_2 \text{RBC}</em>{jt} + \phi_3 \text{Size}<em>{jt} + c_i + \epsilon</em>{it} ]</td>
</tr>
</tbody>
</table>
Table 2

Summary Statistics for the Variables Tested in the Regression Analyses

The statistics are computed based on 1035 cohort-year observations in our panel data sample for the period 1995-2000. Age is the number of years a given cohort of policyholders has been with the current insurer. ExpLoss is the policy-specific expected loss ratio. MS is the insurer’s share of the LTC insurance market. Stock is binary indicator equal to one if an insurer is a mutual firm and four if it is a stock firm. RBC is the ratio of adjusted capital to risk-based capital. L/P is the actual loss ratio for a given cohort of policies, and (L/P)_{t-1} is its lagged value.

<table>
<thead>
<tr>
<th></th>
<th>Cohort Age (Age)</th>
<th>Expected Loss Ratio % (ExpLoss)</th>
<th>Market Share % (MS)</th>
<th>Organizational Structure (Stock)</th>
<th>Risk-Based Capital (RBC)</th>
<th>Actual Loss Ratio % (L/P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>9.127</td>
<td>80.575</td>
<td>2.335</td>
<td>3.559</td>
<td>1.073</td>
<td>70.487</td>
</tr>
<tr>
<td>S.D.</td>
<td>2.641</td>
<td>41.542</td>
<td>4.214</td>
<td>1.103</td>
<td>.0256</td>
<td>67.825</td>
</tr>
<tr>
<td>Min.</td>
<td>5</td>
<td>22.000</td>
<td>.0007</td>
<td>1</td>
<td>.984</td>
<td>0.000</td>
</tr>
<tr>
<td>Max.</td>
<td>21</td>
<td>297.700</td>
<td>24.50</td>
<td>4</td>
<td>1.502</td>
<td>666.525</td>
</tr>
</tbody>
</table>

Correlation Coefficients

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>ExpLoss</th>
<th>(L/P)_{t-1}</th>
<th>MS</th>
<th>Stock</th>
<th>RBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td></td>
<td>.397</td>
<td>.137</td>
<td>.056</td>
<td></td>
<td>.144</td>
</tr>
<tr>
<td>ExpLoss</td>
<td></td>
<td></td>
<td>.238</td>
<td>.071</td>
<td>.066</td>
<td>.042</td>
</tr>
<tr>
<td>(L/P)_{t-1}</td>
<td></td>
<td></td>
<td></td>
<td>-.043</td>
<td>.063</td>
<td>.052</td>
</tr>
<tr>
<td>MS</td>
<td></td>
<td>.021</td>
<td></td>
<td></td>
<td></td>
<td>-.259</td>
</tr>
<tr>
<td>Stock</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.003</td>
</tr>
</tbody>
</table>
Table 3

Regression Estimates of the Effects of Cohort Age and Observable Risk Characteristics on Cohort Loss Ratios

This table contains regression estimates of cohort-specific loss ratios on cohort age and other proxies of cohorts’ observable risk characteristics. Columns (1)-(4) correspond to the four model specifications given in Table 1. The results are based on a panel of 359 policy cohorts with 1035 cohort-year observations for the period 1995 to 2000. Standard errors are corrected for heteroscedasticity using White’s robust covariance estimators and in parentheses. GLS and IV/GLS are generalized estimates of panel data models assuming no individual effects and REM denotes a random effects model. Superscripts ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. The test on $Age^2$ is one tailed.

<table>
<thead>
<tr>
<th>Dependent Variable $(L/P)$</th>
<th>GLS (1)</th>
<th>IV/GLS (2)</th>
<th>REM (3)</th>
<th>Dynamic Panel Model (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-38.89***</td>
<td>-17.76***</td>
<td>-11.46***</td>
<td>-40.04***</td>
</tr>
<tr>
<td>(21.22)</td>
<td>(17.59)</td>
<td>(16.84)</td>
<td>(28.62)</td>
<td></td>
</tr>
<tr>
<td>Cohort age $\text{(Age)}$</td>
<td>11.48***</td>
<td>6.948**</td>
<td>5.995**</td>
<td>12.395***</td>
</tr>
<tr>
<td>(3.978)</td>
<td>(3.367)</td>
<td>(3.253)</td>
<td>(5.27)</td>
<td></td>
</tr>
<tr>
<td>Cohort age squared $\text{(Age}^2\text{)}$</td>
<td>-.464***</td>
<td>-.282**</td>
<td>-.231*</td>
<td>-.450**</td>
</tr>
<tr>
<td>(.189)</td>
<td>(.157)</td>
<td>(.153)</td>
<td>(.233)</td>
<td></td>
</tr>
<tr>
<td>Expected loss ratio $\text{(ExpLoss)}$</td>
<td>.419***</td>
<td>.205***</td>
<td>.222***</td>
<td>.299***</td>
</tr>
<tr>
<td>(.063)</td>
<td>(.049)</td>
<td>(.048)</td>
<td>(.067)</td>
<td></td>
</tr>
<tr>
<td>Organization structure $\text{(Stock)}$</td>
<td>3.892</td>
<td>.852</td>
<td>.948</td>
<td>.108</td>
</tr>
<tr>
<td>(2.453)</td>
<td>(1.694)</td>
<td>(1.746)</td>
<td>(2.534)</td>
<td></td>
</tr>
<tr>
<td>Risk-based capital $\text{(RBC)}$</td>
<td>-.008</td>
<td>.0004</td>
<td>.0002</td>
<td>-.005</td>
</tr>
<tr>
<td>(.202)</td>
<td>(.012)</td>
<td>(.012)</td>
<td>(.020)</td>
<td></td>
</tr>
<tr>
<td>Firm size $\text{(Size)}$</td>
<td>-.557</td>
<td>-.274</td>
<td>-.391</td>
<td>-.181</td>
</tr>
<tr>
<td>(.619)</td>
<td>(.436)</td>
<td>(.438)</td>
<td>(.606)</td>
<td></td>
</tr>
<tr>
<td>Lagged loss ratio $\text{(L/P)_t}$</td>
<td>.482***</td>
<td>.418***</td>
<td>.172***</td>
<td></td>
</tr>
<tr>
<td>(.027)</td>
<td>(.025)</td>
<td>(.067)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\rho: AR\ (1)$</td>
<td>.444***</td>
<td>.070**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(.027)</td>
<td>(.031)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D.W.</td>
<td>2.125</td>
<td>2.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>.077</td>
<td>.335</td>
<td>.325</td>
<td>.08</td>
</tr>
</tbody>
</table>