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Temporal Profitability and Pricing of Long-Term Care Insurance

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Abstract

Equilibrium models of dynamic insurance markets can be bifurcated according to underlying assumptions about whether or not insurers commit to long-term contracts. The difference is substantial in that commitment models imply price highballing over time while no-commitment models indicate price lowballing. Extant empirical studies provide mixed evidence, however. We use long-term care (LTC) insurance data, which allow us both to better control for heterogeneous, observable risk, to examine dynamic profitability and pricing in a relatively young, innovative insurance market. Our tests generally indicate temporal price lowballing, thereby providing support for the no-commitment models.

Introduction

Two predominant types of dynamic pricing models under adverse selection have emerged in the insurance economics literature and the resulting implications contrast substantially. Models based on the assumption that insurers will commit to experience rating schemes over time, often referenced as commitment or semicommitment models, generate predictions of relatively high prices in the early years of policies and relatively low prices in later years (Cooper and Hayes, 1987; Dionne and Doherty, 1994). This pricing pattern is known as highballing. The alternative models are built upon the assumption that insurers will not commit to long-term contracts,

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thereby essentially issuing only single-period contracts (Kunreuther and Pauly, 1985; Nilssen, 2000). These are referenced as no-commitment models and infer a price lowballing pattern over time. The extant empirical evidence from insurance markets indicates conflicting evidence about which type of model best predicts temporal pricing patterns.

In this study, we exploit unique data from the long-term care (LTC) insurance markets that allow us greater control of heterogeneity in observable risk than in the previous empirical research. While prior empirical work has been limited to the examination of profit measures, our data facilitate investigation of both profitability and pricing for nearly all insurers issuing LTC insurance in the United States. We specifically find that loss ratios, an inverse profit measure, increase with policy age, but at a declining rate. We also generate evidence of price stickiness over time. While our findings do not resolve the conflicting results generated previously by researchers, they do provide a clear indication of price lowballing in a relatively young, innovative insurance market. They are also consistent with the results previously generated by D'Arcy and Doherty (1990) for the comparatively mature market for automobile property insurance.

In the next section, we briefly review the relevant adverse selection literature, focusing on models of dynamic 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. Rothschild and Stiglitz (1976) specifically show that informationally disadvantaged insurers can incorporate insurance pricing and contract schemes that give buyers incentives to voluntarily enter into contracts consistent with their risk levels. One such self-selection mechanism is a menu of contracts with a convex-pricing schedule. In a single-period equilibrium, risk separation occurs such that contracts with more comprehensive coverage are chosen by greater-risk individuals at higher unit prices while low risks only can optimize by selecting partial insurance coverage.

Many researchers have proposed modifications to the single-period equilibrium model with risk separation proposed by Rothschild and Stiglitz (see, e.g., Miyazaki, 1977; Stiglitz, 1977; Wilson, 1977). These basic models have been further modified and extended to address insurance pricing over multiple periods of time (see, e.g., Dionne, 1983; Kunreuther and Pauly, 1985; Cooper and Hayes, 1987).

We note that theoretical researchers traditionally assume that adverse selection exists in insurance markets. While some empirical evidence is consistent with the traditional view of adverse selection in insurance markets (Dahlby, 1983; Browne, 1992; Puelz and Snow, 1994; Cohen, 2002), other results are not as supportive (Cawley and Philipson, 1999; Chiappori and Salanié, 2000). In this study, we address the conflicting implications of dynamic models based upon the traditional assumption of adverse selection in insurance markets. We specifically test the implications of dynamic market equilibrium models on LTC insurance profitability and pricing. In the next section, we explore these multiperiod models.

Dynamic Insurance Markets With Adverse Selection

Contracts that reflect commitment to experience-rated, long-term contracts generally produce *ex ante* risk separation (Dionne, 1983; Dionne and Lasserre, 1985). Although commitment between insurers and insureds is frequently assumed in dynamic models, policyholders generally are not subject to such a stringent restriction (Dionne and Doherty, 1994). When firms are assumed bound to long-term contracts while policyholders are free to switch in any given period, second-period competition and probable *ex post* renegotiation complicate the information mechanism in the multiperiod setting (Hosios and Peters, 1989).

Cooper and Hayes (1987) suggest that to counteract incentive problems created by the presence of second-period competition and switching (e.g., high risks pretending to be low risks in the first period and then switching to rival firms in the second period), contracts designed for low risks should initially contain an incremental premium that increases the costs for high risks pretending to be low risks. In equilibrium, high risks then will choose short-term contracts with complete coverage and low risks will purchase front-loaded, long-term contracts with partial coverage and experience rating. A dynamic separating equilibrium occurs with an additional premium imposed on low risks in the first period, generating a profit for insurers. 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 resulting pattern of temporal pricing.

Dionne and Doherty (1994) relax some of the Cooper–Hayes constraints, allowing for *ex post* renegotiation if it is mutually beneficial to insurers and insureds. Their equilibrium outcome is characterized by semipooling of all the low risks and a proportion of the high risks, followed by second-period risk separation through self-selection. Although their model allows for renegotiation, Dionne and Doherty conclude that their semipooling contracts are renegotiation-proof and a price highballing pattern still applies.

Kunreuther and Pauly (1985) and Nilssen (2000) examine the effects of adverse selection in competitive insurance markets assuming that neither buyers nor sellers commit to long-term contracts. Kunreuther and Pauly posit that pooling contracts will be offered in the first period, but 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, a cross-subsidizing menu, or both, depending on the information observed during the first period. In the Kunreuther–Pauly's model, prices are adjusted upward for those who incur claims, while prices for the better risks do not fully reflect their favorable loss record, thereby allowing insurers to extract quasirents. In the Nilssen model, such price adjustments are a possible, but not necessary, result.

The primary implication that differentiates the "no-commitment" models of Kunreuther–Pauly and Nilssen from the "commitment" models discussed previously is the contrasting pricing and profit pattern over time. In particular, net losses are anticipated in the initial period while profits are realized in subsequent periods under the condition of zero long-run profits. The resulting pattern of price adjustment is known as price lowballing (D'Arcy and Doherty, 1990).

Empirical Evidence on Profitability

Because the commitment and no-commitment models predict directly contrasting profit and pricing patterns over time, empirical examination of both the financial performance and prices of cohorts of insurance contracts can provide insight into which type of model better applies to insurance markets. Realizing that direct pricing information is not publicly available, researchers have previously tested loss data for auto property insurers to ascertain underwriting profit patterns for cohorts of personal auto property damage policies. The studies use current year loss ratios, i.e., losses incurred divided by premiums earned, to measure the financial performance of contracts and infer evidence of pricing practices. Based upon the survey data collected from a sample of seven insurers, D'Arcy and Doherty (1990) find that mean loss ratios decline as policy age increases.[1] The sample insurers' firm-level, aggregate loss ratios also decline and converge to the industry mean as the companies age. D'Arcy and Doherty conclude that their findings are consistent with the Kunreuther–Pauly's model which predicts price lowballing.

Dionne and Doherty (1994) examine a sample of more than 80 insurers writing insurance in California during the period 1985–1988. They find a significant, negative relation between their proxy for policy age and loss ratios reported by insurers that tend to insure lower risks. They observe no significant relation between policy age and loss ratios for insurers of more mixed risk classes and a weakly positive relation for those that insure higher risks. They conclude that their results support their own semicommitment model and the Cooper–Hayes's commitment model, both of which predict price highballing.

The empirical studies of adverse selection in insurance markets generally are hampered by very limited data. Because data for the contractual characteristics and pricing of insurance generally are not available on an industry-wide basis, researchers have turned to indirect tests of average profitability for contracts often issued to observably heterogeneous cohorts.[2] Specifically, empirical studies of auto property damage have combined heterogeneous risk classes based on observable characteristics such as age, gender, driving experience, and accident records into a single group. For example, the studies by D'Arcy and Doherty (1990) and Dionne and Doherty (1994) use loss measures aggregated over all policies with the same number of years in force, implicitly ignoring the heterogeneity of the risk classes insured under these contracts. Adverse selection theory implies that empirical tests should be applied to data for observably similar insureds, however (Chiappori and Salanié, 2000). Given the aggregation problems caused by data limitations, researchers should not be surprised by the conflicting empirical results generated previously.

