Cycles in Casualty: An Examination of Profit Cycles in the Insurance Industry

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Abstract

Aggregate earnings for the property-casualty insurance industry have exhibited cyclical behavior for decades. I develop a dynamic model of the insurance industry with endogenous premium setting, risk aversion, and other feedbacks; and use the model to identify strategies to mitigate the cycle. In addition to documenting the insurance industry model this work introduces several strategies for building confidence in system dynamics models when only some data is available. Simulation results suggest that the relative strength of the inputs signals in the premium setting process is the important driver of the stability of insurance industry profits.

1 Introduction

The property-casualty insurance industry has exhibited cycles in profitability for decades, as shown in figure 1. During the 1980's when a cyclical dip in the profitability of insurers threatened their long-term viability, the causes of the insurance cycle were hotly debated among academics and industry professionals. Commonly accepted wisdom within the industry holds that the drops in profitability are caused by unforeseeable major disasters or other exogenous shocks. According to this theory profitability slowly improves after these events pass, as insurers gradually rebuild capital stocks and readjust to the new risk landscape.

Academics also have a host of competing theories on the origin of cycles. Regression analysis by Doherty and Kang (1988) has shown significant correlation between macroeconomic variables and insurer profitability, while numerous econometric models of the price setting and revenue generating process of the industry have suggested that the auto-correlation (cyclicality) of profits might arise endogenously, as shown by Venezian (1985). Nevertheless, the origin of the cycle, and the extent to which it is endogenous to the industry's structure and decision practices, remains unclear.

In this paper I build a medium-scale, behavioral dynamic model of the property-casualty insurance industry to explore the relative contribution of macroeconomic variables, exogenous disasters and endogenous feedback to profit cycles. The model incorporates endogenous formulations for premium setting, loss expectation formation, and standard setting that are approximate to those used in the industry. When these processes are combined to create a simplified but realistic picture of how the industry operates, the results suggest that profit cycles in the insurance industry can be explained endogenously. The macro-economy and the incidence of accidents, while important for determining profitability, are not the cause of the cycle observed in the model.

This modeling work offers a novel dynamic hypothesis within the system dynamics literature on cyclicality. Currently the literature points to negative feedback loops around capacity adjustment as the primary cause of profit cycles. In my model I assume that the insurance industry can adjust its productive capacity instantaneously and at no cost.[1] While this structure makes the model less realistic, cutting this feedback loop allows my model analysis to focus on the central hypothesis, that cycles in profitability for the insurance industry are caused by the delay in adjusting the riskiness of and revenue from the stock of underwriting business.

Many of the decisions made in an insurance company can be modeled as negative feedback processes that use profitability or capital adequacy as signals to adjust policy levers. Because the effects of these decisions accumulate in a stock of currently underwritten policies, the levers managers use to control profit act only with a delay. My conclusion that profit cycles in the insurance industry arise from delayed negative feedbacks is therefore similar to existing work; but, by laying out a new mechanism for the causation of profit cycles this research suggests a host of applications for similar cyclical models in industries where system dynamics modeling has not previously been applied because capacity adjustment was not likely to be a factor in the cyclical forcing of profits.

For parametrization I collate an aggregate data set of financial variables for the property-casualty insurance industry from Compustat, and use it to calibrate the model to the observed historical behavior.[2] The behavior of the model is also analyzed under the effect of separately calibrated, stochastic patterns for the exogenous inputs. Using these inputs I analyze the correlation between the model variables and a broader range of historical variables available for the entire insurance industry. This process is augmented by an implementation of an ARIMA model driven by a simple Markov process for the standard pink-noise generator.[3]

Finally, my analysis suggests an interesting strategy for mitigating the severity of the profit cycle

[1]In fact, the productive capacity of the industry is excluded from the model structure as costs from these sources are treated as a constant function of the amount of work that needs to be done.

[2]Specifically, this means premiums collected, claims incurred and operating profit, as these variables are both salient and available in the Compustat data for the segment of the industry I am interested in.

[3]I use normal probability plot analysis of the historical data for investment returns to calibrate the structure, following Webster et al. (2007) in their analysis of refinery emissions in Houston. The pink noise formulation is covered by Sterman (2000).

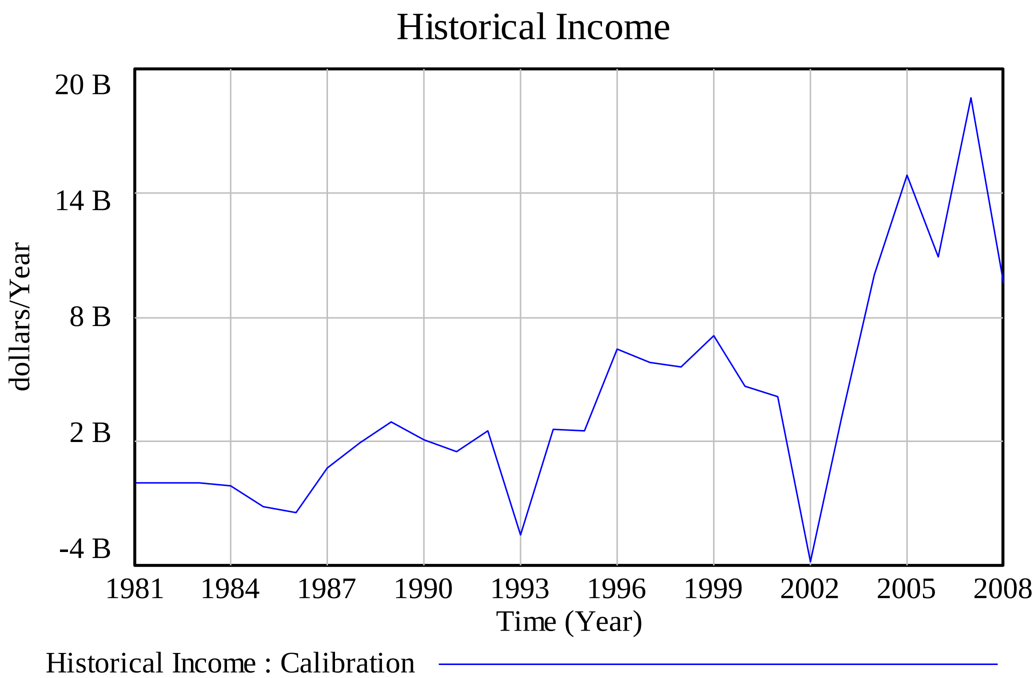

Figure 1: Historical Aggregate Net Income of the Property-Casualty Insurance Industry.

in the insurance industry. In simulation tests the stock of investment capital for the industry is shown to do remarkably little to limit the severity of the cycle when only the target for its level is changed. Actions that ensure high adequacy of capital are only effective when capital is used as the most salient input to decisions effecting the scope of the insurance industry. This result suggests that regulation that focuses on ensuring high capital adequacy will only be effective at creating stable profits if industry actors are fully committed to using the capital stock as the most important determinant of their pricing strategy, rather than focusing on net income.

2 Prior Research

Researchers examined the nature and causes of the insurance cycle extensively during the 1980's and the first half of the 1990's. By the end of that period a substantial body of literature had separated into three groups (Gron 1994).

The first body of research hypothesized that the cycle was caused by interest rate fluctuations and exogenous shocks (Doherty and Kang 1988). Later research within this school of thought added additional macroeconomic variables to the regressions for estimating insurer profitability (Grace and Hotchkiss 1995). Even though these tests improved in explanatory power as they developed, they still could not explain the majority of the variation in combined ratios or operating profit, and did not hypothesize causal directions for the statistical relationships they documented.

A second stream of research focused on excessive regulation as the most likely cause of insurance profit cycles. These capacity-constrained models held that rational expectations and competitive markets would overcome the cycle if regulators would stop limiting the supply of insurance by mandating the level of reserves (Winter 1991). These models tended to be very simple in structure, and were criticized for neglecting two important interactions. The first critique was that insurer bankruptcy is also a large supply shock, and deregulation would likely increase the risk of insolvency. The second was that the limited supply of insurance available was not the only problem during the 1980's liability insurance crisis, and the increasing rate of claims by policyholders was not well explained by variation in the regulatory environment.

The final body of research on the insurance cycle supported a hypothesis that a lagged negative feedback loop within the insurance industry was the cause of the cycle. Since past information must be used for determining present prices, and since these prices are only revealed to be profitable or unprofitable once losses are realized, a simple discrete time model of the premium-setting process in the insurance industry will produce a cyclical output (Venezian 1985). Later work made the connection between this price-setting process and the total surplus capital of the insurance company (Berger 1988). When this link is included in a model, it completes an additional negative feedback loop, since profits increase the capital surplus, which increases competition in the industry, driving prices down and eventually lowering profits.

While this research approach was promising, it suffered from several limitations that kept it from dominating the debate on the causes of the insurance profit cycle (Doherty and Garven 1995). The first limitation was that all of the models published were made analytically tractable by grouping the negative feedback processes they modeled into a very small number of effects. This meant that researchers could not differentiate between the various hypotheses for the cause of cycles in the insurance industry, because each model had to largely exclude the insights from the others. The second limitation was that, because these models excluded the effects of exogenous variables on the profitability of insurers, they could not respond to the research that suggested that cyclical profits were the result of fluctuations in interest rates or other exogenous variables.

From the standpoint of these research efforts this paper lies within, and extends, the third body of work by seeking to explain the insurance cycle through the modeling of endogenous feedback processes. My approach addresses the limitations mentioned above by numerically simulating, rather than analytically solving, the differential equations within the model. This approach allows me to build a model with a richer structure and appropriate exogenous forcing. Competing hypotheses about which macroeconomic fluctuations or specific feedback loops are the most important for causing the profit cycle in the insurance industry can therefore be evaluated here.

Research on the insurance industry has also been a feature of the system dynamics literature, but these papers have largely dealt with managing the quality of the claim adjustment process. Starting with the learning laboratory built for Hanover Insurance,[4] researchers noticed that the low salience of soft variables associated with insurance claim adjusting made the quality of settlements less important to managers than the total productivity of their workforce. This incentivized managers to increase the workload on adjusters, which led to an erosion of the quality of settlements,[5] and raised the total costs of insurance companies (Morecroft 1988; Senge and Sterman 1992). Later studies have taken this theory of service delivery dynamics and applied it to many different settings, including health care (Homer and Hirsch 2006), Toyota's Total Quality Management (Repenning and Sterman 2001) and the service industry in general (Oliva and Sterman 2001). The implementation of system dynamics to solve the problems at Hanover Insurance was an early instance that showed the power of the technique and was cited as a good example of how system dynamics can be used to change the mental models and behavior of managers (Cavaleri and Sterman 1997).

The dynamics of service quality erosion have been applied in many different contexts within the insurance industry (Doman et al. 1995). But surprisingly, the system dynamics literature has not expanded its focus on insurance to explore the question of how the profit cycle in the insurance industry arises. This paper is not without precedent, since the topic of profit cycles has been extant in system dynamics research for decades.

Cyclical profit dynamics in the commodity markets (Meadows 1970), paper makers (Berends and

[4]See Sterman and Moissis (1989)

[5]Quality here is taken to be a measure of the size of the payment relative to some unknown payment size that the customer would accept at minimum. higher quality means lower cash outlays for claims.

Data	Description	Usage	Notes
Operating Income	"Non-life" Income	All	Insurance companies report investment income as "operating"
Premiums Collected	"Non-life" Total Premiums	All	
Claims Incurred	"Non-life" Claims	All	
Nominal GDP	From the BEA	All	All financial data used is nominal.
Claims Expense	"Non-life" Claims Expense	Corr	See section 5.4 for the relationship between claims incurred and claim expense.
Dividends	All firms in SIC 6331	Corr	Only reported at a firm level.
Assets -Total	All firms in SIC 6331	Corr	Only reported at a firm level.
Invested Capital	All firms in SIC 6331	Corr	Only reported at a firm level.
Investment Income	All firms in SIC 6331	Corr	Only reported at a firm level.
Total Expenses	All firms in SIC 6331	Corr	Only reported at a firm level.
Total Liabilities	All firms in SIC 6331	Corr	Only reported at a firm level.
Shareholder's Equity	All firms in SIC 6331	Corr	Only reported at a firm level.
Commissions	All firms in SIC 6331	Corr	Only reported at a firm level.

Table 1: This table is a short description of the data used during model formulation, calibration and testing. Premiums, claims and income were available at the level of the "non-life" insurance industry, while most of the data were only available for the aggregate four-digit SIC code. Because of this, most of the data was used only for testing of correlations as shown in table 6 and section 8. For all of these tests I am assuming that the property-casualty industry represents a constant fraction of the total insurance industry. This is obviously not the case, and to the extent this assumption is incorrect the correlations reported will be biased towards zero.

