A Behavioral Model of Insurance Pricing

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Abstract: We develop a model of price competition between insurers where insurers maximize expected profit subject to a solvency constraint. Insurers base prices in part on expected losses, the estimates of which are updated in a Bayesian fashion. We assume that insurers are overconfident—they overestimate the precision of their private signal about expected losses. This leads insurers to overreact to their private signal on expected losses. The consequence is that prices may cycle and that the distribution of price changes may be positively skewed because of the role played by the solvency constraint. [Key words: cycles, overconfidence, overreaction].

INTRODUCTION

The recurrence of hard or tight markets in property liability insurance is a well-known characteristic of the industry. In soft markets, underwriting standards are relaxed and prices and underwriting profits are low. In hard markets, underwriting standards become restrictive and prices and underwriting profits increase.[1] Following a hard market, prices and profits remain high, then gradually erode as the market softens. Over the last 20

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years, a substantial research effort has been undertaken to understand the causes of these cycles. There are three basic theoretical models that have been employed to analyze the insurance cycle—the financial pricing/ rational expectations model (e.g., Cummins and Outreville, 1987), the capacity constraint model (e.g., Winter; 1988, Gron, 1994), and the financial quality model (e.g., Cagle and Harrington, 1995; Cummins and Danzon, 1997). These models are based on the standard economic model of a competitive market; in particular, these models are based on the assumption that agents on both sides of the market are well informed.

Recent research suggests that these models do not account for the time series properties of property/liability underwriting profits. Choi, Hardigree, and Thistle (2002) compare six alternative models of insurance pricing as explanations of underwriting cycles. They are particularly careful to distinguish between the short-run and long-run implications of the models. They find that the economic loss ratio (Winter, 1988) is stationary, while surplus is not. This implies that (1) there is a long-run equilibrium relationship between prices and discounted losses and (2) there cannot be a long-run equilibrium relationship between the economic loss ratio and surplus. Higgins and Thistle (2000), using data for 1934-1993, find that surplus is a determinant of whether underwriting profits are in a cyclical or non-cyclical regime, but that long-run expected profits do not depend on surplus.[2] Perhaps more importantly, Higgins and Thistle find that the variation in surplus does not account for the short-run variation in profits over the 1972–1988 period—that is, changes in surplus do not account for the hard markets of the 1970s and 1980s. There is also evidence that the length and timing of insurance cycles vary by line of insurance (Venezian 1985; Fields and Venezian, 1989; Lamm-Tennant and Weiss, 1997). There is also some evidence of a structural break in the time series of underwriting profits around 1980 (Leng, Powers, and Venezian 2006; Leng, 2006a, 2006b). Taken together, these factors lead us to consider alternative approaches as possible explanations for the underwriting cycle.[3]

Insurance markets are characterized by substantial incomplete information. For example, insurers generally have imprecise estimates of the expected losses on any pool of policies. Policyholders may be concerned with an insurer's ability to pay claims, but again have only imprecise estimates of the probability of default. In both cases, estimates must be revised as new information becomes available. How new information is processed in updating these estimates has important implications for the functioning of markets.

The purpose of this paper is to examine the impact of incomplete information on pricing and profits in the property-liability insurance industry. We focus on the processing of new information about insurers expected losses as a potential source of insurance underwriting cycles. The model developed is behavioral in the sense that it is based on the psychological bias of overconfidence. While insurers are assumed to be rational in the sense of revising beliefs according to Bayes rule, they are overconfident in the sense that they overestimate the precision of the signals they receive regarding expected losses. This leads to an overweighting of the data in the signal relative to the prior. One of the strongest arguments against abandoning the assumption of full rationality in economic and financial modeling is that by assuming a particular form of irrationality any empirical phenomenon can be explained. However, our "irrationality" is quite limited. We assume that firms misestimate one parameter necessary to the application of Bayes rule in a particular way.[4] Further, the way in which we assume that they misestimate this parameter has a firm foundation in human psychology. The psychological bias of overconfidence is one of the most robust empirical regularities in the psychology of judgment.[5]

We assume that insurers are risk-neutral expected-profit-maximizers who compete in prices. We assume that losses are correlated, and capital is costly so that there is some risk of insolvency. We assume that individual insurers face downward-sloping demands for coverage and that demands depend on the probability of solvency. Insurers have prior estimates of expected losses per policy. They receive private and public information about losses per policy and, based on these signals, revise their beliefs according to Bayes rule. Insurers are overconfident in the sense that they overestimate the precision of their private signal. In the short run, this leads insurers to overreact to new private information about expected losses and to underreact to new public information.