Another problem with the extant empirical research on insurer profitability is that these tests hinge upon the assumption of perfectly competitive markets and, hence, long-term profits of zero. Without the zero profit constraint, the temporal profitability

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[1] The loss ratio generally is defined as losses incurred divided by premiums earned for a single period. See D'Arcy and Doherty (1990) and Dionne and Doherty (1994) for a discussion of the advantages of testing loss ratios rather than underwriting profits.

[2] For example, D'Arcy and Doherty explain that data limitations force them to combine individuals of different classes of observable risk into their sample cohorts.

patterns predicted by alternative theories do not necessarily contrast. Studies of insurance market structure generally conclude that these markets are better characterized by imperfect competition (see, e.g., Dahlby and West, 1986; Schlesinger and von der Schulenburg, 1991; Brown and Goolsbee, 2002), however. We therefore supplement our profitability tests with examinations of LTC insurance price adjustments over time. These tests are not dependent upon the restrictive assumption of perfect competition.

Price Testing

The no-commitment models of Kunreuther and Pauly (1985) and Nilssen (2000) imply that initial risk pooling in insurance markets is likely to spawn monopolistic price distortion and rising profitability in later periods. In particular, insurer managers can gain private information through observation of their insureds' loss experience and price policies in subsequent periods to lock in customers.[3] In a pooling equilibrium in which true risk is not yet revealed, insurers are cognizant of incentives for high risks to under-report accidents (Hosios and Peters, 1989). Both consumer lock-in and accident under-reporting encourage insurers to respond rapidly to unfavorable loss experience, but more slowly to favorable experience. We consequently expect downward price stickiness if no-commitment models apply. In other words, insurers should increase prices quickly when they realize relatively poor loss experience, but should not decrease prices as rapidly when experience is favorable. Researchers have not previously tested for asymmetric price adjustment over time. LTC insurance data are conducive to testing both price adjustments and underwriting profits over time.

RESEARCH DATA

In contrast to prior studies, we are able to examine both time-serial and cross-sectional variation in the profitability and pricing of LTC insurance contracts to draw inferences about the appropriate pricing mechanism. More importantly, our data set allows cohort-specific analyses. In particular, we are able to track data for policy forms, which were issued to policyholders of similar risk. We partition the data by policy form and by the number of years that policyholders have been covered by the form. We then are able to track the data for these policy cohorts for a number of years. Our tests consequently have advantages over prior studies, which examine data aggregated over cohorts of insureds that were issued different policy forms and therefore are likely to have possessed different characteristics at the time of issuance.

We draw our data from the National Association of Insurance Commissioners (NAIC) InfoPro databases of Long-Term Care Insurance Reports and Life and Health Reports. These data include such items as direct premiums earned and loss experience, before reinsurance ceded or assumed, for each policy form reported. All policy forms that meet the requirements of the NAIC Long-Term Care Insurance Model Act, or substantially similar laws and regulations of individual states, are included in the database. Policies sold to policyholders residing outside the United States are excluded.

The sample data encompass the period 1994–1999. Calendar year 1994 is the first year for which data from the LTC reporting forms are available from the NAIC. Our initial

[3] In insurance markets, search and switching costs also can contribute to consumer lock-in (see, e.g., Klemperer, 1995; Schlesinger and von der Schulenburg, 1991).

sample contains all life and health insurers that submitted information required by state insurance commissions and departments. After screening for missing observations and outliers, our final sample contains data for 112 insurers, with a total of 1,863 policy forms and 4,809 cohort-year observations. The total amount of LTC insurance premiums written by the sample insurers in 1999 was $3.6 billion, accounting for nearly 91 percent of all in-force LTC insurance premiums written in the United States.

The NAIC specifically instructs insurers to report combined experience for "forms which provide substantially similar coverage and provisions, which are issued to substantially similar risk classes and which are issued under similar underwriting standards" (NAIC, 2001a, p. 374).[4] Although policy forms are filed with state regulators, no database exists that provides the contractual provisions of each policy form so we cannot develop a strict ordering of these forms based upon the risk assumed in each. Consultations with two LTC insurance actuaries and one insurance commissioner indicate that new policy forms (1) either limit or expand expected claims, such as better definitions of alternative LTC facilities or adding significant benefits, (2) better specify contractual triggers, such as definitions of activities of daily living (ADLs), or (3) address new regulations, such as tax qualified status. Each policy form normally includes menus of options for such contractual provisions as elimination period, benefit amount, benefit duration, and cost of living adjustments. For our sample, the average insurer reports experience for nearly 17 policy forms.

Within the data for each reported policy form, experience for policyholder groups is further disaggregated by the year in which they first purchased the policy.[5] We refer to these policyholder groups as "cohorts" because the members bought similar policies and had to meet similar underwriting standards in the same initial year. For the average policy form in our sample, we have data for 2.6 cohort years. In essence the NAIC-prescribed grouping of reported experience by similar policy forms allows us to control for homogeneity of risk groups and temporal reporting (cohort years) allows us to control for external factors such as changes in industry-wide supply and demand, insurer-specific demand, and the regulatory environment.

We emphasize that our average price estimates for cohorts are aggregate measures segregated by policy form and by cohort year rather than averages of individual policy prices, which are not publicly available in any comprehensive database. While LTC policies essentially are priced on a level premium basis, the premium at issuance is guaranteed renewable, "not" noncancelable, for both individual and group plans. This means that premiums can be raised for an entire class of insureds if justified by adverse claims experience, subject to regulatory approval. In our discussion of the results, we summarize information provided by an insurance regulator on the frequency and magnitude of premium increases.

[4] Different LTC policy forms impound different levels of underwriting risk depending upon the contractual options offered. These options include menus of elimination periods, preexisting conditions clauses, nonforfeiture options, and various triggers for the inception of benefit payments (see, e.g., Doerpinghaus and Gustavson, 1999).

[5] In contrast, D'Arcy and Doherty (1990) study cohorts of individuals that have been with an auto insurer for the same number of years, without respect to their initial risk classifications.

For each policy form the NAIC specifically classifies LTC insurance data by calendar duration. Defined as the year for which experience is reported for the policy form less its year of initial issue, calendar duration indicates how long a policyholder cohort has been insured under the form. So a cohort with calendar duration of 5 years in statement year 1995 first purchased these contracts in 1990. The NAIC-specified calendar duration for each policy form in our sample increases by one during each of the first 5 years of the policy form's lifetime. Once a policyholder cohort reaches a calendar duration of 6 years, the NAIC aggregates it with others covered under the same policy form, but with calendar durations of 6–10 years. Consequently, we only can track a new or existing cohort for a maximum of 5 years before some aggregation occurs. All cohorts with calendar durations exceeding 10 years also are aggregated into a single cohort by the NAIC.

For any one LTC policy form in existence for 10 years or more, a new cohort enters the 6–10 year category each year and a different one moves to the over-10 category. Because this accounting by the NAIC prevents us from tracking the experience for a specific cohort beyond year 5, we simply combine the experience data for cohorts with durations above 5 years into a single cohort. While this procedure unavoidably combines cohorts with some heterogeneous risk characteristics, this limitation is not too severe because aggregation always takes place within the same policy form.

We end up with six cohort classifications in terms of calendar duration, as explained previously. To compute the mean calendar duration for each cohort using the original NAIC-reported data, we initially apply the following rules:

1. For policy cohorts with initial durations of 1–5 years we simply can access the actual calendar duration, increasing duration by one for each additional year in the sample period;
2. For policy cohorts with reported durations of between 6 and 10 years at the start of the sample period we assign an initial duration of 6 years and add one for each additional year in the sample period if an older, over-10 cohort exists for the policy form. Otherwise the 6–10-years cohort is the oldest cohort reported by the NAIC and we use the current calendar year less the original issue year; and
3. For policy cohorts with reported durations of over 10 years at the start of the sample period the calendar duration is always estimated as the current calendar year less the initial issue year.

Finally, to estimate the mean duration for our combined set of cohorts with calendar durations of 5–10 and over-10 years we use a premium-weighted average of the durations estimated via rules 2 and 3.