Romme 2001), airlines (Liehr et al. 2001), and the economy as a whole (Forrester 1991; Sterman 1986) have all been addressed with dynamic modeling, but the vast majority of earlier attempts focused on industries with long lags in capacity adjustment. Because capacity decisions are made using current profit signals, and the appropriateness of their decisions will not be known until capacity is built, the capacity adjustment delay has been widely cited as a cause of profit cycles. While delays still play a role in the insurance profit cycle, the capacity adjustment delay does not, and so the setting of this paper places it apart from existing research.

3 Data Sources

I compile aggregate financial statement data for all firms in the Compustat Fundamental Annual Data Files that have SIC code 6331.[6] Many of these firms are diversified into businesses unrelated to property casualty insurance, and so I only use data classified as "non-life" when calibrating the model. For instance, instead of calibrating the model using total premiums collected by all firms in the industry, I use the separate data item for total non-life premiums collected. Because this more disaggregated data is only available after 1982 only the data from 1982 through 2009 is used during model calibration. Investment results, total capital and several other variables are not recorded in this way, and so I use them only when appropriate for estimation of model parameters and tests of the correlation of the model over a long time horizon. Specifics on the time series I use can be seen in table 1. Two other data series that I use are quarterly nominal GDP for the United States, and average Baa-rated bond yields. These series come from the United States Bureau of Economic Analysis.

[6]Standard Industry Classification 6331. Fire, Marine, and Casualty Insurance.

4 Causal Structure

Figure 2 shows two important balancing feedback loops in my model of the insurance industry. When the stock of capital on hand is large relative to some target, insurers will seek to expand the scope of their offerings by branching out into types of policies that they are less familiar with. A study by Ericson and Doyle (2004) describes this effect well, and from many angles. For instance, they write:

> "One option for insurers faced with uncertainty is to simply refuse to participate in underwriting a particular risk.... Refusal to participate in particular risks also occurs in the process of excluding certain populations from a given insurance pool because they threaten the integrity and profitability of that pool. (2004:17)"

During lean times insurers will look to scale back the types of policies they write by focusing only on the populations where they feel that they have sufficient data to price the risk correctly[7]. In aggregate, this causes the overall value of the property insured to fall. When insurers are well capitalized the opposite happens, as each individual company puts some of its money to use writing policies for clients that it would otherwise avoid because of the high uncertainty of the underlying risk[8]. This adjustment of insurance scope results in an increase in the total underwriting of the industry as well as an increase in the riskiness of the policies written[9], forming the two closely related "Size" and "Risk" balancing loops, respectively.

Both of the loops in figure 2 can also be thought of as arising in part from changes in the price of insurance not captured by total premiums. Smith (1981) and many other scholars in this area discuss the problem that arises out of using premiums as a measure of price, given that the industry employs numerous other incentives when marketing policies. For instance, if deductible increases are implemented as a response to rising cost expectations, the net effect will be a reduction of both the size of claims incurred and the total underwriting exposure compared to what they would be otherwise. Claims will be reduced on new policies because a larger fraction of the loss is covered by the deductible, while exposure will be reduced because the marginal customer will be less likely to insure their assets.

Figure 3 shows another set of balancing loops that result from the expansion of the scope of the industry in my model. Each of these loops is caused by the increase in various components of cost[10]. As costs increase, operating profits fall; *ceteris paribus*, total capital therefore decreases, and capital adequacy becomes lower than it otherwise would have been[11]. This acts to balance the initial expansion of the industry through the balancing "Costs" feedback loop.

Figure 4 brings premiums into the causal structure and completes several new feedback loops. First, excess capital can cause insurers to compete for market share in areas where they already have a presence.[12] This competition reduces premium income, which acts through operating income to make the stock of capital lower than it otherwise would have been, and thus balances the initial increase in capital through the "Price War" balancing feedback loop.

The increases in cost from the scope of the industry also influence premiums. Insurers update information about their claims and expenses, forecast them, and use that information to ensure that they are pricing policies correctly to guarantee future profitability.[13] This "Profit" reinforcing loop acts through the same causal path as the "Price War" loop but in the opposite direction, and reinforces the signal to expand the scope of the industry by keeping prices high enough to justify the added risks.

[7] One of the features of the 1980's insurance crisis was the inability of consumers to find insurance. See Cagle and Harrington (1995) for a capacity-constrained model of that dynamic, Cummins and Lewis (2003) for a discussion of the effect in the case of terrorism insurance, and Winter (1991) for an overview of the experience during the 1980's.

[8] See Myers and Read (2001) as well as section 5.4.

[9] Discussions with industry professionals also indicate that scope changes have an effect on the measurement uncertainty of the underlying risk. When scope expands, insurers have less data, on balance, about the policies they are writing. For a description of the expansion of scope in my model and a justification of this causal link, see section 5.6.

[10] A discussion of how I model the components of cost can be found in section 5.5.

[11] These are all mechanical results of the definition of profit, and the stock of total capital.

[12] Pauly (1974) is a frequently cited early example of price competition in the insurance industry.

[13] Mahler et al. (2001) or any practitioner-oriented book on the insurance industry will provide numerous examples of the process of forecasting insurance underwriting costs.

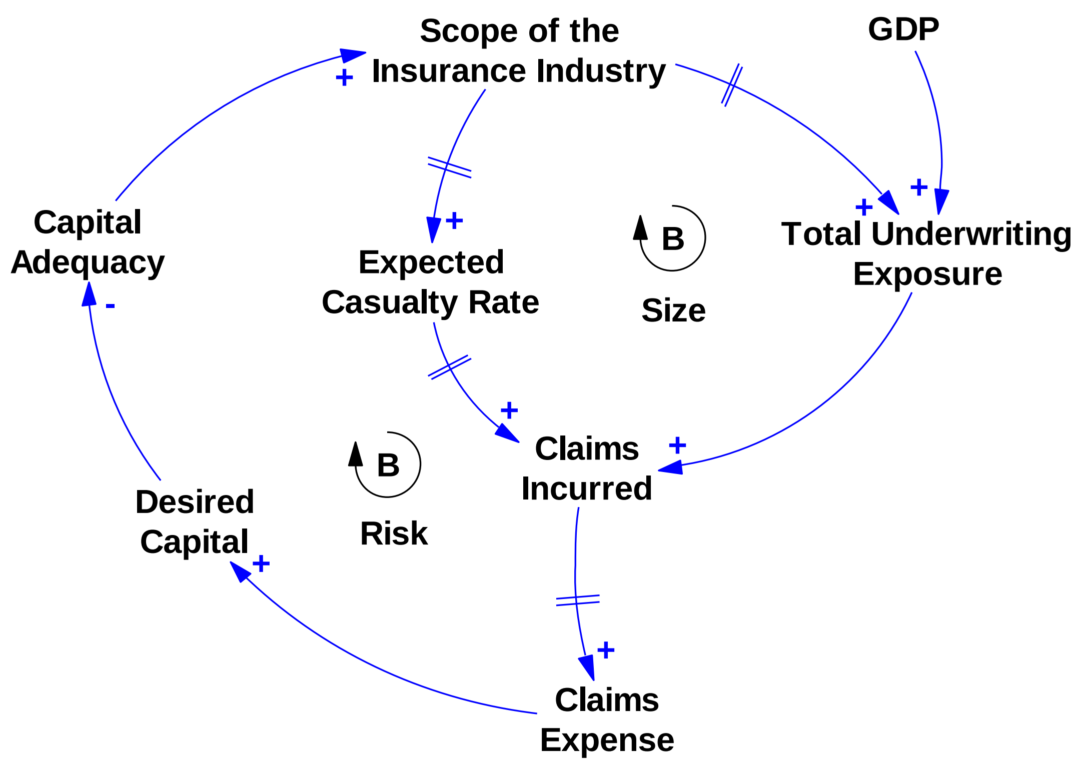

Figure 2: A causal loop diagram of two delayed balancing loops that describe how increases in the adequacy of capital for the insurance industry lead to expansions in the size of the industry as well as the level of risk taken. These two feedback loops result in capital being less adequate than it otherwise would have been.

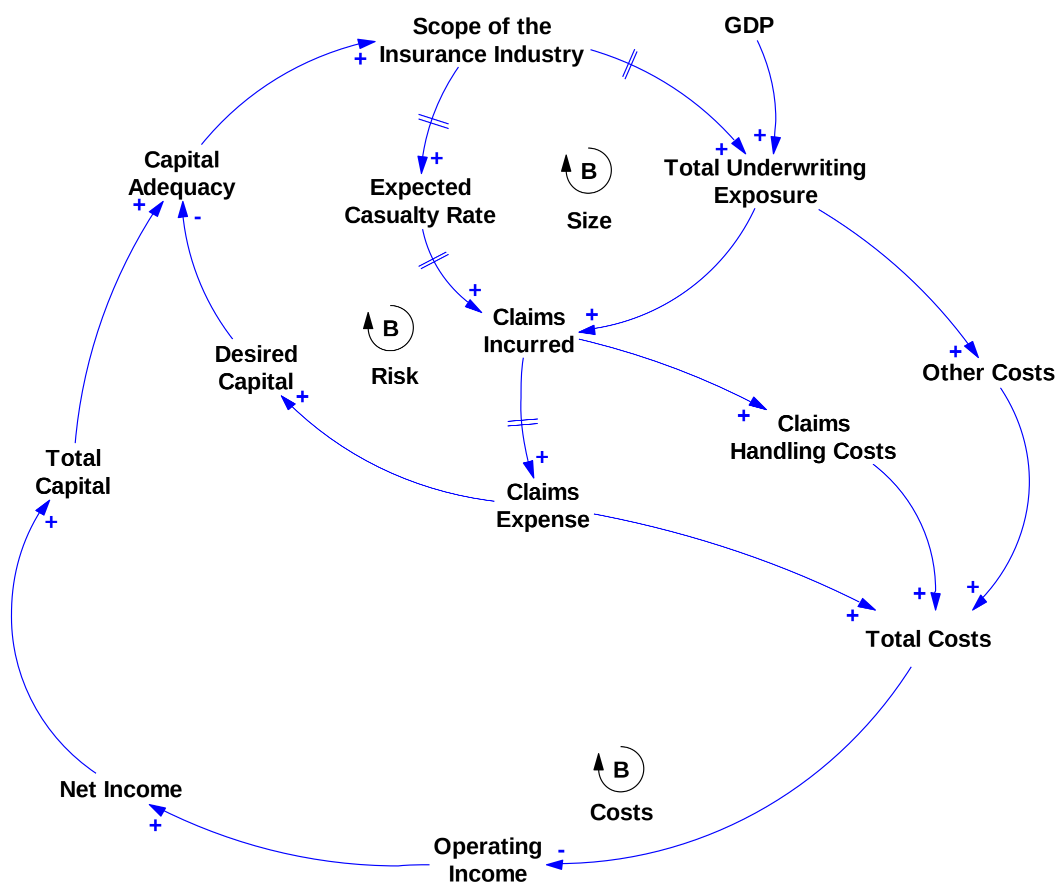

Figure 3: When costs are added to the causal map the effects of increasing scope become more important for the model's behavior. Costs complete another set of strong negative feedback loops with significant delays caused by inertia in the the book of underwriting.

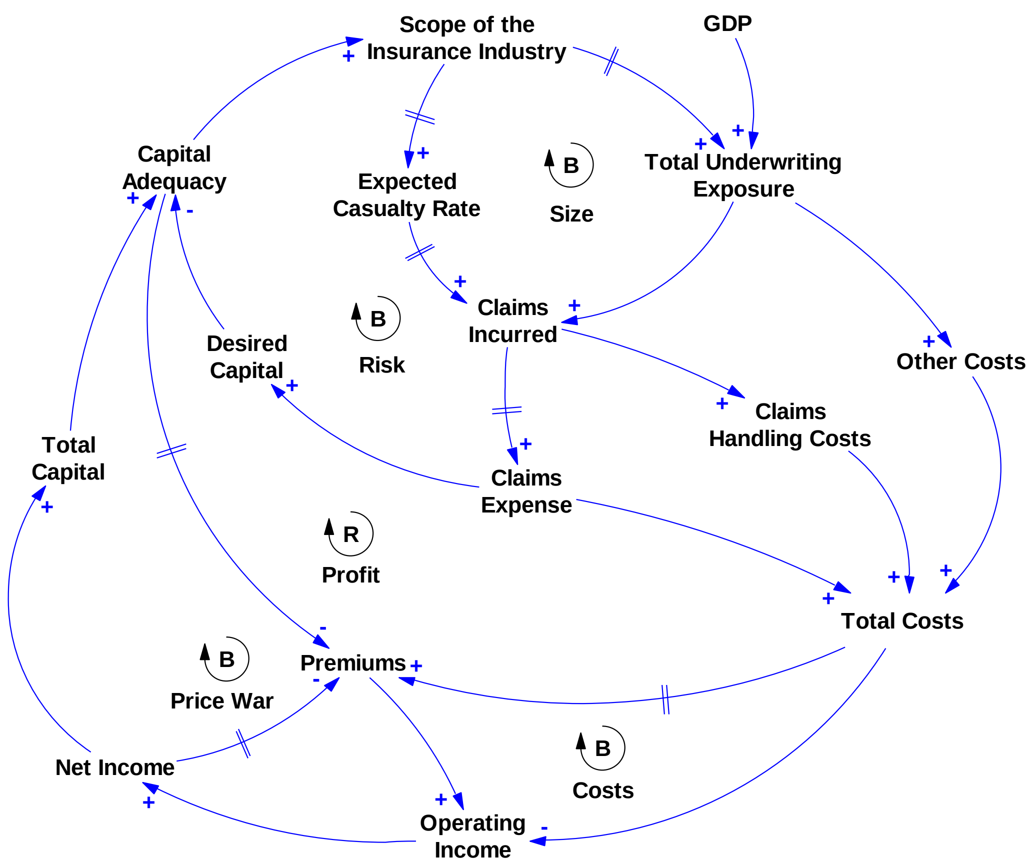

Figure 4: Premiums complicate the causal structure slightly, as they introduce the first reinforcing loop to the diagram. Because premiums respond to changes in costs, their effect is partly to help sustain the expansion of scope and costs caused by capital adequacy. This intended rationality is counterbalanced by an additional balancing loop that describes how capital adequacy itself can keep premiums from rising through the action of intense competition between insurers over market share.