In the insurance literature, our analysis is most closely related to the work by Venezian (1985) and Harrington and Danzon (1994). As in Venezian, the emphasis here is on the problem of predicting expected losses per policy. Venezian's point is essentially statistical, that the OLS forecast errors are serially correlated.[6] In contrast, our analysis is behavioral. Harrington and Danzon (1994) assume that firms have heterogeneous information for forecasting expected losses. We also assume firms have heterogeneous information (i.e., private signals); in contrast to Harrington and Danzon, we explicitly model how the information is processed. As in Harrington and Danzon, our model provides an explanation of underpricing in soft markets. Harrington and Danzon focus on two explanations. First, there may be a "winner's curse" in that firms with the most optimistic forecasts of losses (due to heterogeneous information and/or naïve forecasting) will tend to underprice. Second, moral hazard (due to limited liability and/or insurance guarantee funds) creates incentives for firms to price below expected costs. In our analysis, overconfidence can lead insurers to underprice in response to "good news."

Our analysis is also related to the large volume of recent work on overconfidence in the finance literature.[7] In a framework similar to the one considered here, Daniel, Hirshleifer, and Subrahmanyam (1998) present a model in which investor overconfidence in private signals leads traders to overreact to new information. The overreaction leads to short-term momentum and long-term reversals in asset prices—that is, a cycle. Odean (1998), Kyle and Wang (1997), Wang (1998), Benos (1998), Sheinkman and Xiong (2003), and Peng and Xiong (2006) also provide specifications with overconfidence in the information precision of traders. The excess volatility of security prices is well documented (e.g., Shiller, 1981). Benos (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Odean (1998), Wang (1998), and Sheinkman and Xiong (2003) all propose overconfidence as an explanation of excess volatility. For example, in Benos (1998), overconfident traders move aggressively to exploit their information, leading to larger price changes and greater volatility. DeLong, Shleifer, Summers, and Waldmann (1990), Daniel, Hirshleifer, and Subrahmanyam (1998), Benos (1998), Hirshleifer and Luo (2001), and Wang (1998, 2001), among others, argue that overconfidence leads to excessive trading volume, which also increases volatility. Other recent applications of overconfidence in the finance literature include Bernardo and Welch's (2001) analysis of overconfidence in entrepreneurs and Heaton's (2002) and Malmendier and Tate's (2005) analysis of the effect of overconfidence on corporate investment decisions.

Our model has a number of empirical implications for the time series of insurance prices. An important implication of the analysis is that prices will be cyclical; insurers' overreactions lead to short-term momentum in prices followed by reversals over the long term. Our model also implies that prices will exhibit excess volatility relative to what should be expected based on economic fundamentals. Finally, our model implies that price changes will be asymmetric, since price decreases are bounded below by the solvency constraint. Our model also has implications for cross-sectional analysis. The model implies that insurers' prices should tend to move together. Also, to the extent that larger insurers have more precise estimates of future losses, their prices should be more responsive to private signals and less responsive to public signals than those of smaller firms.

The next section of the paper sets out the basic framework for the analysis. The third section develops the implications of overconfidence for insurance prices. The final section contains concluding remarks.

THE BASIC FRAMEWORK

The basic framework for the analysis is a model of price competition among firms that produce differentiated products. The primary differences from the standard model, which are required to apply the model to the insurance industry, are that costs (losses per policy) are uncertain and that firms are subject to a constraint on the probability of insolvency.

We assume there are n risk-neutral expected-profit-maximizing insurance firms. Policyholders are concerned with the price of insurance and with the probability that claims will be paid. We assume that policyholders are concerned with the insurer's risk of insolvency, but are heterogeneous in the sense that they have different willingness to trade off the price of an insurance policy against its "quality" or the probability of the insurer's solvency. Informational asymmetries (by firms about policyholders and by policyholders about firms) and other differences among firms give rise to switching costs. This implies that the demand for coverage facing a particular firm, given the firm's probability of solvency, is downward sloping. The demand for insurance for firm i is $q_i(p, \alpha)$ where p is the n-vector of prices and α is the n-vector of solvency probabilities. We assume that demand is a decreasing function of i's price and an increasing function of the prices of other firms; we also assume the elasticity of demand is a decreasing function of rivals' prices. We assume that demand is an increasing function of firm i's solvency probability, and a decreasing function of other firms' solvency probabilities. We let p_{-i} and α_{-i} denote the vectors of prices and solvency probabilities of firm i's rivals.