THE PROFIT MODEL

Because product-specific underwriting profits generally are not publicly available, researchers have focused their analyses on loss ratios, particularly for a short-tailed line of insurance, i.e., auto-property damage insurance (D'Arcy and Doherty, 1990; Dionne and Doherty, 1994). With auto insurance, the probability distribution of losses is implicitly assumed to be constant over time. Temporal variations in the financial performance of policy cohorts therefore are deemed attributable to price adjustments made by insurers as they gain new information from insureds' loss experience. In contrast, both LTC policyholders and their contracts age over time, so the probability distribution of losses should shift to the right. In other words, LTC losses will inevitably rise as cohorts age. Consequently, LTC insurer profitability should decline over time, not because of the multiperiod pricing scheme built into contracts to address adverse selection, but because of the rightward shift in the probability distribution of LTC losses over time. To isolate adverse selection effects, we must hold constant the mean of the underlying probability distribution and control for time effects on insurer profitability.

Following the researchers cited previously we use loss ratios to estimate the inverse of underwriting profits 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.[6] 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 jth insurer, we model contract profitability for each insurer as follows:

$$\left(\frac{L}{P}\right)_{it} = \alpha_0 Trend + \alpha_1 Age_{it} + \alpha_2 Age_{it}^2 + \beta \mathbf{X}_{it} + \varphi \mathbf{W}_{jt} + c_i + \varepsilon_{it}, \qquad (1)$$

where L/P is the loss ratio, *Trend* is a linear time trend variable, *Age* is the number of years that the cohort of contracts has been in effect, $\mathbf{X}$ is a vector of contractual characteristics that includes the expected loss ratio and lagged actual loss ratio, $(L/P)_{i,t-1}$, $\mathbf{W}$ is a vector of firm-specific characteristics, such as firm size and organizational structure, c_i is the cohort-specific individual effect, and the error term ε is assumed to have a mean of zero. Because we only can observe limited contractual variables for cohorts, we use individual effects, c_i, to capture the variations in unobservable contractual characteristics across cohorts.

Dependent Variable

In line with the previous research on auto insurance we initially test the current period loss ratio, for which the NAIC uses a 2-year loss development period for LTC claims, but we also test other proxies. For LTC insurance, incurred losses are likely to be quite low in the early years of a policy and they may not fully capture the underwriting risk assumed. As noted by the NAIC, "because of the relatively small claim rates and variable LTC claims, the statistical credibility of LTC insurance experience is lower than the amount of credibility assigned to similar amounts of experience on other types of health insurance" (NAIC, 2001a, p. 373). Considering the relative youth of the LTC market, the incurred loss ratios we initially generate could produce overly generous profit estimates.

To adjust for potential downward bias inherent in incurred loss ratios, we devise a second proxy for loss ratios that is much more conservative. We specifically add net changes in policy reserves during the current period to incurred losses in the numerator. In any reporting period an LTC insurer may adjust policy reserves up or down

[6] See D'Arcy and Doherty (1990) and Dionne and Doherty (1994) for a discussion on the advantage of testing loss ratios rather than underwriting profits.

based upon management perceptions of prospective losses. While such changes in policy reserves normally reflect management's estimates of future losses attributable to both the current and future periods, we have no way to determine the proportion attributable only to the current period. To implement a more conservative measure, our only choice is to add the entire change in policy reserves to incurred losses in the numerator.[7] The resultant loss ratios should be systematically high, so profit estimates will be correspondingly low.

While we adopt the view that temporal profit patterns should reflect the intended policies of insurer management, one can argue that these patterns could emerge because of unintentional, short-term misestimates of future losses by managers. For instance, the paucity of actuarial experience pertaining to LTC exposures conceivably could have caused insurers to systematically underestimate or overestimate losses during the relatively short sample period. The necessary, subsequent adjustments stimulated by actual loss experience then would give the appearance of price highballing or lowballing. NAIC guidelines require managers of LTC insurers to estimate expected loss ratios, as defined in the next section, for future periods at the time a policy is issued and when policy changes or new rates are filed with regulators. We consequently run a third set of tests using expected loss ratios as the dependent variable to see if patterns of expected profitability, which should reflect intended management policies, are similar to actual profitability patterns.

Contract-Specific Variables

We primarily focus upon the estimated coefficient for the policy age-squared variable. A significant and positive coefficient α_2 is consistent with the price highballing implication of the commitment or semicommitment models proposed by Cooper and Hayes (1987) and Dionne and Doherty (1994). A negative and significant α_2 is consistent with the price lowballing pattern suggested by the no-commitment models of Kunreuther and Pauly (1985) and Nilssen (2000).

To see why, recall that we must address the issue of how profitability for a given cohort of policies, i.e., ones issued to observably similar individuals, changes over time. The price highballing models imply a negative relation between profitability and policy age, while lowballing models indicate a positive relation. If we examine an insurance product market in which the true probability of incurred losses for individuals does not change substantially over time, as should be the case for automobile property damage insurance, we should primarily focus on the sign of the coefficient, α_1, in Equation (1).

In contrast to auto property losses, the probability distribution of LTC losses shifts to the right over time as policyholders age and their health deteriorates. Consequently, first-order correlation between loss ratios and policy age, as measured by α_1, should primarily reflect this rightward shift induced by policy age and loss ratios inevitably will rise over time. We cannot know the exact functional form for the relation between loss ratios and the independent variables. For instance the relation between loss ratios

[7] Conversations with members of the Academy of Actuaries' long-term care working group revealed no alternative to including all changes in policy reserves if we wish to adjust the current period loss ratio for future loss development.

and policyholder age could be nonlinear. We therefore include a time trend variable to control for the potentially confounding effects of aging, underwriting, and other factors.

With the mean of the probability distribution of losses held constant by inclusion of the age and time trend variables the second-order correlation captured by α_2 should reflect the effects of adverse selection on the temporal relation between LTC loss ratios and policy age. With price highballing the rate of change in loss ratios with respect to policy age should increase for a given cohort of LTC insurance buyers. In essence a price highballing strategy magnifies the positive time effect on insurer losses and, hence, declines in profitability. 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. The effect of price lowballing essentially mitigates the positive time effect on loss experience for an LTC policy.

Our other control variables are the expected loss ratio, $ExpLoss_{it}$, and the lagged actual loss ratio, $\frac{L}{P}_{i,t-1}$, a group policy indicator, $Group_{it}$, and an interaction term, $Group_{it} * Age_{it}$. To the extent that variations in expected loss ratios across cohorts reflect *a priori* differences in risk characteristics that are observable to risk managers, we expect a positive relation with incurred losses. As mentioned previously, we also test the expected loss ratio as a possible dependent variable representing anticipated profits generated by the intentional pricing policies of management. The lagged-dependent variable, $\frac{L}{P}_{i,t-1}$, is included in our model to capture short-run departures from equilibrium. Temporary effects, such as those arising from slow price adjustments because of adjustment costs or regulatory delay, can be captured by this term.[8] Consequently, we anticipate that costly price adjustments or delays, as quantified by the lagged loss ratio, will be positively related to the current period loss ratios.

Our group policy variable, $Group_{it}$, is equal to 1 if a cohort is insured under a group plan and zero otherwise. Participation in an employer-based LTC insurance generally is voluntary and coverage either guaranteed or subject to minimal underwriting (Pincus, 2000), so group plans could experience more adverse selection. Mitigating factors such as economies of scale, better loss predictability over time because of cohort size, and greater bargaining power and/or subsidization by employers could counter the effects of adverse selection, however. Consequently, the expected relation between group status and profitability is ambiguous. Because individual policyholders generally are older and more likely to be locked into their LTC plans because of ill health or higher search costs, we also control for possible interaction between group status and policy age with the variable $Group_{it} * Age_{it}$.[9]

Firm-Specific Variables

We also control for differences in managerial propensities to accept risk by incorporating firm-specific characteristics, including organizational form, capital adequacy,

[8] See, e.g., Dahlby (1992), for a test of auto insurance price rigidity when price adjustments are costly.