The "Price war" and "Profit" loops are difficult to see clearly in figure 4, and so are shown separately in a simplified causal loop diagram in figure 5.

Figure 6 completes the causal loop diagram of my model by incorporating a set of financial feedback loops stemming from net income and dividends. Income increases total capital,[14] and with a short delay capital is invested and contributes to net income through investment, completing the "Interest" reinforcing loop. The effect of the "Return on Shares" balancing loop created by dividend payments is mitigated somewhat by a counteracting "Return on Equity" reinforcing loop that captures the opportunity cost to shareholders of dividend disbursements. If the income of the insurance industry is high, dividends will be limited so that capital can be reinvested in the business.[15] (NEED CITE)

[14]This occurs mechanically, through its definition and the definition of the stock of total capital.

[15]See Bringham and Gordon (1968), or section 5.8.

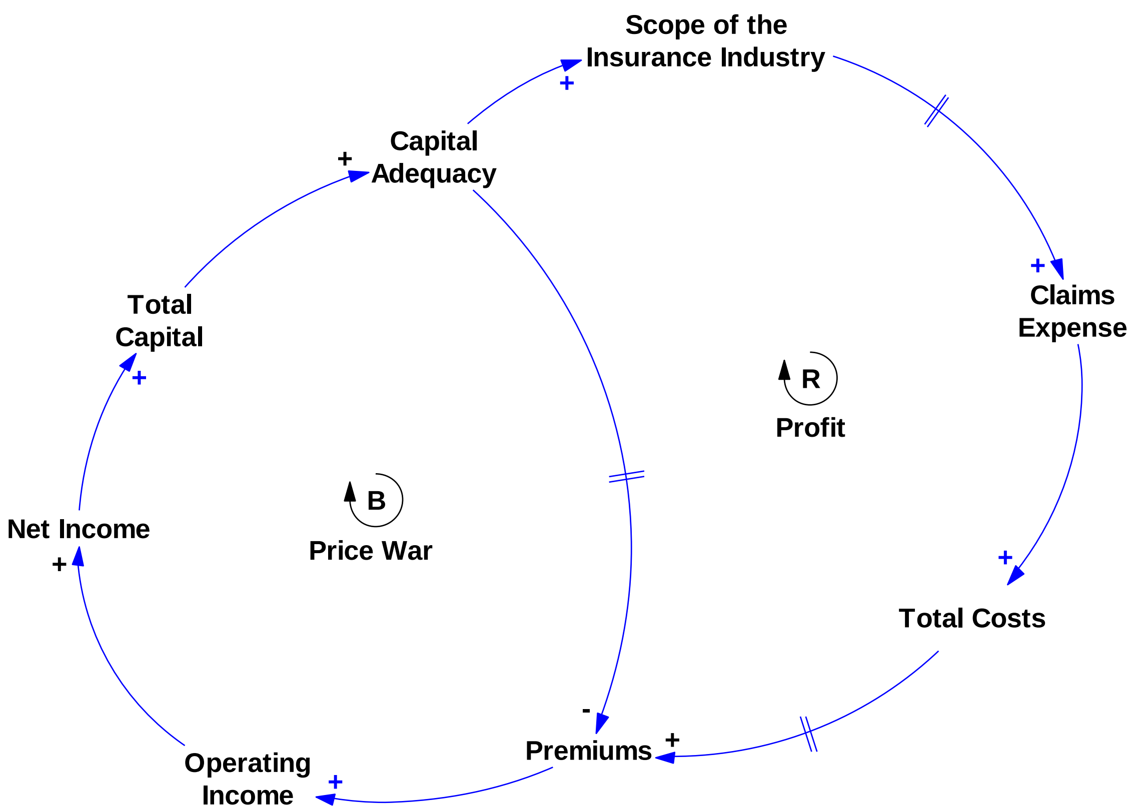

Figure 5: This figure shows a subsection of figure 4. In this simplified diagram the reinforcing action of profit to justify changes in insurance scope is shown in the "Profit" loop. The compensating action of price competition is shown in the "Price War" loop.

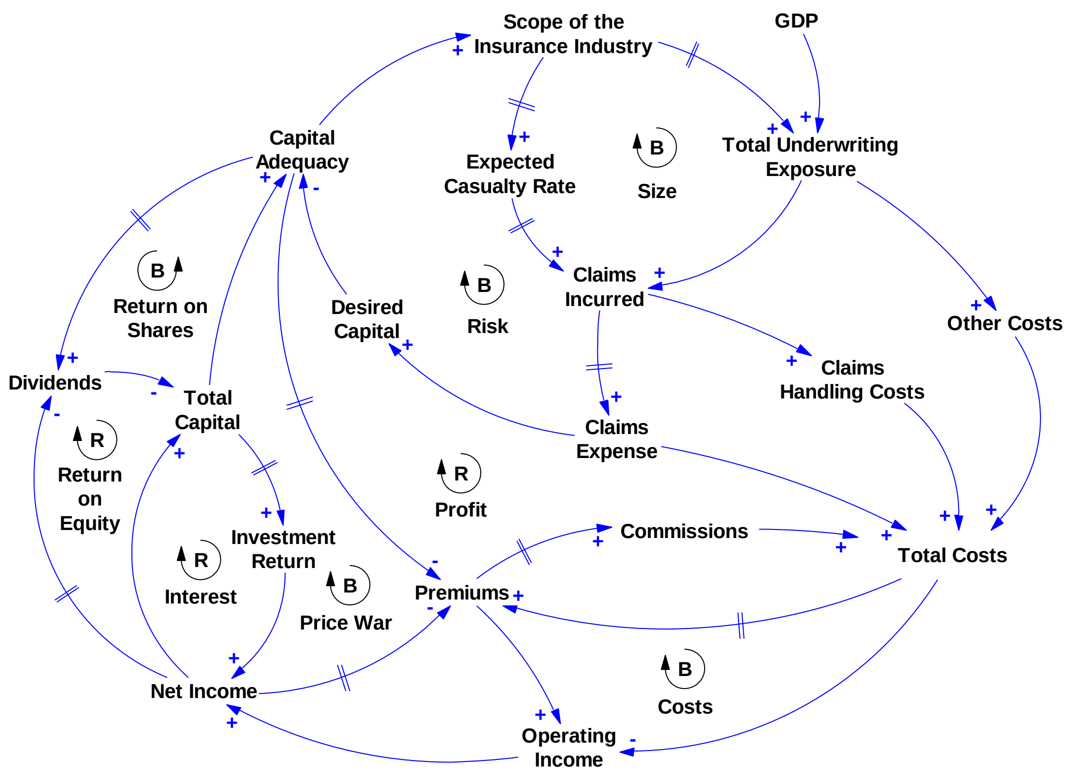

Figure 6: The final causal loop diagram for the insurance industry model, which includes loops around dividends and investment.

5 Model Formulations

The model for the insurance industry starts with a parsimonious formulation for profit shown in equation 1:

$$N_t = R_t - C_t - O_t \tag{1}$$

Where N_t is current net income R_t is total revenue C_t is claims expense and O_t is other operating costs. The formulation for each of these components will be explained in detail in the following subsections.

5.1 Premiums

Millions of dollars are spent every year by insurance companies to ensure that the premiums they charge are adequate to cover the costs they will incur from claims, their operating costs, and a reasonable profit margin. Understandably, the exact heuristics behind the pricing of insurance are a closely guarded secret and involve volumes of data on hazard rates that are not available to academics. Many practitioner-oriented texts do exist, and the basic process of rate making described by them is not significantly different from the process of price setting in other industries. For example, Mahler et al. (2001 page 83) supply an equation to determine the rate per unit exposure on page 83 of their book:

$$Pr = \frac{P_p + F}{1 - V - Q} \tag{2}$$

Where Pr is the premium rate charged per dollar of underwriting, P_p is the pure premium,[16] V is an adjustment for variable costs, and Q is a factor that builds in a profit margin. My model incorporates the concept behind this description of the price-setting process, but translates some of the influences on premiums into functional forms more familiar in the system dynamics literature.

The average premium-per-dollar of underwriting exposure charged by the insurance industry is influenced by the costs they expect to bear in servicing the policy.[17] Many texts on the rate-making process in the insurance industry advocate for insurance adjusters to project this cost forward to account for changes in the value of future expenses. Therefore my model takes the costs calculated by the structures described in sections 5.4 and 5.5 and projects their perceived value forward using the standard third-order forecasting structure to arrive at the expected cost-per-unit underwriting[18]. This variable is then used as part of a multiplicative hill-climbing heuristic (Sterman 2000) in the following way.

First, an indicated premium is calculated as shown in equation 3:

$$TPr_t = (Pr_t) \cdot Ef^{NI} \cdot Ef^{Cap} \cdot Ef^{Cost} \tag{3}$$

Where $TPr_t$is the indicated premium, Pr_t is the current premium per unit exposure, Ef^{NI} is the effect of profit on premiums, Ef^{Cap} is the effect of capital on premiums and Ef^{Cost} is the effect of cost on premiums. Conceptually, Ef^{Cost} can be thought of as the change in the premium indicated by the forecast costs discussed above. It is calculated as the ratio of forecast costs to current perceived costs.[19] Consequently if costs were expected to rise by some percentage, then the indicated premium would be higher than the current premium by exactly the change in cost expected during the policy lifetime.

[16] Pure premium is the term used in the insurance industry to represent the expected claim expense plus the expected costs of claims adjustment. In my model these concepts are kept separate to increase transparency for academics unfamiliar with insurance industry terminology.

[17] See Mahler et al. (2001), or look up the term "trended projected ultimate losses".

[18] This projected value represents the influences from P_p, F, and V in equation 2.

[19] More precisely I use the "expected" current costs as the basis for the forecast, since decision makers do not have access to the current "true" value of costs-per-unit exposure.

Ef^{NI} and Ef^{Cap} are both formulated as power functions that take as their input the current state of the variable in question compared to a "target" state. Ef^{Cap} is calculated according to equation 4:

$$Ef^{Cap} = (CapA)^{S_{Pr2Cap}} \tag{4}$$

Where $CapA$ is the adequacy of capital described in equation 10 and S_{Pr2Cap} is the constant sensitivity of premiums to capital. Given this formulation S_{Pr2Cap} should be negative, because more capital adequacy will result in downward pressure on premiums.

The effect of profit on premiums is calculated according to equation 5:

$$Ef^{NI} = (In^{Adq})^{S_{Pr2NI}} \tag{5}$$

Where In^{Adq} is the adequacy of income and S_{Pr2NI} is a constant sensitivity of premiums to net income. Similar to the effect of capital on premiums, the causal theory behind my model necessitates that S_{Pr2NI} be negative in order for higher income to translate into lower premiums. In^{Adq} is:

$$In^{Adq} = \frac{(1 + ROA)}{(1 + TROA)} \tag{6}$$

Where ROA is the current level of industry return on assets and $TROA$ is the target return on assets, a constant determined during model parametrization. ROA and $TROA$ are fractions, and since it is possible that the model could calculate an ROA that is less than negative one, In^{Adq} could be less than zero, and the formulation in equation 6 would return a floating point error. In order to prevent this from occurring, I employ a sharp maximum so that the lowest possible level of the income adequacy in the model is zero. Given this formulation, if the modeled industry were to lose more money in a single year than it had in total assets, the model would still empty the stock of assets and bankrupt the industry, but the floating point error in calculating income adequacy would be eliminated.

