International Review of Economics and Finance 21 (2012) 1–15

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Dynamics of underwriting profits: Evidence from the U.S. insurance market

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ARTICLE INFO

Article history:
Received 12 February 2010
Received in revised form 22 December 2010
Accepted 31 March 2011
Available online xxxx

JEL classification:
C22
G22

Keywords:
Insurance cycle
Underwriting profits
ARDL approach

ABSTRACT

U.S. property–liability insurance markets have displayed insurance cycles, with their swings in underwriting profits, for nearly a century. Various hypotheses have been developed to explain these fluctuations, as follows: financial pricing hypothesis, capacity constraint hypothesis, financial quality hypothesis, option pricing approach and economic pricing hypothesis. Consistent with previous studies despite of examining whether variables possess unit roots, performing an ARDL bound test on underwriting profits from 1950 to 2009 demonstrates that the economic pricing hypothesis may be the most suitable model for explaining historical insurance pricing. An evident cyclical pattern in underwriting profits is explained as dynamic feed back to the long-term equilibrium. Considerable evidence suggests that the supply effect of risk-averse insurance companies has dominated U.S. insurance markets during the last half century.

1. Introduction

Known as insurance cycles, the dynamics of underwriting profits in property–liability insurance markets exhibit a clear pattern of recurrence and have traditionally been viewed as dynamically shifting back forth between 'hard' and 'soft' markets (see Harrington & Niehaus, 2000 for a review). In practice, soft markets are characterized by readily available coverage and low underwriting profits, while hard markets are characterized by difficulty in obtaining coverage and high underwriting profits. This phenomenon helps maintain long-term profits/losses, cannot easily be eliminated (Feldblum, 1992), and is crucial for insurance operations. By modeling and predicting such fluctuations, insurers can control their operating volatility and thus capital costs. Numerous studies have demonstrated the cyclical nature of historical underwriting profits, especially in the property–liability insurance industry. Based on the most popular research models, the industry cycle can be attributed to five different hypotheses: the financial pricing, capacity constraint, financial quality, option pricing approach and economic pricing hypotheses.

The financial pricing hypothesis indicates that insurance price only reflects the discounted value of costs associated with losses. Thus, only temporary deviation from long-term equilibrium can be explained by random changes in demand and supply, which are inadequate for explaining such large and visible cycles. Cummins and Outreville (1987) built on the financial pricing hypothesis by attributing such cyclical pattern to a second-order process, created by the unique characteristics of the insurance industry, including information, regulatory and reporting lags. Under the same hypothesis, subsequent studies (e.g., Doherty & Kang, 1988 and Lamm-Tennant & Weiss, 1997) also provided consistent results. These models implicitly assume insurers are risk neutral and insurance markets are perfect. Thus, insurers can adjust their capital sufficiently to reduce insolvency risk to a negligible level. Accordingly, underwriting profit is a decreasing function that depends only on interest rate in both the short and long term.

Other studies (Winter, 1988, 1994; Gron, 1994a,b; Doherty & Garven, 1995) applying the capacity constraint hypothesis argue that the insurance cycle is attributable to market imperfections. Because of the imperfections of capital markets, raising insurance prices

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doi:10.1016/j.iref.2011.03.005

became a common method of capital adjustment after insurers experienced unexpected shocks or crises. The analytical results imply that underwriting profits are inversely dependent on capacity in the short term. However, profits do not depend on capacity in the long term. Winter (1994) and Gron (1994a,b) argue that asymmetric information availability in the insurance market prevents insurers from quickly adjusting their capacity to maintain a long-term equilibrium. A negative capital shock, thus, can rapidly increase insurance prices and hence underwriting profits. The existence of this relationship can be tested by examining whether capacity is negatively related to underwriting profits.

Instead of the capacity constraint hypothesis, other studies (Harrington & Danzon, 1994; Cagle & Harrington, 1995) use the financial quality hypothesis and consider endogenous insolvency risk in insurance pricing. The financial quality hypothesis has the same short term implications as the capacity constraint hypothesis. However, the financial quality hypothesis maintains that long-term underwriting profits should depend positively on capacity level, since higher level of financial quality and consumers presumably are willing to pay more for higher quality policies.

Cummins and Sommer (1996) provide an option pricing approach to insurance pricing that considers policyholders to have a short position in a put option on insurer assets. This hypothetical put option is referred to as the insolvency put. The insolvency risk, and thus value of the insolvency put, increase with decreasing insurer capacity. Restated, the underwriting profits increase with insurer capacity in both the long and short term.