[9] A recent survey indicates that the average age of an insured covered by an individual plan is 67, more than 20 years older than the average age of insureds covered by group plans (Coronel, 2000).

and firm size. Our organizational form proxy is a binary variable equal to 1 for stock insurers and zero otherwise. Agency theory suggests that managers of stock insurers should be accorded greater managerial discretion to underwrite risky lines of business (Mayers and Smith, 1981). We therefore expect a positive relation between a stock form and loss ratios.

We use the ratio of total adjusted capital to minimum risk-based capital (RBC), as defined by the National Association of Insurance Commissioners, to estimate capital adequacy. The National Association of Insurance Commissioners developed RBC as an observable measure of an insurer's total risk, including asset portfolio, underwriting, and business risk (Atchinson, 1996). We contend that relatively high RBC ratios indicate that insurance managers are less tolerant of risk because they maintain stronger capital positions. Doerpinghaus and Gustavson (1999) observe a negative relation between RBC ratios and LTC insurance prices and attribute their result to unobservable underwriting risk captured by these ratios. Consequently, we expect RBC ratios to have a negative impact on LTC insurance profitability and pricing.

We alternately estimate firm size with the log of total admitted assets and share (in percent) of the LTC insurance market, but the results are quite similar. We only report results for the market share proxy. Firm size can be associated with greater expertise and resources in screening and sorting risks (Kroner and West, 1995). In markets with imperfect information and product differentiation, size, especially when defined as market share, can enhance market power and produce higher prices (Berger, 1995). We therefore expect a negative relation between firm size and loss ratios.

For testing purposes, our full model follows:

$$\left(\frac{L}{P}\right)_{it} = \alpha_0 Trend + \alpha_1 Age_{it} + \alpha_2 Age_{it}^2 + \beta_1 ExpLoss_{it} + \beta_2 \left(\frac{L}{P}\right)_{i,t-1} + \beta_3 Group_{it} + \beta_4 Group_{it} * Age_{it} + \phi_1 OrgForm_{jt} + \phi_2 CapAdeq_{jt} + \phi_3 Size_{jt} + c_i + \varepsilon_{it}. \tag{2}$$

We apply Equation (2) using the various model specifications and estimation procedures further explained with our subsequent empirical results.

PROFITABILITY RESULTS

Panel A of Table 1 contains summary statistics for the variables used in our regression analyses. The mean policy issue age is 5.4 years, with a standard deviation of approximately 3 years, reflecting the relative youth of the LTC insurance market. The maximum policy age is 22 years, however. We observe a wide range of current year incurred loss ratios, varying from 0 to 634 percent with a mean of 38 percent and standard deviation of about 50 percent. Such a low-mean loss ratio is expected because relatively few claims are made until policyholders become quite elderly. In comparison, our conservative loss ratio estimates, in which we adjust incurred losses for changes in policy reserves, have a mean of 78 percent and standard deviation of 173 percent.

The cohort-specific expected loss ratios filed by insurers have a mean of 41 percent and standard deviation of 33 percent. A t-test for zero-mean prediction error suggests that insurers' expected loss ratios are unbiased estimators of both current year incurred

TABLE 1
Descriptive Statistics for 4,809 Cohort-Year Observations for the Period 1994–1999

Panel A. Descriptive Statistics for Entire Sample

	Incurred Loss (%)	Adjusted Loss (%)	Expected Loss (%)	Policy Age	Market Share	Org. Form	Cap. Adeq.	Group Policy	Time Trend
Mean	38.25	77.9	40.7	5.4	2.6	0.83	6.20	0.175	3.533
SD	49.2	172.9	33.1	3.1	4.3	0.37	7.72	0.38	1.69
Min.	0.0	−4987.3	0.0	1.0	0.0007	0.00	0.70	0.00	1
Max.	634.4	2226.6	297.7	22.0	24.5	1.00	43.64	1.00	6
			Pearson Correlation Coefficients						
Incurred loss (%)	1								
Adjusted loss (%)	0.261	1							
Expected loss (%)	0.459	0.131	1						
Policy age	0.449	0.153	0.738	1					
Market share	−0.050	−0.033	−0.0001	0.007	1				
Org. form	0.058	−0.0153	0.064	−0.007	0.022	1			
Cap. adeq.	0.002	0.001	0.024	0.002	−0.084	0.005	1		
Group policy	−0.053	0.019	0.004	0.058	0.029	−0.285	−0.028	1	
Time trend	0.038	0.013	0.094	0.123	0.080	0.072	0.020	0.100	1

Panel B. Comparative Statistics for Group and Individual Policy Forms

	Incurred Loss (%)	Adjusted Loss (%)	Expected Loss (%)	Policy Age
Mean losses of individual	39.36	76.26	40.45	5.749
policies (n = 3,965)	(48.63)*	(138.69)	(32.95)	(3.405)
Mean losses of group	32.45	85.34	40.96	5.283
policies (n = 844)	(51.57)	(282.73)	(33.69)	(2.998)
t-statistics	3.554	−0.907	−0.298	4.085

*Standard deviations are given in parentheses.

loss ratios, with a t-ratio of -0.06, and our reserve-adjusted loss ratios, with a t-ratio of 0.02. When we apply the mean cohort age of 5 years to bifurcate our sample into a group of older policies with 1,097 observations and a group of younger policies with 3,713 observations, we find that expected loss ratios remain unbiased estimators of both current year incurred and reserve-adjusted loss ratios. Panel A of Table 1 also displays the correlation matrix of the variables used in the model. As expected, policy age is highly correlated with expected losses, but not as strongly correlated with incurred or reserve-adjusted loss ratios.

In Panel B of Table 1, we compare the various measures of loss ratios and policy age for group and individual policies. We find that current year loss ratios are significantly greater at the 1 percent level for individual plans than for group plans. This finding is consistent with the generally older age of the holders of individual policies. When we apply the very conservative adjusted loss and the expected loss proxies, we find no significant differences between individual and group plans, however. Our results also indicate that the policy age of individual plans is significantly higher than group plans although the mean difference is less than 6 months.

Table 2 details the relation of current period, incurred loss ratios with the policy age variables and the previously defined control variables under various specifications. Columns 1 and 2 contain the generalized least squares (GLS) estimates of Equation (2), excluding the lagged-dependent variable. We provide both random and fixed effect estimates in the subsequent columns. The results in columns 3 and 4 do not allow for possible endogeneity of the lagged-dependent variable in a panel data model. The standard transformation used in the panel data method to eliminate individual effects is insufficient for obtaining consistent estimators in models for dynamic panel data, however. We therefore provide dynamic panel model estimates in columns 5 and 6 using alternative instrumental variable (IV) methods. The instrument applied in columns 5 and 6 is the lagged loss ratio, $\frac{L}{P}_{i,t-2}$. We use this single, lagged ratio because of the relatively short time series contained in our unbalanced panel data.[10]

Our estimates in column 5 reflect a standard application of the dynamic panel model to Equation (2) while column 6 estimates are obtained via two-stage regressions. The Appendix contains an explanation of our two-step IV approach. We essentially move the lagged-dependent variable to the left-hand side, using the consistent coefficient estimate for the lagged loss ratio shown in column 5. We then apply the standard panel data method to the transformed equation. The resulting estimators are consistent, although relative efficiency remains unexplored. The estimates for the transformed model shown in column 6 reflect a fixed effects approach.

The time trend variable, our proxy for the time effects of factors other than policy age, is generally positive, but not necessarily significant. In regressions not reported here we omitted the time trend variable with virtually no effect on Age and Age^2. As expected, the coefficients for the variable Age indicate a significant and positive effect on incurred loss ratios for LTC insurance policies in five of our six specifications. Estimated coefficients for our primary variable of interest, Age^2, are negative and

[10] Lagged differences, such as $\frac{L}{P}_{i,t-2} - \frac{L}{P}_{i,t-3}$ can serve as alternative instruments for panel data with sufficiently long time series.