Firms invest financial capital K_i to support the sale of insurance policies. The flow cost per unit of capital is r. The expected present value of losses per policy is denoted x_i. The insurer's prior distribution on per policy loss is $N(\mu_{0i}, h_{0i}^{-1})$, where h_{0i} is the precision of the prior (the variance is $1/h_{0i}$). For simplicity, we assume that all insurers face the same loss distribution.[8] We also assume that the prior does not depend on the number of policies sold; this implies that variation in the loss per policy is due to correlation in losses across policies. The firm is solvent if

$$p_i q_i - x_i q_i + K_i \geq 0,$$

or if

$$p_i + K_i / q_i \geq x_i.$$

Then the solvency constraint is

$$N_0(p_i + K_i/\, q_i) \geq \alpha_i, \tag{1}$$

where N_0 is the (prior) cumulative normal distribution. The solvency constraint is not necessarily due to insurance regulations. The constraint could be the solvency probability needed to maintain a certain financial strength rating.

Prior to receiving information regarding losses per policy, the firm's expected profit is

$$\pi_i(p, \alpha) = p_i q_i - \mu_0 q_i - rK_i, \tag{2}$$

which the firm maximizes with respect to price, subject to the constraint that the probability of solvency is at least α_i. We assume that expected profit is strictly concave in price. The unrestricted profit maximizing price solves

$$\partial\pi_i/\partial p_i = (q_i + p_i\partial q_i/\partial p_i) - \mu_0\partial q_i/\partial p_i = 0. \tag{3}$$

Let p_i^* denote unrestricted profit maximizing price; p_i^* is free of the solvency probability and precision and is increasing in rivals' prices. Also, p_i^* is increasing in the expected loss per policy.[9]

The solvency constraint can be rewritten as

$$p_i \geq \mu_0 + z_{a_i}/(h_0)^{1/2} - K_i/q_i, \tag{4}$$

where z_{a_i} is the $100\alpha_i$ percentile point of the standard normal distribution. The first term on the right-hand side of (4) is the pure premium, the second term is the safety loading, and the third term is the available capital per policy. Letting $\hat{p}_i$ be the lowest price that satisfies the solvency constraint, the solvency constraint becomes $p_i \geq \hat{p}_i$. The minimum price $\hat{p}_i$ is decreasing in the precision of the loss distribution and increasing in the probability of solvency and in rivals' prices.

The insurer sets price at the unrestricted price, p_i^*, if the solvency constraint is not binding and at the minimum price, $\hat{p}_i$, if the constraint is binding. That is, the actual price set by the insurer is $p_{0i} = \max\{p_i^*, \hat{p}_i\}$. This is the insurer's best response function. Since both p_i^* and $\hat{p}_i$ are increasing in p_{-i}, so is p_{0i}. A Nash equilibrium exists, and, under reasonable restrictions, is unique (Vives, 1990; Milgrom and Roberts, 1990).[10]

One implication of this model is that, since best response functions are upward sloping, the prices of firms will tend to move together. That is, let θ be any parameter that increases the firm's marginal profitability ($\partial^2\pi_i/\partial\theta\partial p_i \geq 0$ for all i). Then in equilibrium, $\partial p_{0i}/\partial\theta \geq 0$, the prices of all firms increase. Thus, for example, an increase in the expected loss per policy increases the prices of all firms. Similarly, $\partial p_{0j}/\partial \alpha_i \geq 0$ and $\partial p_{0j}/\partial K_i \leq 0$ for all i and j—that is, equilibrium prices are nondecreasing in the solvency probability and nonincreasing in the capitalization of any individual firm.[11]

OVERCONFIDENCE AND BAYES RULE

To examine the effect of overconfidence on insurance prices, we extend the model to three periods. In period 0, the firm has only its prior information. We assume that each firm receives both private and public signals regarding the loss per policy. The private signal is received in period 1 and the public signal in period 2; losses are realized at the end of period 2. The prior estimate of losses is then updated each period according to Bayes rule. We assume that insurers are overconfident in that they overvalue the private signal they receive about estimated losses per policy.