I accomplish the adjustment of premiums towards the indicated level with equation 7:

$$Pr_t = \int \left[\frac{(TPr_t - Pr_t)}{\tau_P} \right] dt + Pr_0 \tag{7}$$

Where Pr_t is the current premium per unit exposure charged on average, τ_P is the delay time associated with changing premiums, Pr_0 is the initial premium per unit exposure and TPr_t is the premium indicated from equation 3. The instantaneous premium Pr_t is then recorded in a co-flow to the aging chain of total underwriting exposure, and the total premium income of the industry is calculated as:

$$PrInc = Pr^{Avg} \cdot U_t \tag{8}$$

Where $PrInc$ is the flow of premium income, Pr^{Avg} is the average premium per unit exposure calculated by the co-flow, and U_t is the total underwriting exposure of the industry, discussed in section 5.6.

5.2 Capital Adequacy

One of the liquidity ratios used by analysts and regulators covering the insurance industry is the "claims solvency ratio" or:

$$CSR = \frac{CI_t}{PrInc} \tag{9}$$

Where CSR is the claims solvency ratio, and CI_t is the flow of claims incidence for the industry. I do not directly compute the claims solvency ratio for determining capital adequacy; rather, adequacy of capital in the model is calculated following equation 10:

$$CapA = ZIDZ(\frac{Cap}{DCap}) \tag{10}$$

Where $CapA$ is the adequacy of capital, $ZIDZ$ is the "zero if division by zero" operation, Cap is the current total capital of the industry and $DCap$ is the current desired capital, calculated as shown in equation 11:

$$DCap = DCSR \cdot CI_t \tag{11}$$

Where $DCSR$ is the desired claims solvency ratio, which is a constant estimated during model calibration.

5.3 Investments and Capital

I model the stock of investment capital as shown in equation 12:

$$Cap_t = \int (OCF + Inv - Div)dt + Cap_0 \tag{12}$$

Where Cap_t is the current total capital, OCF is the operating cash flow[20], Inv is the flow of investment income, Div is the flow of dividends being paid to shareholders, and Cap_0 is the initial capital stock of the industry. The flow of investment income is calculated as shown in equation 13:

$$Inv = Cap_t \cdot R\% \tag{13}$$

Where $R\%$ is the percentage return on investment gained by the insurance in industry each year. The formulation for the percentage return on investments is exogenous, and a detailed description of how it is modeled is included in the section 6.2. For the process of fitting the model to historical data, the percentage return on invested assets was set to be the historical investment return. R_t from equation 1 is then:

$$R_t = Pr^{Avg} \cdot U_t + Cap_t \cdot R\% \tag{14}$$

5.4 Claims Costs

The total dollar value of claims incurred by the insurance industry is shown in equation 15:

$$CI_t = U_t \cdot LF_{avg} \cdot (1 + \varepsilon) \tag{15}$$

Where CI_t is the flow of claims incurred by the industry, U_t is the total underwriting exposure of the industry, LF_{avg} is the average fraction of dollars underwritten that result in a claim each year and ε is an exogenous noise term that is only used in the long-horizon statistical tests of the model, explained in section 8. The determination of the total underwriting exposure is described in subsection 5.6.

The percentage of underwriting that generates a claim is not constant in the model. As discussed in section 5.6 and 4, insurers seek out more business when they are more financially healthy, and in the process insure risks that have both a higher absolute level of exposure[21] and a higher exposure measurement uncertainty.

[20] Because I exclude depreciation, taxes and physical capacity from the model, there are no flows from these sources, making operating cash flows an appropriate name for the flow recorded here. The financial data for the insurance industry includes investment income in operating income, and so throughout this paper I use net income and operating income interchangeably to refer to that concept. In the model, operating cash flow is separate from net income in order to make my formulations general enough for future modelers to extend.

[21] Level of exposure here means the fraction of dollars underwritten that will result in a claim every year. I use this term interchangeably with "casualty rate."

The specific functional form for the riskiness of new policies in the model is a constant normal level of loss, multiplied by an adjustment factor that varies as a power function of the normalized scope of the industry. This relationship is shown in equation 16.

$$LF_t = NLF \cdot (\frac{Sc_t}{NSc})^{S_{CR2SC}} \tag{16}$$

Where NLF is the normal underwriting loss fraction, and is estimated during model calibration, Sc_t is the current scope of the industry, NSc is the normal scope, and S_{CR2SC} is the sensitivity of the casualty rate to insurance scope. This loss fraction is applied only to newly underwritten policies, and is recorded in the co-flow structure for the riskiness of current underwriting. The average loss fraction for the entire book of underwriting business is calculated using a co-flow of the total dollars underwritten[22] to arrive at LF_{avg}.

Claims incurred then flow into a stock of pending claims, as shown in equation 17:

$$CP_t = \int (CI_t - C_t - CD_t)dt + CP_0 \tag{17}$$

Where CP_t is the stock of claims pending adjustment, C_t is the claims expense, CD_t is the flow of claims that are denied and CP_0 is the initial level of pending claims. Claims expense and claims denied sum together to the outflow from a first-order material delay of CP_t such that:

$$\frac{CP_t}{\tau_C} = C_t + CD_t = F_{CP} \cdot \frac{CP_t}{\tau_C} + (1 - F_{CP}) \cdot \frac{CP_t}{\tau_C} \tag{18}$$

Where τ_C is the average delay in adjusting claims and F_{CP} is the fraction of claims that are paid. I estimated the fraction of claims paid with a regression of non-life insurance claims incurred on total non-life claims expense. The result, that 84.7% of claims are paid on average, was highly statistically significant, with a standard error of 0.02 on an estimate of 0.847 and an R^2 of 95%.

5.5 Other Operating Costs

In formulating "other operating costs" I assume that costs primarily arise from claims-handling costs and commissions. Claims-handling costs represent all of the administrative costs arising from claims, and are modeled as a constant fraction of the flow of adjusted claims, as shown in equation 19:

$$Cost_{CH} = CP_t \cdot F_{CHC} \tag{19}$$

Where $Cost_{CH}$ is the costs arising from handling claims and F_{CHC} is the fractional cost of handling one dollar of claims. The justification for this formulation comes from the Hanover Insurance "Claims Game" documented by Sterman and Moissis (1989)[23], where the authors make the simplifying assumption that the administrative costs from claims adjustment varies linearly with the number of cases. Since my model is less concerned with the details of how costs from claims vary in time, the same assumption here should have little effect on the model's fit.

Commissions are a common practice in the insurance industry, and are paid to independent insurance agents after they persuade a customer to buy a policy[24]. Most commissions are paid in the first year that the policy is active, and are built into the premium paid by the customer; however, some commission payments continue for multi-year policies and renewals. With this in mind, I model commissions as a material delay of deferred commission payments, proportional to the inflow of premiums written. The flow of commission expenses use an empirically estimated delay time, as shown in equations 20 and 21 :

[22] See Sterman (2000).

[23] See page 68, table 6

[24] See Regan and Tennyson (1996) for a description of the commission system in property-casualty insurance.

$$Com_P = \int (Pr_{New} \cdot F_{PCC} - Cost_{Com})dt + Com_0 \tag{20}$$

$$Cost_{Com} = \frac{Com_P}{\tau_{Com}} \tag{21}$$

Where Com_P is the deferred liability of commission costs pending, Pr_{New} is the flow of new premiums written[25], F_{PCC} is the fractional cost of commissions per dollar of new premiums written, $Cost_{Com}$ is the flow of actual commissions costs being paid, Com_0 is the initial level of pending commissions costs[26], and τ_{Com} is the average delay for commissions payments.

5.6 Demand for Underwriting

Conceptually, the demand for insurance should be proportional to the stock of assets in the economy. Unfortunately the stock of assets in the economy is not a variable that is easily measurable, and so reliable data on its level are not available. For this reason, many academics researching insurance assume that the demand for insurance is proportional to the flow of investment, which is some unknown fraction of the gross domestic product[27]. Therefore my model uses the nominal gross domestic product as the basis for the demand for underwriting. Some fraction of that flow is considered to represent investment in insurable assets, creating a stock that proxies for the assets in the economy, as shown in equations 22 and 23:

$$A_t = \int (GDP_t - \frac{A_t}{\tau_A})dt \tag{22}$$

$$Assets = F_{GDP2Un} \cdot A_t \tag{23}$$

Where $Assets$ is the proxy my model uses for the level of assets in the economy, F_{GDP2Un} is the fraction of the annual GDP that represents those assets, τ_A is the average life of capital[28], A_t is an intermediate stock that accumulates the flow of GDP and the flow of assets being removed from the pool of insurable capital and GDP_t is the flow of exogenous, nominal gross domestic product. This level of assets desiring insurance does not directly represent the demand for dollars of underwriting however, as other important effects must be taken into account.

$$DesIns_{Consumer} = Assets \cdot Ef^{PE} \tag{24}$$

Equation 24 shows the effect of premiums on the proportion of the assets from equation 22 that are insured. Ef^{PE} represents the effect of the price elasticity of demand for insurance, and its inclusion should be justified briefly. Many previous studies on the insurance industry have assumed that demand for liability insurance is price inelastic, and that assertion has been supported by empirical studies[29] as well. Automobile insurance, homeowners insurance, and marine insurance are often mandatory, and so changes in the cost of insurance will shift the distribution of customers between companies in the industry but will have a relatively small effect on the overall demand for insurance until price changes become so extreme that they influence demand for the underlying goods being insured[30]. Rather than assume that the price elasticity is zero however, it is better practice to include the elasticity of demand

[25] This flow is collected in a co-flow of written premiums that follows a standard formulation for a co-flow with aging chain. More information on these formulations is available in the appendix.

[26] Set in dynamic equilibrium to be $\tau_{Com} \cdot Pr_{New} \cdot f_{PCC}$, by Little's Law

[27] See Smith (1981) among others.

[28] There is no reason to assume that the average life of capital in my model is identical with the actual physical life of capital in the economy or with the life of capital assumed for depreciation. Here the concept is the "insurable" life of capital, i.e. the length of time on average capital investments will be considered as worthy of insurance by their owners.

[29] See for example: Cagle and Harrington (1995), Strain (1966) and Weiss and Chung (2004)

[30] Feldblum (1999) describes the price elasticity of demand for property liability insurance in detail.

to price and let model calibration determine the value of the parameter. The exact formulation for the effect of price on demand that I use in the model is shown in equation 25:

$$Ef^{PE} =(\frac{Pr_t}{Pr_{Ini}})^{\eta_P} \tag{25}$$

Where Pr_t is the current premium per dollar of exposure, Pr_{Ini} is the normalizing initial premium charged per dollar of exposure and η_P is the price elasticity of demand.

The demand for insurance is also affected by the income elasticity of demand. Consumer income in the model is represented by exogenous GDP, and normalized by GDP's initial level, as shown in equation 16:

$$Ef^{Inc} =(\frac{GDP_t}{GDP_{Ini}})^{\eta_I} \tag{26}$$

Where GDP_t is the current nominal GDP, GDP_{Ini} is the normalizing initial GDP and η_I is the income elasticity of demand, which is positive. This effect combines with the price elasticity of demand to arrive at the adjusted desired level of insurance as shown in equation :

$$DesIns =DesIns_{Consumer} \cdot Ef^{Inc} \tag{27}$$

Two important concepts for the determination of the demand for insurance have now been calculated by the model. The first is the level of insurance *a priori*, and the second is the level of demand for insurance that can actually be served by the industry after considering price and income effects. Once the model has calculated this desired level of insurance, the calculation of the inflow to the aging chain for total underwriting exposure is accomplished by way of the standard stock management structure, as shown in equation 28:

$$U_{in} = Max(\frac{DesIns - U_t}{\tau_U} + U_{Out} \ , \, 0) \tag{28}$$

Where U_{in} is the inflow of underwriting to the industry,Max denotes the maximum function, U_t is the current level of total underwriting exposure[31], τ_U is the delay in adjusting underwriting to its desired level and U_{Out} is the outflow of underwriting, analogous with replacement purchases in the stock management formulation.

5.7 Scope

The "scope" of the industry is an important feature of my model and has already been discussed conceptually in section 4. The mathematical formulation for this effect is the smooth adjustment of scope towards an indicated scope that is multiplicatively influenced by two effects:

$$Ef_{Cap2Sc} =(CapA)^{S_{Cap2Sc}} \tag{29}$$

$$Ef_{Inc2Sc} =(In^{Adq})^{S_{Inc2Sc}} \tag{30}$$

Where Ef_{Cap2Sc} is the effect of capital on scope, $CapA$ is the capital adequacy of the industry discussed in equation 10, S_{Cap2Sc} is a constant denoting the strength of the relationship between capital and

[31] Underwriting is tracked by a third order aging chain in the model, for more information on this formulation please see the appendix.