TABLE 2
Regression Estimates of LTC Contract Profitability Determinants (Dependent Variable: Experience Year Incurred Loss Ratio)

Independent Variables	REM/GLS (1)	FEM/GLS (2)	REM/GLS (3)	FEM/GLS (4)	Dynamic Panel/IV (5)	Dynamic Panel/IV (6)
Constant	−5.689	–	−8.365	–	–	−17.03
	(2.132)		(2.051)			(2.415)
Time trend (*Trend*)	0.0436	1.699***	1.173**	−1.893	−0.300	3.004***
	(0.116)	(2.649)	(2.176)	(0.298)	(0.067)	(3.311)
Policy age (*Age*)	8.496***	8.547***	6.299***	10.625*	8.674***	8.537***
	(12.089)	(7.579)	(5.940)	(1.676)	(2.009)	(5.173)
Age squared (Age^2)	−0.322***	−0.308***	−0.248***	−0.195**	−0.169	−0.332***
	(6.559)	(4.195)	(3.595)	(1.952)	(0.984)	(3.241)
Expected loss (*ExpLoss*)	0.383***	0.322***	0.269***	0.282***	0.233***	0.312***
	(12.67)	(7.994)	(7.805)	(4.285)	(2.929)	(6.615)
Group policy (*Group*)	−0.441	−7.429	−4.618	−4.992	−2.814	−10.806*
	(0.145)	(1.446)	(1.117)	(0.565)	(0.466)	(1.638)
Group/age interaction ($Group * Age$)	−1.189**	−0.555	0.127	0.361	−0.068	−0.204
	(2.271)	(0.762)	(0.200)	(0.329)	(0.087)	(0.229)
Organizational form (*OrgForm*)	3.880**	5.949**	4.276*	7.149	2.718	3.566
	(2.013)	(2.003)	(1.743)	(0.791)	(0.287)	(0.977)
Capital adequacy (*CapAdeq*)	−0.059	0.126	0.0776	0.346**	0.190	−0.025
	(0.710)	(.794)	(0.509)	(2.049)	(1.594)	(0.082)
Firm size (*Size*)	−0.581***	−0.478**	−0.449**	0.085	0.162	−0.399
	(3.647)	(2.010)	(2.221)	(0.228)	(0.287)	(1.368)
Lagged loss ratio $(\frac{L}{P})_{i,t-1}$	–	–	0.256***	−0.031	0.037	–
			(15.299)	(0.538)	(0.671)	
Adjusted R^2	0.255	0.577	0.3165	0.4943	–	0.2136

Sample size = 4,809; t-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

significant in five of the six regressions. So while loss ratios rise over time because of the rightward shift in the probability distribution of LTC losses discussed previously, they do so at a decreasing rate, which suggests price lowballing.

Among the contract-specific control variables, only the expected loss ratio (*ExpLoss*) is consistently significant and the coefficients have the anticipated, positive sign. To the extent that expected loss ratios filed by managers serve as a viable proxy for observable underwriting risk, this finding supports the expected, positive relation between observable risk and relative losses. The estimated coefficients for group policy effects are consistently negative, but generally not significant. Our profitability results suggest that LTC insurers are adequately pricing differences in risk between individual and group plans.

The coefficients generated for our firm-specific control variables normally have the expected signs. For instance, the organizational form coefficients indicate that managers of stock insurers are more tolerant of underwriting risk, resulting in higher incurred loss ratios, but this relation is statistically significant in only three specifications. Similarly, the impact of firm size is negative in four of the six regressions and significantly so in three specifications. Countervailing influences confounded prediction regarding the influence of group plans and our results indicate that the group effect is rarely significant. We did expect our proxy for capital adequacy, the RBC ratio, to have a negative impact on loss ratios, but this proxy generally has no significant effect.

The lagged-dependent variable, which we implement to capture temporary departures from long-run equilibrium caused by adjustment costs or regulatory delays, is significant and positive only for the random effects model (REM). In contrast, the lagged effect is insignificant in both the fixed effect models (FEM) and dynamic panel models, in which adjustments are made for possible endogeneity of the lagged-dependent variable. A Hausman test comparing REM and FEM estimates in columns 3 and 4 produces a test statistic of 79.65, which favors the FEM specification. Based on the lagged-effect estimates in columns 3 and 4, we surmise that current and lagged loss ratios are not significantly related.

Table 3 supplies results for regressions applied to the current year, incurred loss ratio adjusted for policy reserve changes. Although this dependent variable impounds a generally excessive estimate of future losses attributable to the current period, which is reflected in some loss of fit as indicated by a lower, adjusted R^2, our regression results do not differ greatly from those generated previously. Once again, the coefficients for our primary variable of interest, Age^2, indicate a profit pattern consistent with price lowballing in five of the six specifications.

The effects for both policy age and the expected loss ratio are in the expected direction and significant for five of the six specifications. The results for other control variables are comparable to those reported in Table 2, with few coefficients significantly different from zero. The notable exception is the group policy variable, which is significantly negative in five of the six specifications. Considering the difference in these results compared to those based upon incurred loss ratios, our results suggest that group insurers are relatively less conservative in adjusting reserves on LTC plans than are insurers issuing individual policies.

TABLE 3
Regression Estimates of LTC Contract Profitability Determinants (Dependent Variable: Reserve-Adjusted Loss Ratio)

Independent Variables	REM/GLS (1)	FEM/GLS (2)	REM/GLS (3)	FEM/GLS (4)	Dynamic Panel/IV (5)	Dynamic Panel/IV (6)
Constant	2.412	–	21.395	–	–	32.118
	(0.328)		(2.410)			(1.972)
Time trend (*Trend*)	5.567***	3.349	4.985***	−80.33***	−1.349	2.824
	(5.070)	(0.357)	(3.884)	(5.871)	(0.063)	(1.219)
Policy age (*Age*)	20.265***	20.45**	9.790***	10.82***	14.468	14.095***
	(11.212)	(2.102)	(4.398)	(7.267)	(.588)	(3.381)
Age squared (Age^2)	−1.109***	−1.060***	−0.542***	−0.906***	−0.582	−0.739***
	(9.168)	(6.99)	(3.778)	(4.652)	(0.904)	(2.734)
Expected loss (*ExpLoss*)	0.1701***	0.342***	0.153**	0.500***	0.398**	0.175
	(2.332)	(2.810)	(2.255)	(3.387)	(2.065)	(1.286)
Group policy (*Group*)	−18.254**	−49.03***	−30.89***	−66.00***	−45.726	−61.41***
	(2.044)	(3.399)	(3.408)	(3.733)	(1.223)	(3.444)
Group/age interaction ($Group * Age$)	1.424	4.061**	3.631***	7.044***	3.244	6.742***
	(1.169)	(2.009)	(3.013)	(2.607)	(0.924)	(2.657)
Organizational form (*OrgForm*)	−1.763	20.252*	−0.695	8.063	8.997	−10.72
	(0.361)	(1.754)	(0.149)	(0.670)	(0.358)	(1.015)
Capital adequacy (*CapAdeq*)	0.415	0.198	0.786	0.007	0.385	0.542
	(0.652)	(0.302)	(1.254)	(0.007)	(1.026)	(0.913)
Firm size (*Size*)	−0.387	1.236**	−0.379	1.079**	1.199	−0.404
	(0.896)	(2.191)	(0.966)	(1.897)	(1.515)	(0.493)
Lagged loss ratio $(\frac{L}{P})_{i,t-1}$	–	–	0.211***	−0.068**	0.055	–
			(10.376)	(2.070)	(1.315)	
Adjusted R^2	0.1754	0.3035	0.1583	0.3443	–	0.270

Sample size = 4,809; *t*-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

In our final set of profitability tests, we examine the effects of our age and control variables on the expected loss ratios filed by LTC insurers. Our results, displayed in Table 4, generally are quite consistent with our previous tests. The coefficients for policy age are significantly positive in all specifications while the Age^2 coefficients are consistently negative, significantly so in four specifications. The goodness of fit is the best of our three profit proxies, which simply indicates that managers are factoring in the contractual and firm characteristics in our model when developing their predictions of profits.

Once again, few of the control variables are shown to have a significant impact on our profit proxy. Our organizational form coefficients are significantly positive in two specifications, but significantly negative in another, and insignificant in the rest. No other control variable is significant in more than one specification. The group variable is not significant in any specification, further indicating that the unique findings reported in Table 3 are attributable to different reserving practices for group LTC insurers compared to insurers of individuals.