All the above models assume that insurance companies are risk neutral. An alternative hypothesis is the well-known classical model provided by Sandmo (1971) and Leland (1972), which assumes risk aversion on the part of the firm. Risk aversion implies that the insurance company must be compensated for bearing insurance risk. That is, the price of the insurance policy must strictly exceed its expected cost, including both policy expenses and the expected present value of claims, by an amount sufficient to compensate the firm for assuming the associated risk. In the short term, insurance price is a strictly positive risk premium and is decreasing with increasing in the amount of surplus. This constraint also holds in a long-term equilibrium and can be interpreted as implicitly defining normal expected profits. Such expected profits must include compensation for the risk due to the unpredictable nature of policyholder claims. Therefore, the risk premium is positive, and increases with decreasing insurer capacity in the long-term equilibrium.

According to Choi, Hardigree, and Thistle (2002), both short-term and long-term analyses are required to differentiate the above five hypotheses. Table 1 summarizes various results from different hypotheses regarding underwriting profits. The table reports somewhat inconsistent evidence and implies the existence of discrepancies in interpretation.

For the past decade, empirical analyses of insurance industry volatility focused on whether insurer lagged surplus (i.e., the proxy of capacity) determines underwriting profits. As Harrington and Yu (2003) note, earlier studies extensively utilized conventional regressions and ignored the question of whether underwriting profits are stationary. Most of earlier empirical analyses employed regressions that extensively used *changes* in interest rate and capacity proxies to examine how different *levels* of underwriting profits were related. However, such models could lead to spurious regression because of misspecification. Previous studies appear to leave both the nature of underwriting profits and the capacity proxy ambiguous. To solve the above weaknesses, this study proposes a more flexible and robust empirical methodology and seeks to provide further insight into this context by simultaneously assessing the long term and short term effects.

2. Brief review of prior research

Earlier empirical analyses relying on regression have reached inconsistent findings and still leave some ambiguous interpretations. Niehaus and Terry (1993) found that regression coefficients of lagged surplus on insurance prices display opposite signs during different sample periods. Furthermore, Gron (1994a) applied lagged policyholder surplus to current-period GNP as a proxy for capacity. The findings of Gron support the capacity constraint hypothesis for short-tail lines of insurance (i.e., auto liability, auto physical damage, and homeowner coverage). Surprisingly, the coefficients are not for long-tail converged (i.e., general liability insurance) which are the most affected line during the financial crisis. She suggested that this undesirable result was attributable to insurer loss reserve management activities. Cummins and Danzon (1997) use policyholder lagged surplus rather than historical average surplus to proxy for capacity. They identified a positive correspondence between underwriting profits and the lagged capacity measure, a relationship unexplainable under the capacity constraint framework. They argue that such a positive relationship can be explained by the shock effect on the insurance demand. An increase of capital that reduces insurer insolvency risk increases insurance

Table 1
Summary of implications of underwriting profits for alternative hypothesis.

Hypothesis	Interest rate		Capacity	
	Short term	Long term	Short term	Long term
Financial pricing hypothesis	−	−	.	.
Capacity constraint hypothesis	−	−	−	.
Financial quality hypothesis	−	−	−	+
Option pricing approach	−	−	+	+
Economic pricing hypothesis	−	−	−	−

Notes:
1. "−"means negative impact on underwriting profit.
2. "+"means positive impact on underwriting profit.
3. "." means no specific impact on underwriting profit.

price, supporting the financial quality hypothesis. Higgins and Thistle (2000) employ the logistic smooth transition regression to test for a regime shift and estimate the speed of the transition between the regimes. Analytical results show that capacity significantly determines short term underwriting profits. However, this finding is inconsistent with the capacity constraint or financial quality hypotheses. They also find that interest rate does not significantly determine underwriting profits, implying that no models support the hypothesis, and thus that an appropriate model merits further investigation.

Regarding the development of more robust and effective empirical methods for testing insurance pricing models, a growing body of literature analyzes determinants of underwriting profits using time series approaches or econometric techniques. Fung, Lai, Patterson, and Witt (1998) took the first step of employing variance decomposition under a vector autoregression model (VAR) to show that the responses of premiums to surplus during the first two years. The results appear inconsistent with the capacity constraint hypothesis. Fung et al. argue that such results can be attributed to institutional factors and give a reasonable interpretation of the combined effects of capacity constraint and rational expectation using the institutional lags hypothesis.