	Estimate	Standard Error	t-stat	R^2
Constant	-22.7	7.2	-3.1	97.2%
CI	3.81	0.126	30.25	

Table 2: The equation for the regression reported is $CRes = \alpha + \beta \cdot CI + \varepsilon$ run over the period from 1982 through 2009. $CRes$ is aggregate claims reserves reported and CI is aggregate claims incurred.

scope, Ef_{Inc2Sc} is the effect of income on scope, In^{Adq} is the adequacy of income measured according to equation 6, and S_{Inc2Sc} is the strength of the relationship between income and scope. The indicated scope is an adjustment around a constant normal level using the structure shown in equations 31 and 32:

$$Sc_{Ind} = Sc_{Norm} \cdot Ef_{Cap2Sc} \cdot Ef_{Inc2Sc} \tag{31}$$

$$Sc_t = \int (\frac{Sc_{Ind} - Sc_t}{\tau_{Sc}})dt + Sc_{Ref} \tag{32}$$

5.8 Dividends

The model's formulation of dividend policy is extremely parsimonious. Dividends in the model are simply a constant fraction of net income, constrained to always be a positive number, as shown in equation 33:

$$Div = Max(N_t \cdot Div_{Ratio}\ ,\ 0) \tag{33}$$

Where Div_{Ratio} is the constant dividend payout ratio, Max denotes the sharp maximum function, $N_t$is the flow of net income from equation 1 and Div is the dividend payment flow. Because dividends only affect net income indirectly through their effect on the stock of invested assets a more complex formulation was prohibitive given my model's focus. Initially the insurance industry model had a formulation for dividends based off of Sterman (1981), however extensive testing revealed that the net effect of the formulation was to hold dividends at a roughly constant fraction of net income.

5.9 Exclusion of Reserves for Claims

Reserves are an important concept for insurance executives. Regulators require insurance companies to estimate reserves against foreseeable losses in many areas, and the companies are required to account for these reserves as liabilities on their financial statements. I choose to exclude these reserves from my model for several reasons. First, the data suggest that reserves are not very interesting dynamically. Econometric analysis of reserves for claims shown in table 2 indicates that they can be modeled in aggregate by a linear function of the claims expense.

The second reason is more operational. While reserves are treated as liabilities by accountants, they are liabilities in an accrual sense only, and so they are still contributing to the investment income of the insurance industry until they are realized as negative cash flows. From the standpoint of my model the inclusion of reserves would have been simple, but would have added nothing of causal importance.

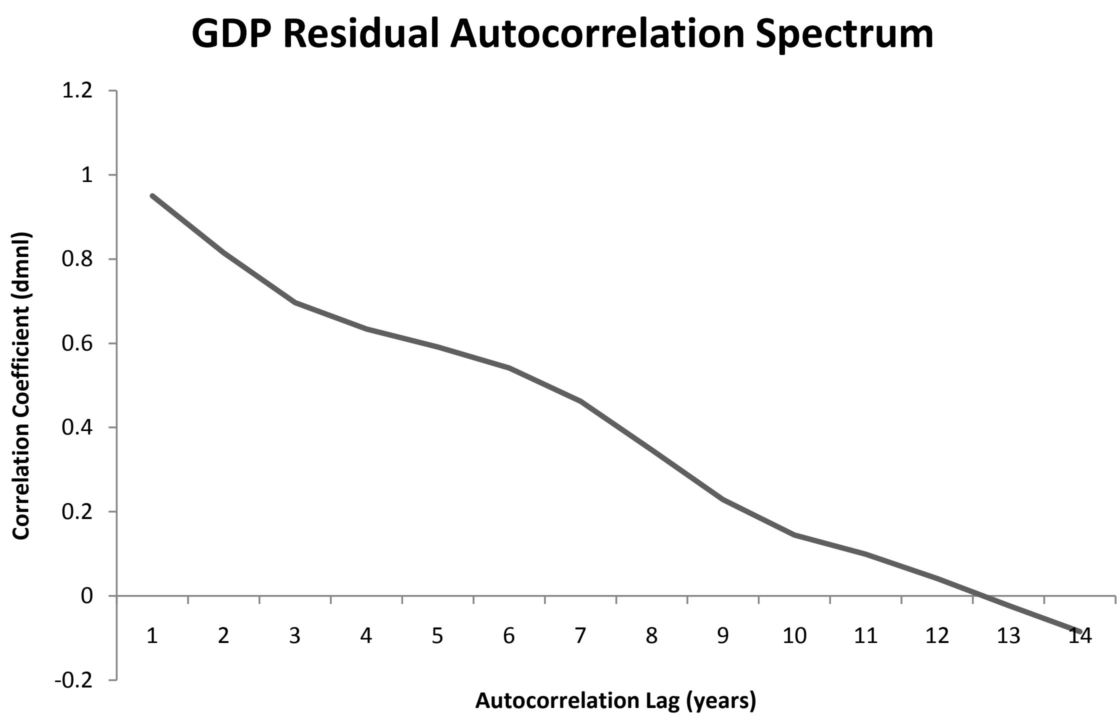

Figure 7: Autocorrelation Spectrum of the Residuals from De-trended Nominal GDP.

6 Parametrization of the Statistical Properties of the Exogenous Inputs

6.1 Gross Domestic Product

The model uses nominal GDP to drive the demand for insurance, as described in section 5.6. In order to perform tests of the statistical properties of the feedback structure in the model shown in section 8 I analyzed the statistical properties of nominal GDP and designed a random process using this analysis that could stand in for the historical time series.

De-trended[32] nominal GDP shows significant auto-correlation. Following the process outlined by Oliva and Sterman (2001) I estimated the autocorrelation time of the pink noise in nominal GDP by computing the autocorrelation spectrum of the residuals from the trend removal procedure.

Figure 7 shows the autocorrelation spectrum of the residuals from the de-trending procedure. The decrease in the autocorrelation falls roughly linearly with the lag, consistent with the evidence that GDP often displays first-order $^1/_f$ noise over long time horizons[33]. To see why the linear decline in autocorrelation implies first-order noise consider first that by the Wiener-Khinchin theorem, the power spectral density of a random process is the Fourier transform of its autocorrelation function. Over the domain we are interested in, the autocorrelation spectrum is well approximated by a triangle function. Since the Fourier transform of a triangle is the sinc function squared, it follows that:

$$\ln(Sectral\ Density) \cong \ln\left(\frac{\sin(\lambda)}{\lambda}\right)^2 = 2\left[\ln(\sin(\lambda)) - \ln(\lambda)\right] \tag{34}$$

[32]The trend referenced was a best fit exponential curve of the quarterly nominal GDP recorded from 1989 through 2009.

[33]See Baillie (1996)

When the result of equation 34 is plotted against $\ln(\lambda)$ it is linear for large λ because $\sin(\lambda)$ is bounded, showing that the spectrum of the noise in de-trended nominal GDP is approximately first order[34]. Unreported tests show that the autocorrelation of the noise in the residuals is not statistically different from zero after nine years of lag. The model therefore uses nine years as the noise correlation time in the pink noise generator function[35]. I also calculated the standard deviation of the residuals from the de-trending procedure to be four percent of the mean of the time series, and use this value as the GDP noise standard deviation in my model. The fitting process for de-trending nominal GDP showed an average of 3.7% growth per year, so stochastic GDP is modeled in my simulations as an exponential growth path at 3.7% per year multiplied by the output of the pink noise generator[36].

6.2 Investment Returns

I created a historical time series of annual investment percentage returns for the insurance industry by dividing the total invested capital of firms in SIC 6331 by the sum of the reported investment income. Unreported regression tests to model the time series of investment returns for the insurance industry showed that distribution is highly correlated with the yield from corporate Baa rated bonds, however even when considering a diverse set of other financial instruments[37] the negative skew and the high variance of the distribution of returns for the insurance industry could not be matched by a linear model alone. Because of this, I model investment returns by adopting an analysis that Webster et. al (2007) use for modeling ozone emissions near Houston. In that study the authors break the observed output of the stochastic process into several distinct patterns of behavior, each hypothesized to be driven by a separate probability density function.

The normal probability plot of the data for insurance industry investment return shown in figure 8 exhibits several interesting characteristics. First, the observations form a function that tends to be concave, which along with the negative skewness calculated from the data suggest a left skewed probability density function, even when factoring in the non zero mean of the data. Second, a visual inspection of the plot suggests that there are two distinct patterns of behavior for investment return volatility[38]. One pattern has relatively low variance while the other has relatively high variance but does not persist for a long period of time. Specifically, I computed linear estimates for different segments of the plot. These estimates suggest that investment returns can be modeled as a random normal process that switches between a standard deviation of 2.8% and a standard deviation of 6.9%. The low variance regime transitions to high variance roughly 23% of the time that it is active, and the high variance regime transitions back to low variance 83% of the time that it is active. The details of these estimations are shown in table 3.

Because an implementation of a stochastic process identical in form to the one employed by Webster et al. (2007) would require six separate probability density functions, and because economists have developed many models of the evolution of interest rate levels, I have chosen to use the technique described above to estimate only the variance of the distribution and the likelihood of transition between the two variance levels. In order to model the mean of the stochastic process for investment returns I turn to the one-factor, short-rate Vasicek model (James and Webber 2000). This model is described by the following equation:

---

[34] One definition of first order $1/f$ noise is that it has a power spectral density function that falls linearly with frequency on a log-log plot.

[35] Sterman (2000) Appendix B-2

[36] This simple formulation for GDP is a good tradeoff between complexity and realism. Because the stochastic flow of DP is only used for long horizon tests of the correlation between the model and random inflows the slower oscillation around the growth path for nominal GDP that is caused by business cycles and inflation was excluded from this analysis.

[37] Aaa rated bonds, returns on the S&P 500, treasury notes and fixed maturity treasury bonds, as well as the interest rate carry were all tested as candidates for the linear ARIMA model.

[38] The indication of the number of random normal processes needed to model the data comes from the number of best fit lines needed to estimate the plotted relationship. I depart from Webster et al. (2007) here in that I do not model the evolution of the mean of the stochastic process through a probability density function, but rather implement the Vasicek short-rate model, as discussed later.

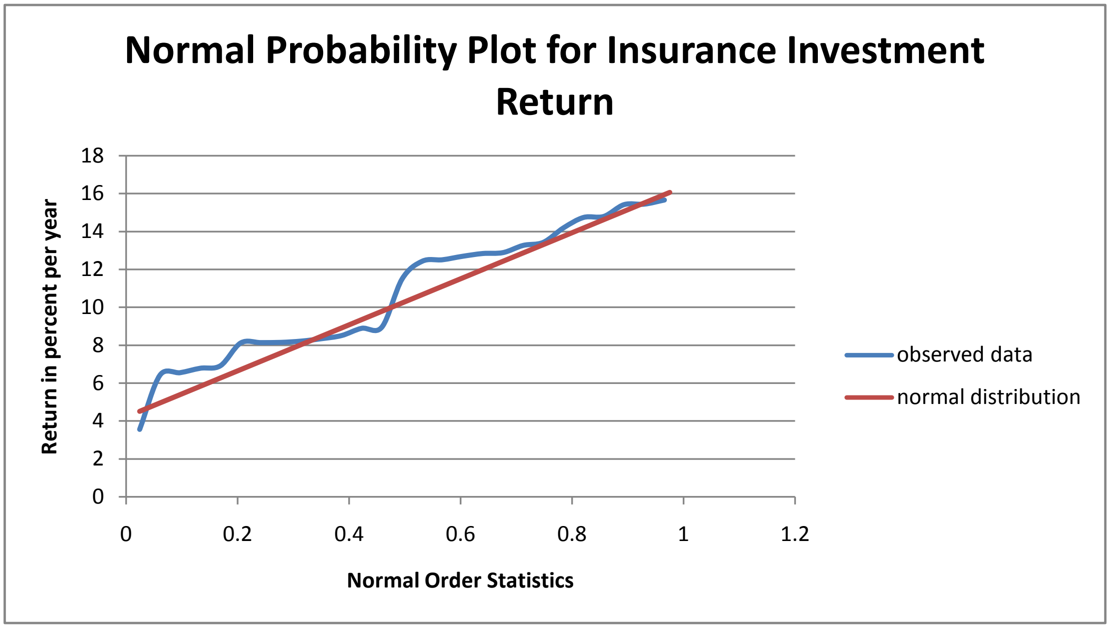

Figure 8: The normal probability plot of investment returns to the insurance industry is shown in this figure. The observed data depart from a normal distribution by tending to show negative skew, and a discontinuous probability density function that has a component with low variance (slope) and a separate component with high variance (slope).