PRICING RESEARCH DESIGN

While data limitations have confined other researchers to tests of profitability, we are able to examine more direct pricing proxies. We next describe the data and tests that allow us to more directly investigate the temporal pricing of LTC insurance.

Data

The NAIC reports earned premiums by LTC policy form and calendar duration. We can estimate mean prices for these policy cohorts by dividing premiums earned by the number of insured lives. Focusing on temporal price adjustments, we include any policy cohort with at least two consecutive years of data in our sample. Because LTC insurers file annual expected losses with regulators, our observations over 2 or more years allow us to estimate the impact of unexpected losses in the previous period on current price adjustments. We define unexpected loss as mean actual loss in the previous period less the mean expected loss for that period.

For our final sample of 2,240 observations during the period 1994–1999, the mean annual rate of change for our price proxy is approximately 16.7 percent with a standard deviation of 42.5 percent. LTC insurance policies generally are issued on a guaranteed renewable basis and NAIC model regulation (NAIC, 2001b), adopted by many states, requires insurers to adjust premiums on a class basis, so the scope of price adjustment activity should not be surprising.

The use of premiums earned to estimate average prices and the resulting price changes represents a limitation in our study. We would prefer to use premiums written on different policy forms, but these data are not reported to the NAIC. The premiums earned measure particularly could be a problem in the first year of a policy because the amount reported reflects the premiums earned for, on average, a half year at best, yet we initially divide this amount by the entire number of insureds at the end of the year. Consequently, our estimate of the average first-year premium for a policy is likely to be downward biased. This timing lag on premiums earned will continue in subsequent periods, but should not produce such an extreme bias as in the first year. In fact, when insurers limit or discontinue sales of a policy form, the lag in premiums

TABLE 4
Regression Estimates of LTC Contract Profitability Determinants (Dependent Variable: Expected Loss Ratio)

Independent Variables	REM/GLS (1)	FEM/GLS (2)	REM/GLS (3)	FEM/GLS (4)	Dynamic Panel/IV (5)	Dynamic Panel/IV (6)
Constant	0.599	–	−0.526	–	–	−2.985
	(0.441)		(0.241)			(1.125)
Time trend (*Trend*)	0.241	0.515	0.141	16.517	−0.153	0.051
	(1.256)	(1.307)	(0.438)	(1.434)	(0.007)	(0.131)
Policy age (*Age*)	8.946***	9.336***	2.444***	2.516***	5.422*	9.214***
	(28.144)	(15.517)	(4.659)	(5.657)	(1.766)	(15.131)
Age squared (Age^2)	−0.109***	−0.115***	−0.044	−0.078**	−0.056	−0.110***
	(4.541)	(3.171)	(1.29)	(2.086)	(0.596)	(2.95)
Group policy (*Group*)	−0.829	−3.834	−3.258	3.713	3.465	−2.724
	(0.521)	(1.305)	(1.478)	(1.059)	(0.745)	(0.964)
Group/age interaction ($Group * Age$)	−0.161	0.337	0.458	−0.347	−0.026	0.227
	(0.606)	(1.007)	(1.572)	(0.758)	(0.030)	(0.620)
Organizational form (*OrgForm*)	3.666***	1.446	2.713***	−7.158***	−5.889	2.512
	(3.360)	(0.752)	(2.430)	(2.926)	(1.427)	(1.368)
Capital adequacy (*CapAdeq*)	−0.072	0.199	0.359***	0.211	0.084	0.264
	(1.587)	(0.947)	(2.385)	(0.944)	(0.512)	(1.296)
Firm size (*Size*)	−0.058	0.064	0.149	0.303***	0.434	0.089
	(0.658)	(0.423)	(1.585)	(3.370)	(1.322)	(0.635)
Lagged loss ratio $(\frac{L}{P})_{i,t-1}$	–	–	0.790***	−0.042	0.226	–
			(44.123)	(0.506)	(0.523)	
Adjusted R^2	0.5515	0.5902	0.7961	0.8576	–	0.5734

Sample size = 4,809; t-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

earned, combined with the normal attrition in insured lives, will produce an upwardly biased price estimate. Such a phenomenon probably occurs frequently in the rapidly evolving LTC insurance market as insurers replace older policy forms with newer ones containing provisions perceived as more up-to-date by buyers.

To address the potential downward bias likely for our price estimates on new policies, we also test a reduced sample that excludes all cohorts insured by first-year policies. The reduced sample contains 1,852 observations for which our mean price change estimate is 8.9 percent with a standard deviation of 74.2 percent.

For our full sample, the mean unexpected loss ratio is only −0.94 percent, but these ratios for cohorts ranged from −207.8 percent to 498.9 percent, with a standard deviation of 45 percent. The number of unexpected gains exceeds the number of unexpected losses by a margin of two to one during our sample period. The mean rate of policy renewal during the sample period stands at 85 percent, with a standard deviation of 17 percent. For the reduced sample, the mean unexpected loss ratio and mean rate of policy renewal are 0.93 percent and 86.75 percent, with standard deviations of 52.68 percent and 15.73 percent, respectively. We also separately calculated the mean price change, unexpected loss ratios, and rates of policy renewal for individual and group policy cohorts and found no significant differences.

As a final check on the robustness of our pricing results, we use an alternative mean price measure that could mitigate potential temporal biases caused by a mismatch in premiums earned and the number of insured lives at year end, especially for the first year of policy issue. In this new mean price proxy, we simply change the denominator by applying the average of the number of insured lives reported at the beginning and end of each year. For a first-year policy the number of insured lives at the beginning of the year is zero. The denominator therefore will be halved and the estimated mean price doubled in the first year. The end result inevitably will be reduction of possible upward bias in the estimates of pricing over time. We note that our adjustment is crude and ignores nonlinearities in purchasing patterns, such as seasonality effects.

The Pricing Model

We specify the following panel data model to examine how LTC insurers adjust prices in response to past loss experience:

$$\begin{aligned}\Delta p_{it} &= \beta_1(UnexpLoss)_{i,t-1} + \beta_2(UnexpLoss * D)_{i,t-1} + \gamma\mathbf{Z}_{it}\\ &\quad + \lambda Growth_{j,t-1} + c_i + T_t + \mu_{it},\end{aligned} \tag{3}$$

where Δp_{it} is the percentage change in mean LTC policy prices for cohort i at time t and $UnexpLoss_{t-1}$ is the unexpected loss ratio for the previous period. The binary indicator D equals 1 if unexpected losses are positive in period $t-1$, and 0 otherwise. The interaction term, $(UnexpLoss * D)_{i,t-1}$, therefore reflects asymmetric pricing adjustments in response to unanticipated losses compared to unexpected gains in the previous period. The vector $\mathbf{Z}$ represents three characteristic variables specific to each policy cohort, including the contract renewal rate, policy age, and group status. $Growth_{j,t-1}$ is the growth rate of total premiums sales for insurer j at time $t-1$, c_i

represents cohort-specific individual effects, T_t captures time effects, and μ_{it} is a random error term with an expected mean of zero.

We expect most insurers to react to unexpected losses by raising prices over time and this should be reflected in a positive coefficient for our unexpected loss variable. Our primary variable of interest is the interaction term of the unexpected loss ratio and indicator variable, however. If insurers are more likely to increase prices after unexpected losses than to decrease prices after unexpected gains, the coefficient for the interaction term should be positive.

Low renewal rates diminish insurers' ability to recover initial expenses and can reduce expected investment income because of transactions costs. Insurers can respond by raising prices to shift costs to the remaining policyholders (Black and Skipper, 2000; Hendel and Lizzeri, 2003). Low renewal rates also are often linked to low risks that do not renew their policies. The resulting increase in the risk of the remaining pool is another reason that renewal rates should be negatively related to pricing adjustments.