The loss per policy, x, is drawn from a normal distribution with mean μ_0 and precision h_0^{-1}—that is, $x \sim N(\mu_0, h_0^{-1})$. The private information signal received by insurer i at date 1 is

$$s_{1i} = x + \varepsilon_{1i}, \tag{5}$$

where $\varepsilon_{1i} \sim N(0, h_1^{-1})$ and h_1 is the true precision of the private signal. The insurer is overconfident and overestimates the precision of the private signal, treating the precision as if it is βh_1, where $\beta > 1$; we say the insurer is "properly calibrated" if $\beta = 1$. One interpretation of this assumption is that the insurer has more confidence in its own estimates of expected losses than in estimates from service agencies such as the Insurance Services Office.

The public information signal received by all insurers is

$$s_2 = x + \varepsilon_2, \tag{6}$$

where $\varepsilon_2 \sim N(0, h_2^{-1})$ and h_2 is the precision. Both private and public signals are unbiased estimates of per policy losses. While the errors ε_{1i} are independent across firms and independent of ε_2, insurers' private signals are correlated with each other and with the public signal.

Private Signals

Applying Bayes rule, the insurer's revised estimate of the loss per policy in response to the private signal is

$$\mu_1 = E(x \mid s_1) = (h_0\mu_0 + \beta h_1 s_1)/(h_0 + \beta h_1), \tag{7}$$

which is the average of the prior and the signal, weighted by their relative precisions, where the firm-specific subscript is suppressed. The posterior estimate of the precision is $h_0 + \beta h_1$, which is greater than the true precision. The posterior mean may also be written

$$\mu_1 = \mu_0 + \beta h_1(s_1 - \mu_0)/(h_0 + \beta h_1) = \mu_0 + w_1(s_1 - \mu_0),$$

where the second term is the revision due to the signal. Compared to an insurer who is properly calibrated ($\beta = 1$), overconfidence increases the magnitude of the revision in beliefs. In this sense, overconfidence leads to an overreaction to the private signal. Despite this, if the underlying distribution of x is stationary, the insurer will eventually learn the correct loss per policy. After T private signals the posterior mean is $E(x \mid \cdot) = (h_0\mu_0 + T\beta h_1 \bar{s}_1)/(h_0 + T\beta h_1)$, where $\bar{s}_1$ is the mean signal, and, as $T \to \infty$, this converges to x by the strong law of large numbers.

Now consider the effect of the private signal on the insurer's best response. We say a private signal is "good news" if it is below the prior mean, $s_1 < \mu_0$, and "bad news" if it is above, $s_1 > \mu_0$. The effect of the signal on the unrestricted profit maximizing price, denoted $p_1{}^*$, is straightforward. Good news leads to a downward revision in average loss per policy and a decrease in price. Bad news has the opposite effect.

The private signal also affects the minimum price implied by the solvency constraint. We let $\hat{p}_{1i}$ denote this minimum price based on the private signal. The solvency constraint in (3) becomes

$$p_{1i} \geq \mu_1 + z_{a_i} / (h_0 + \beta h_1)^{1/2} - K_i/q_i. \tag{8}$$

We want to determine whether $\hat{p}_{1i}$ is larger or smaller than $\hat{p}_{0i}$. The question is whether the right-hand side of (8) is larger or smaller than the right-hand side of (4). The pure premium increases or decreases as there is bad news or good news. The safety loading decreases whether the news is good or bad. Thus, good news shifts the right-hand side of (8) downward, which reduces the minimum price, $\hat{p}_1$. If the news is bad, but "not too bad," the effect on the safety loading dominates and $\hat{p}_1$ decreases. If the news is sufficiently bad, then the effect on the pure premium dominates and $\hat{p}_1$ increases. This is true whether the insurer is properly calibrated or overconfident. Overconfidence increases the magnitude of the downward revision in $\hat{p}_1$ in response to good news. If the news is bad, then the effect of overconfidence is to decrease the smallest value of the signal for which $\hat{p}_1$

increases.[12] That is, overconfidence tends to increase the magnitude of the change in $\hat{p}_1$, especially in response to good news.