Low Variance Regime	*Section 1*	*Section 2*	*Estimated σ*	*Transition to High Chance*
Slope	9.15	6.79	2.82	22.73%
Intercept	6.66	5.85		
High Variance Regime	*Section 1*	*Section 2*	*Estimated σ*	*Transition to Low Chance*
Slope	47.99	47.15	6.90	83.33%
Intercept	-14.54	1.46		
Vasicek Model Parameters	*Estimate*	*Dimensions*		
Tau - Adj. Delay	1	year		
b - Average	10.44%	%/year		

Table 3: The estimates obtained from the analysis of investment returns to the insurance industry show two clear regions of behavior. The figure also summarizes the transition probabilities for the Markov process modeled and the parameters used in the Vasicek model for investment returns.

	μ	σ	U_c	U_s	U_m
Modeled Random Process	.1076	.033	0.89	0.08	0.03
Historical Investment Return	.105	.036	-	-	-
Percentage Difference	2.5%	-9.3%			

Table 4: Statistical measures of fit between the historical investment returns and my stochastic formulation for returns are shown above. The values given for the modeled random process are the average of five hundred model runs from a test that varied the random noise seed of returns.

$$\frac{dr}{dt} = \frac{(b-r)}{\tau}dt + \sigma dW_t \tag{35}$$

Where r is the interest rate, b is the long term mean of the process generating interest rates, τ is the mean reversion time of the process[39], σ is the standard deviation[40], and dW_t is a Wiener-type white noise process[41]. This model formulation is very similar to the "pink-noise" generator that is standard in the system dynamics literature. I justify my decision to deviate from the standard partly so that I can make a connection between the two approaches, and partly to highlight how I incorporate the Markov process for the variance of the investment returns over time. I use the term Markov to describe the fact that the standard deviation of returns can inhabit one of two discrete states, and that the transitions between these states occur based on a draw from a uniform random variable. In the model the current "state" of the variance of investment returns is a stock whose net flow is determined by a comparison of a uniform random variable and a cutoff level for state transition that is dependent the current state. The details of this formulation can be found in the appendix.

Overall this formulation for investment returns has statistical behavior that is close to the historical time series. Table 4 shows the statistics of fit to substantiate that claim. On average, stochastic returns have a standard deviation within 0.04 of the observed standard deviation, and a mean within 0.003 of that observed. Ninety-five percent of the five hundred simulations in this sensitivity analysis showed that at least three quarters of the error between the simulated and actual data was due to differences in their covariance, rather than their mean or variance[42], and the average Theil U_c over the entire set of simulations was nearly 0.9.

7 Endogenous Model Parametrization

7.1 Initialization

7.2 Parameters Estimated and their Interpretation

Table 5 documents the parameters estimated by my calibration of the model. I arrived at these estimates through a multi-dimensional minimization of the root mean square error (RMSE) scaled by the variance of each historical data series, using the Davidon–Fletcher–Powell method. Explicitly, the objective function of the calibration process was:

$$Minimize \left\{ \left[\frac{(PrInc_H - PrInc_t)}{\sigma^2_{HPr}}\right]^2 + \left[\frac{(C_H - C_t)}{\sigma^2_{HC}}\right]^2 + \left[\frac{(NI_H - NI_t)}{\sigma^2_{HNI}}\right]^2 \right\} \tag{36}$$

[39] Or the adjustment delay of the negative feedback loop, in system dynamics terminology.

[40] Itself a random variable in my implementation, and modeled as a Markov process

[41] "Brownian Motion", implemented in discrete time as N(0,1)/ SQRT(dt) where dt is the time step and N is a normal distribution with mean 0 and standard deviation of 1.

[42] i.e. 95% of the 500 simulations had a Theil inequality statistic Uc greater than 0.75.

Calibrated Model Parameters	**Lower Bound**	**Estimate**	**Upper Bound**
Average Delay for Claim Investigation (*years*)	1.499	2.678	4.6
Claim Handling Costs per Dollar of Claims (*dmnl*)	0.01	0.036	0.12
Commission per Dollar of Premium Written (*years*)	0.148	0.25	0.29
Critical Claims Solvency Ratio (*years*)	0.799	1	1.788
Desired Insurance Adjustment Time (*years*)	2.352	5.11	9.181
Dividend Payout Ratio (*dmnl*)	0	0.11	0.442
Income Elasticity of Demand (*dmnl*)	0.436	0.453	0.465
Insurable Life of Capital (*years*)	8.149	14	16.37
Natural Casualty Rate (dmnl/year)	0.048	0.06	0.067
Normal Fraction of Assets Desiring Insurance (*dmnl*)	0.031	0.041	0.041
Other Cost per Dollar of Exposure (dmnl/year)	0.002	0.015	0.019
Price Elasticity of Demand (*dmnl*)	-2.3	-1.5	-0.908
Sensitivity of Expected Casualty Rate to Scope (*dmnl*)	0.4	1	3.48
Sensitivity of Premiums to Capital (*dmnl*)	-0.106	-0.088	-0.086
Sensitivity of Premiums to Net Income (*dmnl*)	-1.275	-1.03	-0.743
Sensitivity of Scope to Capital (*dmnl*)	0	0.2	0.472
Sensitivity of Scope to Income (*dmnl*)	0	0.2	3.985
Time Horizon for Reference Costs (*years*)	1.4	3.2	6.7
Time to Adjust Net Income Perception (*years*)	1.18	2	2.03
Time to Change Insurance Scope(*years*)	0.62	1.2	1.795
Time to Change Premiums (*years*)	0.2	0.56	1.7
Time to Pay Commissions (*years*)	0.23	0.35	0.512
Time to Perceive Trend in Costs (*years*)	0.72	0.9	2.3

Table 5: The parameters estimated during my calibration of the insurance model to historical data. The units of each parameter are shown next to its name, with dmnl used interchangeably with dimensionless, fraction and percent. The 95% confidence intervals employ the non-parametric bootstrap procedure of Dogan (2007) with N=1000.

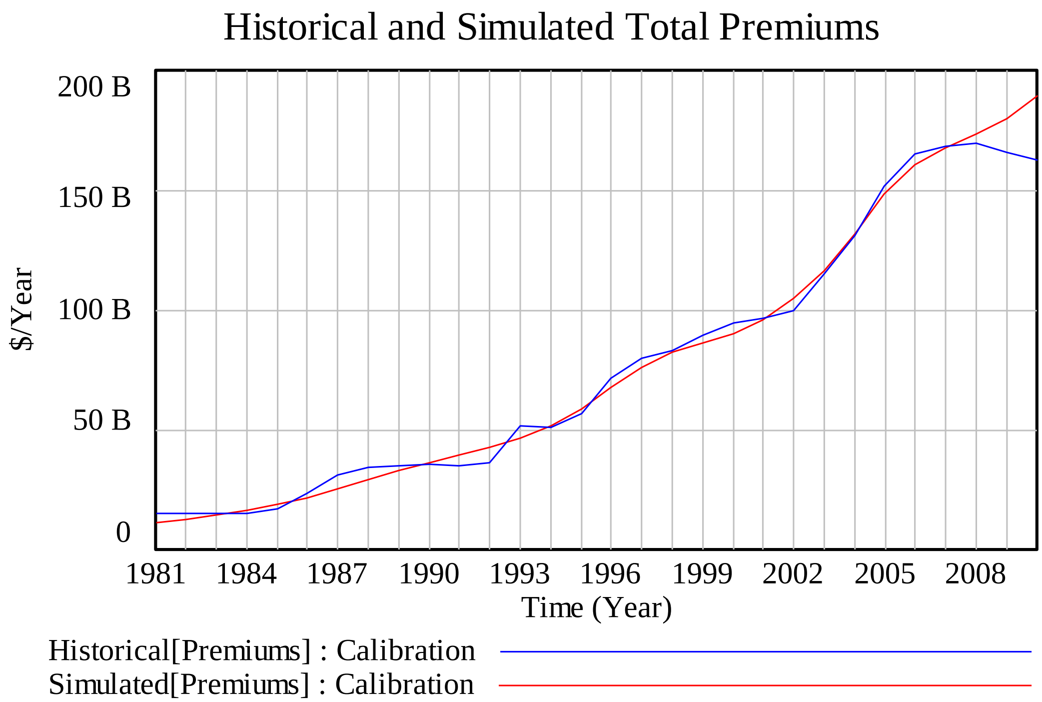

Figure 9: A comparison of the historical path for premiums and the simulated path in the model. The model fits the historical data well, and captures important cyclical dynamics.

This combines the work of Sterman (1984) with the technique of trading-off between dimensions when fitting large models by weighting more variable series less than ones with lower variance that is used by weighted least squares estimation.

In order to calculate the 95% confidence intervals reported in the table I follow the process outlined by Dogan (2007). Specifically, I use the residual between the simulated and historical output of the model to create one thousand bootstrapped[43] data sets, and re-parametrize the model for each of these data sets starting from my original parameter estimates. The output of that process is a sample (N=1000) of the possible values for each of the parameters, when the largest and smallest 2.5% of the sample are excluded for each parameter the remaining maximum and minimum estimates form the confidence interval bounds.

7.3 Model Fit to Historical Data

The fit of simulated premiums with historical premiums is shown in figure 9. Overall the model does a good job of tracking the path of premiums collected by the industry. The Theil U statistics for the simulation show that over 91% of the estimation error in premiums is due to random fluctuations[44] rather than differences between the mean or variance of the two time series. The RMSE of the simulation scaled by the mean of the historical data series is 5.62% at the end of the model run.

The simulated path for claims, compared with the historical data, is shown in figure 10. The

[43] The bootstrap sampling is non-parametric.
[44] U_c=0.919

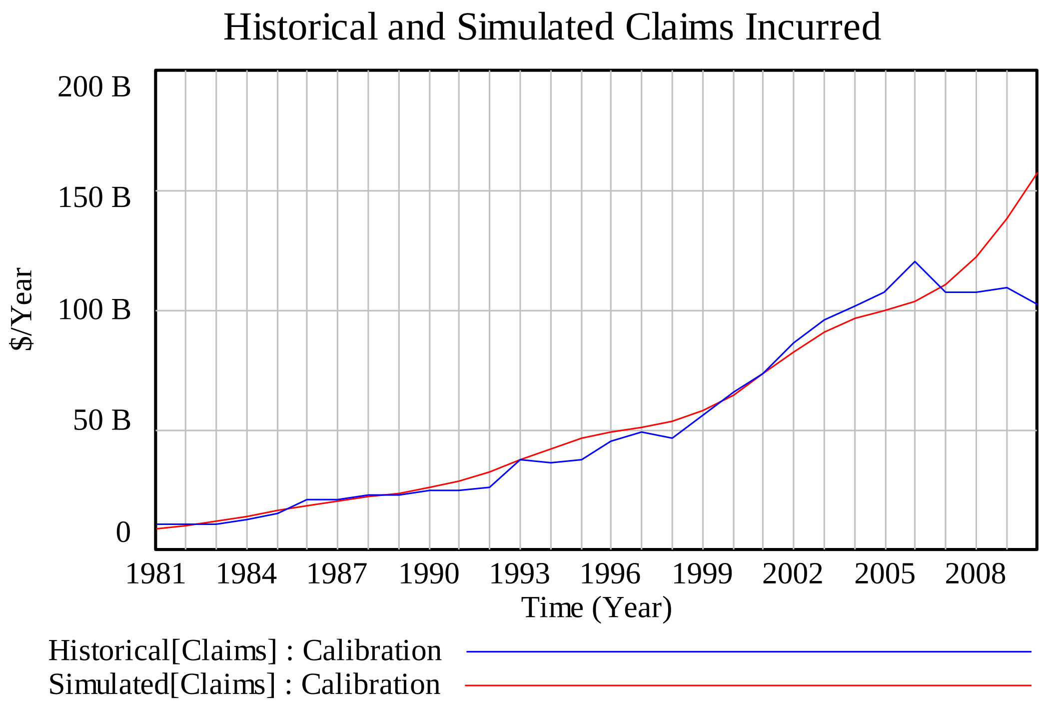

Figure 10: The simulated path of total claims incurred in the model, plotted with the historical path of claims incurred.

simulation fits the growth of claims in the industry fairly well, and very closely estimates the variance[45]. The RMSE of the simulated claims, scaled by the historical mean, provides some reason to be confident in the models output, at 15%.

The fit of the model to historical profits is shown in figure 11. Visual inspection of the simulated course of profits for the insurance industry, shown in figure 11, shows a regular cycle in reported profit for the simulated industry, with a cycle period of very close to the 6-7 years measured from the historical data. The evolution of profits in the model is statistically similar to the historical path history. In particular, the simulated series for profit shows a 67.5% R^2 with actual profit through 2008[46], and has a Theil statistic U_c of 86.1% which indicates that relatively little of the estimation error for profit comes from a misrepresentation of its mean or variance.

7.4 Comparison with Other Data Series

There is a considerable amount of publicly available financial data on the insurance industry as a whole, however the types of data that are reported by the SEC specifically for the "non-life" insurance industry are more limited. The model calibration procedure was run using only the time series that were both important and reported separately from the aggregate, namely the total premium income, total claims incurred and operating income.