The rate of renewal is likely to be correlated with the unobserved error component of the price change equation. This can occur because at any time t, the decisions to renew a policy are at least partially a function of current price changes. Contracts with larger, positive price adjustments are less likely to get renewed. We therefore use instrumental variables to provide consistent estimators. In principle, the lagged variables of other regressors can serve as valid instruments so we implement the unexpected loss ratio lagged two periods and policy age lagged one period.[11]

Because the policy age variable should reflect the increasingly poor health of policyholders over time and therefore the degree of consumer lock-in, we expect a positive relation between price adjustments and policy age. The relative youth of insureds covered by group LTC plans leads us to expect a more gradual increase in incurred losses for group policyholders and a negative coefficient for our group variable. Because both policy age and group status could conceivably affect the volatility of unexpected losses, we also implement interaction terms. The lagged growth rate is included to capture relative demand shifts during the sample period. If insurers are monopolistic competitors, changes in relative demand can affect prices. The time effect, T_t, controls for changes in industry-wide conditions.

PRICING RESULTS

Table 5 shows pricing test results for our full sample. To address the potential endogeneity of the renewal rate variable we apply a two-stage least squares (2SLS) regression method. More specifically, we adopt the procedure of Bowden and Turkington (1984) and use the unexpected loss ratio lagged two periods and its value squared as our instrumental variables. We also run our price adjustment model for the reduced sample, which excludes all first-year policies, and the results are shown in Table 6. Our primary variable of interest is the interaction effect between the dummy for positive unexpected loss ratios and the lagged, unexpected

[11] The lagged renewal rate cannot serve as the instrument because of its correlation with the potentially endogenous variable.

TABLE 5
Full Sample Regression Estimates of LTC Pricing Adjustment Determinants (Dependent Variable: Ratio of Relative Change in Premiums to End-of-Period Insured Lives)

Independent Variables	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
Constant	170.49	169.49	−30.172	−110.70
	(15.04)	(14.59)	(0.255)	(0.891)
Unexpected loss	1.028***	0.836***	2.996**	3.342**
($UnexpLoss_{t-1}$)	(4.214)	(3.196)	(2.163)	(2.023)
Unexpected loss interaction	–	0.275***	–	0.3892**
($(UnexpLoss * D)_{i,t-1}$)		(2.038)		(1.893)
Renewal rate	−1.970***	−1.977***	−0.232	−0.0930
	(17.02)	(17.594)	(0.178)	(0.797)
Renewal rate/unexpected loss	−0.0127***	−0.013***	−0.0339**	−0.0412**
interaction	(5.184)	(5.354)	(2.200)	(2.144)
Age	0.768	0.344	2.3162**	2.3091**
	(1.334)	(0.564)	(2.250)	(1.977)
Age/unexpected loss	0.013	0.019	−0.0063	−0.0036
interaction	(1.115)	(1.631)	(0.390)	(0.196)
Group policy	17.91***	18.76***	23.847***	27.630***
	(3.535)	(3.694)	(2.804)	(2.976)
Group policy/unexpected loss	0.255**	0.310***	0.2212	0.2986
interaction	(1.981)	(2.358)	(1.044)	(1.262)
Lagged firm growth	−0.0006	−0.0003	−0.0014	−0.0012
($Growth_{j,t-1}$)	(0.207)	(0.089)	(0.382)	(0.288)
R^2	0.2090	0.2109	–	–

Sample size = 2,240; t-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

loss ratio. For comparison purposes, we run our regressions with and without this variable.

As expected, our evidence indicates a strongly positive relation between unexpected loss ratios in the previous period and current period price adjustments for both the full and reduced samples. In other words, insurers respond to unexpected losses (gains) with price increases (decreases). Our main variable of interest, the interaction between unexpected losses and a binary dummy for gains, also is positive and highly significant for both the full and reduced samples. This finding suggests that LTC insurers react more strongly to unexpected losses than to unexpected gains when they make price decisions. We conclude that this finding provides evidence of downward price stickiness, which is consistent with price lowballing.

The OLS estimates for both the full and reduced sample models indicate the expected negative relation between current period price adjustment and the prior period rate of renewal. Our 2SLS procedure better handles possible endogeneity issues, however, and these results suggest that renewal rates do not significantly affect pricing changes. We generally find a significantly negative interaction effect

TABLE 6
Reduced Sample Regression Estimates of LTC Pricing Adjustment Determinants (Dependent Variable: Ratio of Relative Change in Premiums to End-of-Period Insured Lives)

Independent Variables	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
Constant	193.01	191.62	−44.92	−66.75
	(13.53)	(3.895)	(0.237)	(0.500)
Unexpected loss	1.012***	0.809	2.983**	3.317*
($UnexpLoss_{t-1}$)	(3.520)	(1.208)	(2.006)	(1.895)
Unexpected loss interaction	–	0.284***	–	0.427**
($(UnexpLoss * D)_{i,t-1}$)		(2.337)		(1.874)
Renewal rate	−2.190***	−2.198***	0.417	0.572
	(5.868)	(4.269)	(0.203)	(0.397)
Renewal rate/unexpected loss interaction	−0.0128***	−0.0133*	−0.0343**	−0.0421**
	(4.525)	(1.875)	(2.105)	(2.078)
Age	0.3465	−0.0492	2.153	1.848
	(0.470)	(0.045)	(1.134)	(1.355)
Age/unexpected loss interaction	0.0154	0.0233	−0.0030	0.0051
	(1.085)	(1.319)	(0.148)	(0.249)
Group policy	22.27***	23.25***	31.03*	33.12***
	(3.468)	(8.346)	(1.869)	(2.863)
Group policy/unexpected loss interaction	0.306**	0.359*	0.2806	0.316
	(2.050)	(1.823)	(0.750)	(1.190)
Lagged firm growth	−0.0006	−0.0003	−0.0015	−0.0005
($Growth_{j,t-1}$)	(0.189)	(0.435)	(1.388)	(0.106)
R^2	0.2330	0.2355	–	–

Sample size = 1,852; t-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

between renewal rates and unexpected losses. In the full-sample regressions the policy age coefficient in the 2SLS coefficients is significantly positive, which suggests larger pricing adjustments on older policies. Such a finding is consistent with prices rising in proportion to the increasing rate of deteriorating health as policyholders age and/or the decreasing effect of initial underwriting over time. The policy age coefficient is not significant for the reduced sample. Considering the omission of first-year policies in this sample, these results are more consistent with diminishing underwriting effects over time. The uniformly insignificant coefficient for the lagged firm growth variable indicates that shifts in relative demand during the sample period do not have a significant impact on the prices of existing LTC policies.

Our estimates indicate a highly positive relation between group status and upward price adjustment. To check this result we analyzed LTC insurance rate changes since 1990 reported to the California Department of Insurance (2003) during 2002 and 2003 for three states. We chose California, Florida, and Illinois because we anticipated a relatively high volume of LTC purchases in those states.

TABLE 7
Full Sample Regression Estimates of LTC Pricing Adjustment (Dependent Variable: Ratio of Relative Change in Premiums to Mean Number of Insured Lives)

Independent Variables	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
Constant	−13.91	−14.38	−178.85	−184.35
	(1.683)	(1.742)	(2.099)	(1.526)
Unexpected loss	0.3161*	0.2497	1.547**	1.558**
($UnexpLoss_{t-1}$)	(1.909)	(1.460)	(2.028)	(2.363)
Unexpected loss interaction	–	0.0771*	–	0.0594
($(UnexpLoss * D)_{i,t-1}$)		(1.768)		(0.850)
Renewal rate	0.0672	0.067	1.870**	1.919***
	(0.735)	(0.744)	(2.008)	(2.547)
Renewal rate/unexpected	−0.003*	−0.0029*	−0.0158**	−0.0165**
loss interaction	(1.770)	(1.76)	(1.962)	(2.384)
Age	0.1773	0.144	1.333**	1.282**
	(0.921)	(0.204)	(2.000)	(2.131)
Age/unexpected loss	−0.0043	−0.0033	−0.0182*	−0.0179**
interaction	(1.170)	(0.903)	(1.934)	(2.119)
Group policy	4.418**	4.695**	6.407**	6.779**
	(2.114)	(2.221)	(2.154)	(2.252)
Group policy/unexpected	0.1041*	0.123**	0.1675**	0.183**
loss interaction	(1.764)	(1.984)	(2.048)	(2.187)
Lagged firm growth	−0.00008	0.0001	−0.0003	−0.00017
($Growth_{j,t-1}$)	(0.314)	(0.057)	(0.205)	(0.108)
R^2	0.0324	0.0351	–	–

Sample size = 2,311; *t*-statistics are in parentheses.
***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

In Illinois insurers filed rate increases for 23 group and 87 individual plans during the period 1990–2003. This discrepancy is not surprising because individual plans account for the vast majority of sales and group participants are relatively more youthful so increases are less likely to be justified.[12] The average group plan increase was 59 percent in Illinois while the average individual plan increase was only 40 percent. Relatively similar increases were applied in California and Florida. This direct evidence is supportive of our results regarding the group plan effect. We conjecture that in the relatively young marketplace for LTC insurance, for which loss experience is extremely limited, large employers were able to extract deeply discounted premiums from some insurers. As claims developed, these insurers raised their premiums substantially and this effect dominated the mitigating influence of the generally younger group participants who are less likely to file LTC claims.