As before, the best response is $p_1 = \max\{p_1{}^*, \hat{p}_1,\}$. Good news decreases both $p_1{}^*$ and $\hat{p}_1$, so p_1 decreases in response to good news. Overconfidence leads insurers to underestimate average losses per policy and consequently set prices lower than they otherwise would. This suggests that realized underwriting profit margins are likely to be below expectations. This is especially problematic for firms that are on or close to their solvency constraint since overconfident firms underestimate the price needed to maintain their solvency probability. This suggests that, over time, such firms will find that their capital is eroded and their actual default probabilities are increasing. Eventually, such firms will need to obtain an infusion of capital or increase prices; such price increases may need to be substantial.

If the news is "not too bad," then $p_1{}^*$ increases and $\hat{p}_1$ decreases. If the solvency constraint is not binding then p_1 increases, and if the constraint is binding then p_1 decreases. Again, this situation is likely to create problems for firms that are on their solvency constraint. However, overconfidence makes it more likely that $\hat{p}_1$, hence, p_1, will increase in response to bad news. If news is sufficiently bad, then both $p_1{}^*$ and $\hat{p}_1$ increase, so p_1 increases; again, overconfidence magnifies the response.

The responses to good news and bad news may be asymmetric. This asymmetry arises for firms that are on or close to the solvency constraint. There is no upper bound on price increases in response to signals that losses will increase. However, price decreases in response to signals that losses will decrease are limited by the solvency constraint. This is true even if overconfident firms underestimate the price needed to maintain a given probability of solvency.

It seems reasonable to expect the precision of the private signal to depend on the size of the insurer, with larger insurers having more precise private signals. The weight, w_1, is increasing in the precision h_1. This implies that larger insurers will react more strongly than smaller insurers to the same signal, whether it is good news or bad news.

Public Signals

At time 2, insurers also receive public signals of average losses per policy. The insurer's revised estimate of the loss per policy in response to the public signal is

$$\mu_2 = E(x \mid s_1, s_2) = (h_0\mu_0 + \beta h_1 s_1 + h_2 s_2)/(h_0 + \beta h_1 + h_2), \tag{9}$$

which is the average of the prior and both signals, weighted by their relative precisions. The posterior precision is $h_0 + \beta h_1 + h_2$, which is greater than the true precision. The posterior mean may also be written

$$\mu_2 = \mu_1 + w_2(s_2 - \mu_1) = \mu_0 + w_1(s_1 - \mu_0) + w_2(s_2 - \mu_1)\ , \tag{10}$$

where $w_1 = \beta h_1/(h_0 + \beta h_1)$ and $w_2 = h_2/(h_0 + \beta h_1 + h_2)$. The last term is the revision due to the public signal. Since w_2 is decreasing in β, overconfidence decreases the magnitude of the revision in beliefs compared to a properly calibrated insurer. Again, if the underlying distribution of x is stationary, μ_2 will converge to x, and as the number of signals approaches infinity the insurer will eventually learn the correct loss per policy.

We say a public signal is good news if it is below the prior mean, $s_2 < \mu_1$, and bad news if it is above, $s_2 > \mu_1$. The effect of the public signal on the profit maximizing price, p_2, is essentially the same as the effect of the private signal. Good news leads to a downward revision in average loss per policy and a decrease in price. Bad news that is not too bad increases p_2^* and decreases $\hat{p}_2$, while news that is sufficiently bad increases price unambiguously.

While overconfidence reduces the reaction to the public signal, the net effect of the public and private signals is an overreaction. That is, let μ_2' denote the properly calibrated posterior mean and assume $|s_1 - \mu_0| = |s_2 - \mu_1|$ so that both signals contain the "same amount of news." Then, so long as the prior is not too diffuse, if $s_1 - \mu_0 > 0$, then $\mu_2 - \mu_2' > 0$, and if $s_1 - \mu_0 < 0$, then $\mu_2 - \mu_2' < 0$, regardless of whether the public signal is good news or bad news. That is, the effect of the private signal dominates.