[45]Theil U_m=0.045 U_s=0.008

[46]R^2 is an appropriate metric to use for profits, as the time series has a high variance relative to its mean. The R^2 for claims and premiums are very high, but this is a mechanical result of their exponential growth paths. On the other hand, RMSE over the mean of profits would artificially inflate our perception of the error, since the mean of profits is very low over the length of the model run. Sterman (1984)

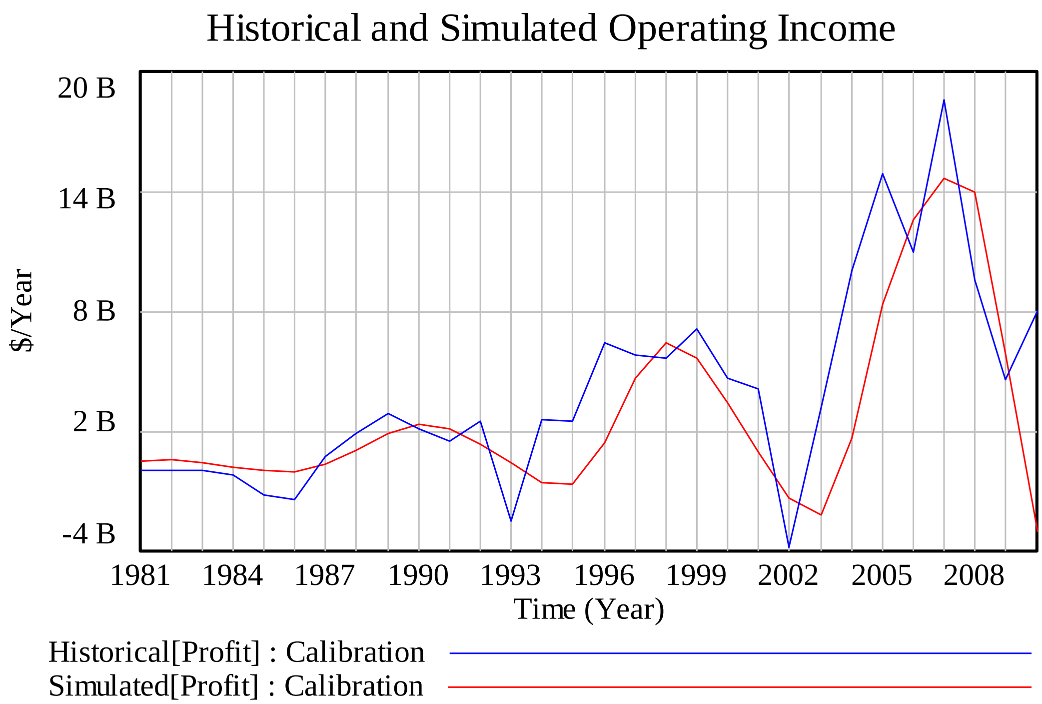

Figure 11: The simulated path of insurance industry profits plotted with the historically observed path of profits. Many of the features of the historical path are emulated by the model.

SIC 6331 Variable	R^2	Slope	t-stat
Assets	0.797	0.093	10.098
Claims paid	0.940	0.091	20.128
Dividends	0.049	0.049	0.112
Invested capital	0.553	0.043	5.668
Investment income	0.417	0.046	4.309
Total Liabilities	0.942	0.055	20.566
Stockholders equity	0.688	0.041	7.568
Commissions expense	0.822	0.080	10.956
Total Expense	0.946	0.077	21.345

Used in Calibration	$\frac{RMSE}{\mu}$	U_m	U_s	U_c	R^2
Operating Income	0.772	0.095	0.044	0.861	0.675
Premiums Collected	0.056	0.005	0.076	0.919	0.994
Claims Incurred	0.150	0.045	0.008	0.947	0.957

Table 6: Statistics of fit for the insurance model are shown in the table above. The first set of variables is not available at the level of aggregation needed to undertake point by point estimates, therefore I report regression slopes, t-statistics and R^2. The second set of variables reports the root mean square error over the mean, the Theil U statistics of fit and the R^2.

The rest of the available data still has the potential to be of use in evaluating the model's fit, if reasonable assumptions are made about the relationship between the reported data and the concepts embodied in my model's formulations. Table 1 from section 3 reports each of the data series I used during this modeling effort, as well as their level of aggregation with respect to the property casualty insurance industry. Table 6 reports the statistics of fit between my model's output and all of the data series I employed. For SIC 6331 variables these tests assume that the unobservable time series for the property casualty insurance industry are correlated with the data for the overall insurance industry, but are not point for point matches. Regression slope statistics are reported, with standard errors, R^2 and t-statistics, as a test of this assumption. Each of these regressions is of the form $Sim = \alpha + \beta \cdot Hist + \varepsilon$ where Sim is the simulated data and $Hist$ is the historical data over the time period from 1982 through 2010.

Overall The simulated variables, excepting only dividends, show a high correlation with their historical time series, have statistically significant regression slope estimates, and are all on the same order of magnitude.

8 Stochastic Tests of Model Fit

In settings such as the insurance industry, where random variations in exogenous variables are widely held to have a large effect on the time series of data available[47], a comparison of the correlations between variables can help to validate the causal relationships in the model, since random exogenous influences are more likely to effect the value of the variables than their long term relationships between each other. Additionally, such an analysis allows us to better understand how the exogenous forcing in my model of the insurance industry compares to the effect of exogenous variables in the historical data series.

Table 7 shows the correlation matrices from a series of tests on historical and simulated model data. The first matrix shows the Pearson correlation coefficients between the historically observed data series over the period from 1982 until 2009. The second matrix shows the same set of correlations calculated from the simulated data, but instead of only running the model from 1982 until 2009 I use

[47] See section 2 for a discussion of the role of exogenous time series in prior research on the insurance industry.

Historical	TA	CI	CE	DIV	Cap	Inv	TL	Inc	P	SE	Com	TE	GDP
TA	1												
CI	0.98	1											
CE	0.96	0.97	1										
DIV	0.47	0.46	0.50	1									
Cap	0.94	0.97	0.90	0.40	1								
Inv	0.91	0.86	0.83	0.52	0.82	1							
TL	1.00	0.99	0.96	0.43	0.95	0.89	1						
Inc	0.74	0.70	0.68	0.23	0.69	0.81	0.72	1					
P	0.99	0.98	0.98	0.50	0.92	0.90	0.98	0.77	1				
SE	0.98	0.96	0.96	0.56	0.90	0.93	0.97	0.76	0.98	1			
Com	0.93	0.96	0.96	0.39	0.93	0.74	0.95	0.61	0.93	0.90	1		
TE	0.98	0.99	0.98	0.48	0.95	0.87	0.98	0.72	0.99	0.97	0.95	1	
GDP	0.98	0.97	0.99	0.53	0.90	0.87	0.97	0.70	0.99	0.98	0.93	0.98	1

Simulated	TA	CI	CE	DIV	Cap	Inv	TL	Inc	P	SE	Com	TE	GDP
TA	1												
CI	0.99	1											
CE	0.99	1.00	1										
DIV	0.83	0.83	0.84	1									
Cap	1.00	0.99	0.99	0.83	1								
Inv	0.88	0.89	0.89	0.78	0.88	1							
TL	0.99	1.00	1.00	0.85	0.99	0.88	1						
Inc	0.78	0.75	0.77	0.95	0.78	0.70	0.78	1					
P	0.99	1.00	1.00	0.85	0.99	0.88	1.00	0.78	1				
SE	1.00	0.98	0.98	0.82	1.00	0.88	0.98	0.78	0.98	1			
Com	0.99	1.00	1.00	0.85	0.99	0.88	1.00	0.78	1.00	0.98	1		
TE	0.99	1.00	1.00	0.84	0.99	0.89	1.00	0.77	1.00	0.98	1.00	1	
GDP	0.99	0.98	0.99	0.83	0.99	0.85	0.98	0.76	0.98	0.98	0.98	0.98	1

Difference	TA	CI	CE	DIV	Cap	Inv	TL	Inc	P	SE	Com	TE	GDP
TA	0												
CI	0.01	0											
CE	0.03	0.02	0										
DIV	0.37	0.37	0.34	0									
Cap	0.06	0.02	0.09	0.43	0								
Inv	-0.03	0.03	0.06	0.27	0.06	0							
TL	0.00	0.01	0.04	0.42	0.04	-0.01	0						
Inc	0.04	0.05	0.10	0.71	0.09	-0.11	0.06	0					
P	0.01	0.02	0.02	0.35	0.07	-0.02	0.02	0.02	0				
SE	0.01	0.03	0.03	0.27	0.10	-0.05	0.01	0.01	0.00	0			
Com	0.06	0.04	0.04	0.46	0.06	0.14	0.05	0.17	0.07	0.08	0		
TE	0.01	0.00	0.02	0.36	0.04	0.01	0.02	0.05	0.01	0.02	0.05	0	
GDP	0.01	0.01	0.00	0.30	0.09	-0.01	0.01	0.05	0.00	0.00	0.05	0.00	0

Table 7: This figure shows the correlation matrices for the data obtained historically and the data simulated, as well as the difference in measured correlation between the two sets. The first matrix shows the correlations between the historical data from 1982 until 2009. The second matrix shows the correlation between simulated variables driven by stochastic exogenous inputs when simulated for 1000 years. The final matrix shows the difference in the two sets of correlations calculated as $(Simulated - Historical)$. TA is total assets, CI is claims incurred, CE is claims expense, DIV Mahler, H. C., & Dean, C. G. (2001). Foundations of Casualty Actuarial Science. Casualty Actuarial Society.is total dividends, Cap is investment capital, Inv is investment income, TL is total liabilities, Inc is income, P is total premiums, SE is shareholders equity, Com is commissions expense, TE is total expenses and GDP is nominal gross domestic product.

the stochastic random variables for nominal gross domestic product and investment return described in section 6 to drive the model over a long time horizon. The correlations documented are for one thousand years of simulated data using these exogenous inputs. The final matrix in table 7 records the difference between the historically observed correlations and the simulated ones, and reveals several insights on the relationship between the historical variables and my simulation.

First, the correlations suggest that many of the relationships in my model closely capture the statistical comovement between insurance industry variables. In fact the only variable that shows a consistent difference between the simulated correlation coefficients and the historically observed ones, is dividends.

The evidence from table 7 suggests that my parsimonious formulation of dividends in the model may overestimate the degree to which dividends issued by insurers correlate with important financial data. Future modelers in this space should potentially consider more complex formulations for insurance dividends, however I chose to leave the simpler formulation in my model. The overall effect of this decision is minor, because the variable I am most interested in is income, which excludes dividends, and in my estimation the face-validity benefits from expressing a feedback-rich formulation for dividends are easily outweighed by the costs of a marginally poorer model fit.

9 Examination of the Cause of the Insurance Profit Cycle

One of the research questions left unsettled in the literature on the insurance profit cycle is whether the cycle owes its cause primarily to the endogenous feedback processes created by the decision rules of the industry's actors, or whether fluctuations in exogenous inputs are primarily to blame. The following subsections will attempt to address this question through several tests that use both my model and the exogenous data available.

9.1 Exogenous Influences on the Insurance Industry

Figure 12 shows the major exogenous influences on the insurance industry plotted against time, as well as the aggregate net income for "non-life" insurance reported to the SEC.

Visual inspection of the figure does not reveal an obvious correlation between GDP and the net income of the insurance industry, though in 2001 and in 2009 dips in net income occur contemporaneously with falling GDP. Argument by example yields conflicting evidence however, as the drop in profitability in the early 1980's occurs contemporaneously with rising GDP, and the drop in GDP in the early 1990's is not nearly as large as the drop in the late 1990's yet both coincide with sizable drops in insurance operating income. Basic statistical analysis of the time series also reveal little of interest, as correlations between the exogenous time series and insurer profits are negative and not statistically significant, with the correlation coefficient between insurance net income investment return measured to be -0.109, and the coefficient between GDP and insurance net income calculated to be -0.068.

9.2 Test of the Model's Impulse Response

Because an examination of the exogenous inputs do not allow us to make definitive conclusions about their role in the cycle, I built the model with the capability of starting it in dynamic equilibrium. Starting from that state, I shock the model with a momentary increase in GDP to test how income responds. When the exogenous forcing of historical GDP in the model is removed and investment income is set to a constant fraction, the model is shocked from equilibrium by a discrete time Dirac delta function at the beginning of year 10. GDP immediately returns to its initial level after this "pulse." The response of net income, shown in figure 13, provides strong evidence for an endogenous source of the insurance profit cycle.