Table 7 contains results for the revised mean price proxy, in which we average the number of insured lives in the denominator. We find evidence of managers adjusting

[12] For the insurers in our sample, group plans accounted for approximately 27 percent of all in-force policies, but only 14 percent of premiums in 1999.

current period premiums to reflect unexpected losses in three out of four specifications reported in Table 7. These findings are quite consistent with our previous results. The results for our primary variable of interest, the unexpected loss interaction term, are not as strong, however. In our OLS specification the effect is positive at the 10 percent level, but it becomes insignificant when the 2SLS procedure is applied. We therefore conclude that application of our revised price proxy at least partially mitigates the downward price stickiness indicated in our previous results.

Among the control variables, the group policy effect and the interaction effect between group policy status and unexpected losses are consistently significant and both are uniformly positive. These results are quite similar to those observed in the previous tests of pricing adjustments. The renewal effect becomes significantly positive in the 2SLS specifications, which contrasts with the negative relation observed in our previous tests. The interaction effect between renewal rates and unexpected losses remains significantly negative, however, thereby indicating that insurers adjust prices less fully with respect to unexpected losses for polices with higher renewal rates.

Our application of the revised mean price proxy substantially reduces the goodness of fit for our models, as indicated by R^2 values. Further examination reveals that the mean price change is 5.75 percent with a standard deviation of 153.4 percent when we apply the revised proxy. While the new price proxy should reduce potential upward bias in the rate of mean price changes over time, it also produces large increases in the variance of our dependent variable. Such variation is generally associated with large variance in least squares estimators and we suggest that this phenomenon likely contributes to the weaker price stickiness observed in Table 7.

SUMMARY AND CONCLUSIONS

Dynamic adverse selection models applied to insurance markets have generated very different implications. Specifically, models built upon assumptions of commitment or semicommitment by sellers to long-term policies imply temporal price highballing while those for which sellers make no long-term commitments indicate a lowballing pattern. In this study, we use cohort-specific data for LTC insurance to test the two competing propositions. Our results show that while the loss ratios on a given cohort of policyholders tend to rise over time in a pattern consistent with the long-term nature of LTC insurance contracts, the rate of increase actually declines significantly. This decreasing marginal effect of policy age is consistent with the rising temporal profit pattern known as price lowballing. Our evidence from the LTC insurance markets therefore is supportive of the Kunreuther–Pauly and Nilssen models, which indicate that dynamic equilibria in markets with adverse selection involve risk pooling with short-term contracts and subsequent price distortions. Our findings also are in line with the empirical results of D'Arcy and Doherty (1990).

Low market penetration and the concomitant paucity of actuarial experience with regard to LTC claims offer an alternative explanation for why insurers issue pooling contracts. Less than 10 percent of the elderly and a much lower percentage of the near-elderly have purchased LTC insurance and less than 1 percent of employers sponsor LTC plans (Employee Benefits Research Institute, 2000; Doerpinghaus and

Gustavson, 2002).[13] With such limited actuarial data many insurers probably do not have the information and expertise to offer separate contracts for a wide variety of risk classes. This explanation is arguable in a market for which reinsurers are thought to provide underwriting expertise and actuarial experience, however (Collett, Austin, and White, 1999).

Consistent with our expectation of price lowballing, we generally find evidence that insurers adjust prices more fully in response to unexpected losses than unexpected gains. Such downward price stickiness is indicative of insurers' ability to capture rents over time using a price lowballing strategy. Thus, both our indirect tests of insurer temporal profitability and our direct tests of price adjustments support dynamic adverse selection models that predict risk pooling and no commitment by insurers to long-term, experience-rated contracts.

The reader could surmise that regulatory restrictions may cause the results reported in this study. In particular, if insurers use fixed loss ratios to determine rate schedules filed with regulators, then premiums will increase with expected claims (see, e.g., NAIC, 2001b, pp. 1–3). Insurers therefore could have incentives to initially underestimate policy losses so they can sell LTC insurance at lower prices and attract greater market share. When actual losses ultimately exceed the initial predictions, regulators will be more likely to allow premium increases and insurer profitability will rise. Our evidence that the expected loss ratios filed by insurers are unbiased estimators of incurred loss ratios runs counter to this interpretation, however.

Empirical researchers testing alternative theories of insurance pricing under adverse selection have focused their efforts on auto property insurance, which represents a mature market with short loss development periods. While we do not claim to resolve the conflicting evidence from auto insurance markets, we do extend the previous research by providing insight into the pricing practices of insurers in a young, innovative market for which little actuarial experience is available and loss development is lengthy. Because LTC insurance contracts are, by definition, long-term one might expect commitment pricing schemes to be built into policies, which implies temporal price highballing. Our findings provide at least preliminary evidence that adverse selection produces price lowballing in relatively, new innovative markets that is not unlike what some have observed in the very mature auto property insurance markets, however.

We are confident that researchers eventually will gain access to more complete data on insurance contract attributes that will allow them to explore temporal price adjustment issues in greater detail in the future. Differences between group and individual markets should be of particular interest in light of our preliminary results. We also anticipate that researchers will explore the effects of market maturity, along with search and switching costs, on temporal pricing. Finally, the impact of financial innovation on temporal pricing patterns strikes us as an issue worthy of further investigation.

[13] Among the reasons offered for low LTC purchase rates are consumer misinformation, family subsidization, medical underwriting, and a possible Medicaid crowd-out effect (see, e.g., Doerpinghaus and Gustavson, 2002; Brown and Finkelstein, 2003).

APPENDIX

We begin with the standard IV approach to the general form of a dynamic panel model (see, e.g., Greene, 2000):

$$y_{it} = c_i + \mathbf{X}'_{it}\beta + \lambda y_{it-1} + \varepsilon_{it}, \tag{A1}$$

where y_{it} and y_{it-1} are the current and lagged dependent variables, respectively, c_i is the individual effect, $\mathbf{X}_{it}$ is a vector of independent variables, and ε_{it} is a zero-mean error term. The presence of the lagged-dependent variable, y_{it-1}, complicates the following transformation used to eliminate the individual effect, c_i:

$$y_{it} - y_{it-1} = (\mathbf{X}_{it} - \mathbf{X}_{it-1})'\beta + \lambda(y_{it-1} - y_{it-2}) + (\varepsilon_{it} - \varepsilon_{it-1}), \tag{A2}$$

because y_{it-1} is correlated with the first-order moving average error term. Researchers have proposed different instrumental variables for efficient estimation of Equation (A2) (see, e.g., Anderson and Hsiao, 1982; Arellano, 1989; Ahn and Schmidt, 1995). For instance, if the time series is sufficiently long, then the lagged-dependent variables or their differences, such as y_{it-2}, y_{it-3}, or $y_{it-2} - y_{it-3}$, can serve as efficient instruments.

In our two-step approach, we first use Equation (A2) to obtain a consistent estimator of λ, $\hat{\lambda}$. Then, we insert $\hat{\lambda}$ back into Equation (A1) and move the lagged-dependent variable to the left-hand side to obtain:

$$y_{it} - \hat{\lambda} y_{it-1} = c_i + \mathbf{X}'_{it}\beta + \varepsilon_{it}. \tag{A3}$$

We then obtain consistent estimators by implementing Equation (A3) with a standard panel model.

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