The precision of the public signal may be independent of the size of the insurer, but is likely to depend on the size and homogeneity of the statistical reporting agency with which the insurer is affiliated. The weight on the public signal, w_2, is increasing the precision of the public signal, h_2, but decreasing in the precision of the private signal, h_1, and in β, the degree of overconfidence. If larger insurers have more precise private signals than smaller insurers then they will revise prices less than smaller insurers in response to the same public signal.

CONCLUDING REMARKS

Existing models of underwriting cycles, based on the economic model of a competitive market, assume that agents on both sides of the insurance market are well informed. Insurance markets are characterized by substantial incomplete information. We examine insurers' processing of information regarding expected losses as a potential source of underwriting cycles. The model developed is behavioral in that we assume insurers are overconfident, an assumption that has a strong foundation in psychology. Overconfidence is modeled as an overestimate of the precision of the insurers' private information. Overconfidence leads insurers to overreact to their private information. Thus, overconfidence increases the volatility of insurance prices. Increased volatility of insurance prices due to overconfidence may be a contributing factor in insurance cycles.

Overconfidence may be a contributing factor in soft markets. If firms receive private signals that losses are decreasing, then overconfidence increases the downward revision in prices. In particular, overconfidence leads them to underestimate the minimum price necessary to maintain a given level of default risk. If the private signal indicates losses have fallen and the public signal indicates losses have risen, for overconfident firms the net effect of the private and public signals will be to underprice. The underestimates of expected losses and minimum prices can be expected to lead to the erosion of capital over time. As capital erodes, the number of firms that are on or near their solvency constraints increases. Such firms are more vulnerable to shocks to capital and to bad news about expected losses.

One implication of the model is that the changes in prices in response to information may be asymmetric. This is more likely if signals indicate that large changes in losses are occurring so that the resulting price changes will be large. Upward revisions in prices occur in response to bad news that expected losses per policy are increasing. Downward revisions in prices in response to good news that losses are decreasing are limited by the solvency constraint.

The formal analysis is based on a model of a monoline insurer. However, it seems reasonable to believe that the precision of both private and public signals varies by line of insurance. It also seems reasonable to believe that insurers' overconfidence varies by line of insurance. If insurers have more precise data or are more overconfident about certain lines of insurance, then the pattern of cycles will differ by line of insurance. Our formal model also assumes that the underlying economic structure is stable. Thus, our model does not account for structural breaks *per se*. Any structural break must necessarily be the result of a change in some underlying parameter or functional relationship. For example, the central problem analyzed here is that of forecasting expected discounted future losses. Then, as suggested by Leng, Powers, and Venezian (2002), a structural change in interest rate policy could lead to a shift in the distribution of the discounted losses and therefore a structural change in the time series of underwriting profits.

Our model also has implications for cross-sectional analyses of insurance prices. We assume that insurers produce differentiated (by their risk of insolvency) policies and compete in prices. As a consequence, the model predicts that insurers' prices should tend to move together. It seems reasonable to think that larger insurers have more precise private estimates of losses per policy than smaller insurers. If so, then larger insurers should have a greater reaction to any given private signal than smaller insurers. Larger insurers should also have a smaller reaction to any given public signal than smaller insurers. Finally, we should point out that we assume that coverage is optional and that there is no price regulation. Thus, the model applies more directly to commercial lines than to, say, homeowners insurance.

For such a behavioral model to have long-run explanatory power there must be some mechanism that allows overconfidence to persist in the marketplace. It is frequently argued that rational economic agents (investors, firms) will drive irrational agents out of the market; see Sandroni (2000, 2005a, 2005b) for one such argument. DeLong, Shleifer, Summers, and Waldmann (1990), Daniel, Hirshleifer, and Subramanyam (1998), Benos (1998), Hirshleifer and Luo (2001), and Wang (2001) all argue that overconfident investors can survive and even dominate the market in the long run. More generally, Slezak (2003) shows that inter-temporal predictability (i.e., cycles) of asset prices "is robust to the inclusion of dynamic rational agents under very weak conditions" (p. 525) and that irrational agents will typically survive. We should also point out that overconfidence is one of a number of behavioral biases that are known to affect decision making. For example, it is known that individuals systematically misperceive the laws of probability and that individuals tend to overweight small probabilities and underweight large probabilities.