Figure 13 presents compelling evidence that the structure that generates net income in the insurance industry adds cyclical component to signals from exogenous influences such as GDP. Even though GDP

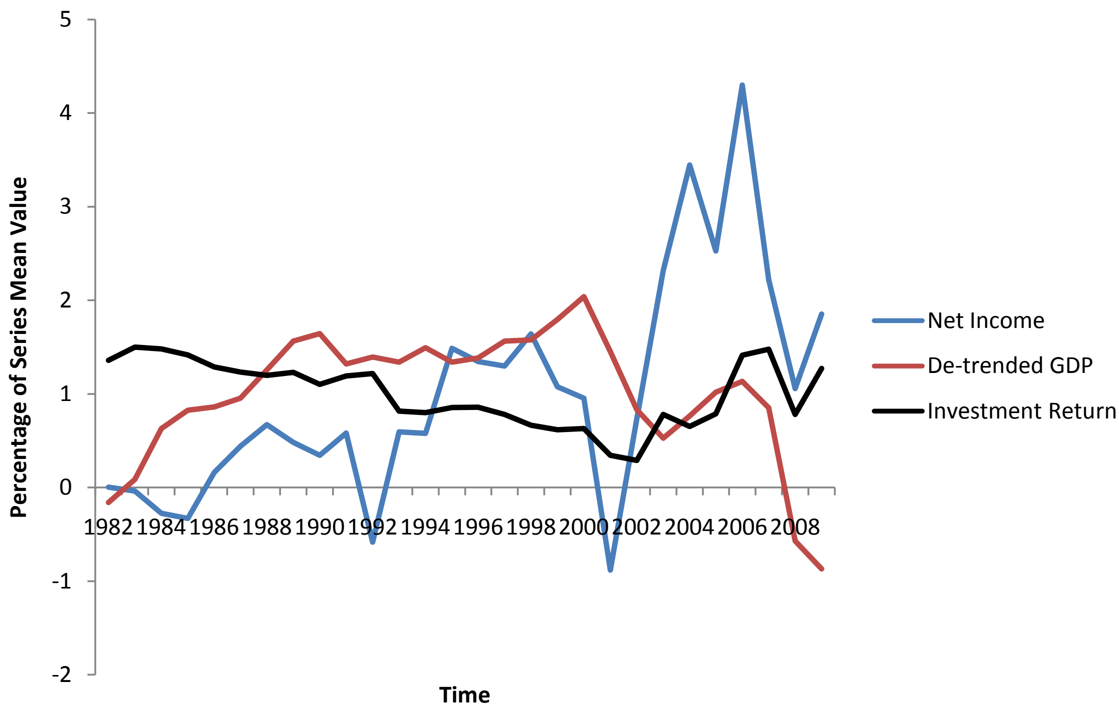

Figure 12: Net Income and Exogenous Influences, plotted against time as percentages of their mean values. GDP is de-trended nominal GDP and investment return is the percentage return on total invested assets.

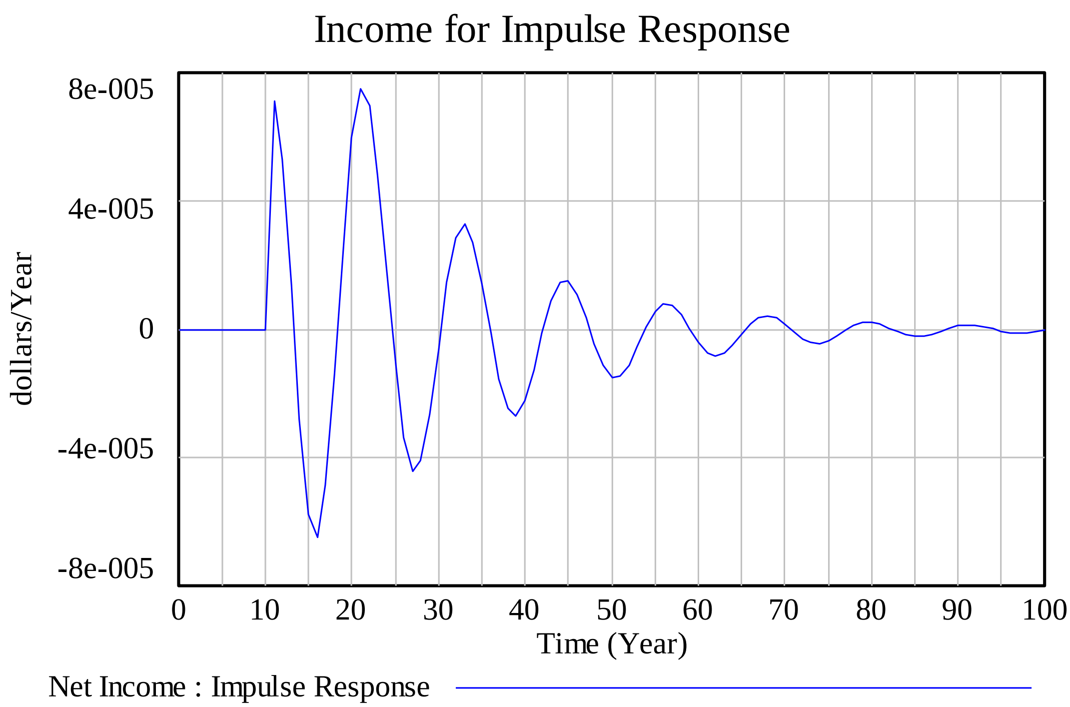

Figure 13: This figure shows the response of net income to a momentary increase in GDP during the simulated year 10. The impulse response of net income displays a clear cyclical mode, with a period very close to the one observed historically.

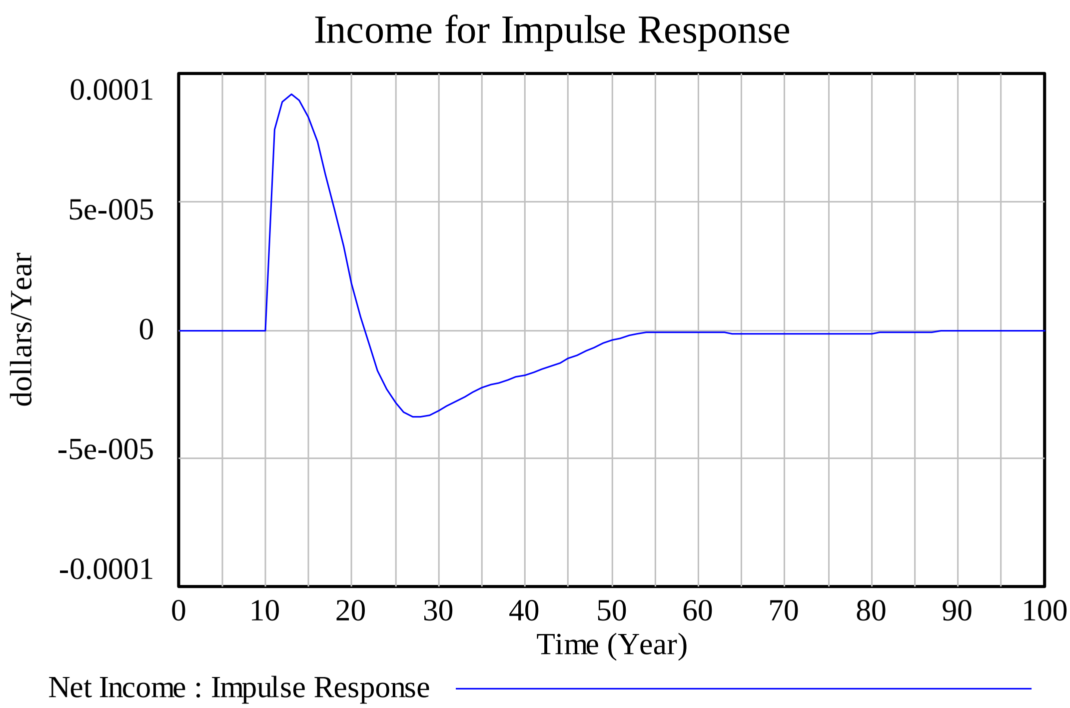

Figure 14: When capital targets are much higher than estimated by my historical calibration of the model, and the adequacy of capital is a much stronger input into the scope expansion decisions of the industry, the impulse response shown in this figure results. This combined policy was by far the most effective at damping the cycle produced by my model.

is very important for the evolution of profits in the insurance industry, the impulse response of my model indicates that profit cycles in insurance would persist for many years even if the economy were somehow brought into equilibrium.

The oscillation in figure 13 is not attenuated by changes to many of the parameters in the model. In fact, my analysis of the system's impulse response revealed only one policy that was successful in causing the impulse response of profit to stabilize, as shown in figure 14. Interestingly this policy way inherently multivariate in nature. Not only do capital requirements need to be increased, through increasing the critical solvency ratio, but the importance of capital adequacy in the decisions controlling premium setting and scope needs to be considerably larger than was estimated during my model calibration. If only capital requirements are changed, the period of the oscillations enlarges, but the damping is negligible. If capital is made a more important input for decisions, but targets for the level of capital are held constant the system's impulse response is actually made less stable by the change.

This type of test is one of the many benefits of feedback rich dynamic models. Not only can they replicate historical data, but they can provide us with more general information about the effect of the structures we are interested in. On the one hand, my analysis in this section provides support for the hypothesis that insurance profit cycles are driven by the characteristics of the industry rather than the idiosyncratic path of the exogenous inputs to the industry. In addition however, the impulse response tests indicate that profit cycle severity may be reduced more fully when changes to the target level of capital are combined with increases in the importance of capital in decision making. In the next section I will explore how the historical path of profits might have been altered had policies informed

		σ/μ	$\Delta\%$
Base-model scaled profit variability		1.47	N/A
Univariate Tests			
Premiums Reactive to Capital		1.45	-2%
Scope Reactive to Capital		2.78	89%
Higher Reserve Target		1.18	-20%
Multivariate Tests			
Target and Premiums		0.91	-38%
Target and Scope		1.59	8%
All Three Policies		0.83	-44%

Table 8: The results for tests of several policies for mitigating the insurance industry profit cycle are shown in this table. The standard deviation of net income, scaled by its mean, is shown in the column labeled σ/μ and is computed over the entire model run. "Premiums Reactive to Capital" sets the importance of capital adequacy signals for premium setting equal to the importance of profit signals. "Scope Reactive to Capital" increases the importance of capital adequacy in the scope setting decision. "Higher Reserve Targets" simulates a situation where reserve requirements are increased such that insurers now desire twice the level reserves. Multivariate tests combine the indicated policies. Overall, policies that focus on both higher and more salient reserves result in the largest decrease in the severity of the profit cycle.

by these insights been implemented.

10 Policies for Reducing the Cycle in Insurance Industry Profits

Informed by the analysis of the impulse response of the model, sensitivity tests of both the univariate and the multivariate effect of several policy levers on the scaled profit variability[48], described in table 8, show that policies that combine higher reserve targets with an increase in the importance of capital in determining the path of the industry are the most effective at reducing the cycle. Higher reserve requirements alone do reduce cycle severity somewhat. When these requirements are combined with an increased willingness of decision makers in the industry to use capital adequacy in their premium and scope setting decisions however, profit stability is increased considerably more.

This result presents an interesting case for the implementation of reserve requirements by regulators. If industry actors view increased requirements as cumbersome or puntitive they may continue to reguard short-term profit signals as the more important measure of the financial health of their companies. If this happens, the model indicates that the full effect of capital for creating aggregate profit stability will not be felt. On the other hand, if the insurance industry views higher capital targets as not only required, but inherently important for competitive decisions, then the model suggests that the profit cycle can be reduced considerably.

[48] When testing policies for mitigating the profit cycle in the insurance industry I use a ratio of the standard deviation of profit to the mean of profit as my primary statistical focus. This ratio, which I call the scaled profit variability, is a good summary measure of the intensity of the profit cycle in an industry because it captures how variable profits are without improperly labeling high average profits as unappealing simply because of their mechanically higher standard deviation. The variance scaled by the mean would be equally appealing, but is functionally equivalent.

11 Conclusion

This work focused on the documentation of a profit cycle model in the property casualty insurance industry, a setting without a significant delay for adjusting productive capacity. Tests of the model's output present evidence that the key determinants of the severity of the profit cycles in the industry are the level of capital and the salience of the signals about capital adequacy in decision making.

Section 9 presented evidence that the cycle in profits of the insurance industry is endogenously generated, rather than exogenously forced. The modeled industry responded to a delta function in GDP with a long-lasting cyclical oscillation. The cyclical nature of the model's impulse response can only be eliminated when capital targets are combined with an increased importance of capital in decision making, adding evidence that policies that do not address the high salience of insurer profit signals may not fully address the cause of profit cycles in the insurance industry.

These results begin to point towards the salience of profit signals as a dynamic that exacerbates profit cycles across diverse settings. While capacity expansion delays are certainly causal to some profit cycles, the identification of cycles in insurance and the suggestion that they can be reduced through policies that mitigate the intensity competition over is a potentially promising area for further research, challenging the belief that competition always strengthens an industry.

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