Finally, the behavioral model described here cannot be the entire story of cycles. Even an overconfident insurer ultimately discovers the true value of expected losses if the distribution is stationary. Thus, cycles would eventually become muted. For a long-run cyclical pattern to exist, there must be shocks to the expected loss distribution. What our modest efforts here suggest is one possibility of why the pattern of premium and profitability cycles may not be perfectly correlated with observable loss or surplus shocks.

NOTES

[1] See, e.g., Winter (1991, pp. 118–120) for a description of the typical features of a hard market and Harrington (1988) for a discussion of the financial performance of the property/liability insurance industry focusing on the 1975–1977 and 1984–1987 periods. Cycles are not unique to

the U.S. insurance industry; see Cummins and Outreville (1987), Lamm-Tennant and Weiss (1997), and Chen, Wong, and Lee (1999) on international comparisons.

[2] More precisely, Higgins and Thistle find that when the premium-surplus ratio is low, underwriting profits follow an AR(1) process, and when the premium-surplus ratio is sufficiently high, underwriting profits follow a cyclical AR(2) process. Underwriting profits follow a cyclical AR(2) in 1948–1954 and 1968–1993.

[3] A review of other recent empirical literature on cycles suggests that the current evidence can only be characterized as inconclusive. Harrington and Niehaus (2000) survey the literature on insurance cycles, as does Harrington (2004). Other recent evidence includes Gron and Winton (2001), Harrington and Yu (2003), and Weiss and Chung (2004).

[4] We should point out that insurers in our model are not fully rational Bayesians in that they do not update their estimate of the precision over time. If they did so, we would expect overconfidence to disappear over time.

[5] See Lichtenstein, Fischhoff, and Phillips (1982) for an excellent summary of early work in the area and the March 1996 special issue of *Organizational Behavior and Human Decision Processes* and the September 1997 issue of the *Journal of Behavioral Decision Making* for a sampling of more recent research on overconfidence. Some evidence suggests that experts tend to be more overconfident than novices (Griffin and Tversky, 1992). Evidence also suggests that overconfidence is greater for difficult tasks that require judgment and for tasks where feedback is noisy and delayed (Einhorn, 1980).

[6] This problem is compounded if non-stationary data are regressed on a linear time trend, since this introduces spurious cycles into the residuals (Granger and Newbold, 1974).

[7] Stracca (2004) provides a survey of the behavioral financial analysis of asset prices, contrasting behavioral finance with the mainstream approach based on expected utility maximization and rational expectations. Barberis and Thaler (2003) provide a broader survey of behavioral finance.

[8] Loss distributions may differ across insurers due to differences in, e.g., underwriting standards. Relaxing the assumption of a common loss distribution complicates the model, but has no qualitative effect on the results.

[9] Since we are taking the firm's capital as fixed, this is a model of short-run price determination. The best available empirical evidence suggests that insurer capital has only a short-run effect on prices.

[10] The firm will operate only if $p_{0i} \geq \mu_{0i}$. We assume there is a maximum price, p_i^{max}, above which quantity demanded is zero. Then the firm's strategy space can be taken to be $[\mu_{0i}, p_i^{max}]$. Under the assumptions on demands, $\partial^2\pi_i/\partial p_j\partial p_i \geq 0$. Then the game is supermodular (e.g., Milgrom and Roberts, 1990, p. 1264) and a pure strategy Nash equilibrium exists. If own effects dominate cross effects, so that a "dominant diagonal" condition also holds (e.g., Milgrom and Roberts, 1990, p.1271), the equilibrium is unique. Note also that, since the firm can earn a strictly positive expected contribution margin by charging a price slightly above μ_{0i}, the solution to the unrestricted profit maximization problem must be in the interior of the strategy space, consequently, $p_{0i} > \mu_0$, hence, the equilibrium is interior.

[11] The inequalities are strict if the solvency constraint is binding for firm *i*.

[12] Letting f_0 denote the right-hand side of (4) and $f_1(s_1)$ denote the right-hand side of (8), $\hat{p}_1$ decreases if $f_1(s_1) - f_0$ is negative and increases if it is positive ($f_1 - f_0$ is increasing in s_1). The effect of a change in β on the root of $f_1(s_1) - f_0 = 0$ is in general ambiguous, but should be negative for most parameter values. Then overconfidence decreases the value of the smallest signal for which $f_1(s_1) - f_0 \geq 0$ and increases the smallest value if the signal for which $\hat{p}_1$ increases.

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