Moreover, based on pre-tests for a unit root, some studies use cointegration analysis to analyze the long-term relationship between underwriting profits and the insurance capacity proxy to test insurance cycle theories. These studies argue that underwriting profits and other variables are not stationary (e.g., Haley, 1993; Grace & Hotchkiss, 1995). This argument implies that the conventional regression approach is not appropriate for analyzing determinants of underwriting profits. Haley (1993) points out that underwriting profits and short-term interest are cointegrated and have a negative long-term relationship. Grace and Hotchkiss (1995) test not only short-term interest rates but also the inclusion of general economic variables. Empirical results indicate that while a long-term relationship exists between short-term interest rates and general economic variables, economic fluctuation has little short-term impact on underwriting profits, suggesting that the cycle is endogenous to the industry. Choi et al. (2002) stress the importance of separating the implications of long- and short-term, and report that economic loss ratio is $I(0)$, while interest rate and surplus series are $I(1)$. This implies that neither interest rate nor surplus can be cointegrated with economic loss ratio. Harrington and Yu (2003) apply GLS ADF tests under different assumptions to the AR(2) data generating process (DGP) to demonstrate that underwriting profits are stationary. Stationary underwriting profits imply that there is no need to utilize cointegration analysis and that conventional regression methods are appropriate for analyzing underwriting profits after controlling for deterministic influences. The results of Harrington and Yu may be lacking because they assume that the underlying DGP follows an AR(2) process and thus may not be appropriate in underwriting profits (Leng & Venezian, 2003). The problems arising from non-stationarity and autocorrelation in levels of regressors can possibly be avoided by differencing. However, the aforesaid data transformation of the variables may ignore or destroy the systematic characteristics of the time series. For example, if one of the variables is fractionally integrated, simply differencing may cause error term correlation, resulting in unclear answers. Haley (2007) noted the limitations of univariate analysis as a pre-test while evaluating underwriting profits and argued that the inclusion of a time trend factor in DGP (i.e. Harrington & Yu, 2003) may not be appropriate. He concludes that placing too many a priori requirements eliminates information and possible models.

A critical issue in time series regression analyses is whether underwriting profits and relevant explanatory variables are stationary. Least square regression provides meaningful inferences only when the regress and regressors are either all stationary or cointegrated. As noted above, previous studies did not clarify the characteristics of underwriting profits, implying that efforts must be made to develop a more robust empirical model, since some question variables may be stationary and others may be non-stationary. This study deals with such empirical issues by use of ARDL approach to cointegration. This method is applicable to test the single long-term relationship between underlying variables without requiring firm knowledge that variables in analysis are definitely $I(0)$ or $I(1)$ (See Mills & Markellos, 2008). Given the uncertainty concerning the time series properties of the variables, this methodology appears most appropriate in this context.

3. Data and methodology

3.1. Data

The objective of this paper is to construct an empirical model exploring the dynamic behavior of underwriting profits as well as to scrutinize previous empirical findings. Underwriting profits usually refer to insurers' underwriting returns which are the profits without including investment returns. We provide two proxies of underwriting profit. The first one is one minus combined ratio, which is traditionally employed for evaluating in insurance industry. The second one is one minus economic loss ratio (ELR), where the economic loss ratio is the ratio of an estimate of discounted losses to premiums net of expenses. Approximation method to estimate ELR follows the procedure in Winter (1994). We apply annual U.S. insurance industry-wide data for all lines combined during the period 1950–2009 from *Best's Aggregates and Averages* published by A.M. Best Company.

On the other hand, capacity generally refers to the degree of aggregate industry to supply insurance coverage without increasing the level of insolvency risk. It is related to the volume of policies that can be supported by the industry's capital base. An increase in insolvency risk is attributable to either a decrease in insurers' capital or an increase in their future claim payment. Therefore, a good measure of capacity should positively correlate with policyholders' aggregate surplus while negatively correlate with future claim payments. We employ three kinds of capacity proxy in this context. One is the ratio of lagged policyholders' surplus to current GNP which is called as relative wealth (Gron, 1994a). GNP could be a proxy of the quantity of goods and services that can be insured. The policyholders' lagged surplus, which reflects insurers' capacity at the beginning of a new period, are reported at the end of previous year from *Best's Aggregates and Averages*. The de-trended relative wealth, which is the residual of the regression between relative wealth and linear trend, is also reported as anther capacity proxy. Such proxy is suggested by Gron (1994a) because it reveals the excess capacity from their long-term equilibrium. To obtain a better control for the impact of future claim payments for policies written in the current calendar year, the ratio of lagged aggregate policyholders' surplus to lagged net written premiums is also used. Such ratio is the inverse version of the well known Kenney ratio which is traditionally used for evaluation purpose and regulation concerns. This proxy of capacity has also been utilized by Choi et al. (2002). Finally, we employ the three-month Treasury bill rates, which are collected from the Federal Reserve Bulletin, as the interest rate proxy in our study. Table 2 represents descriptive statistics of relevant variables in this study.

3.2. Methodology

We employ the ARDL approach by Pesaran, Shin, and Smith (2001) as a cointegration framework. Let UP_t represents the proxy of underwriting profit of industry at current time t, r_t and c_t denote the interest rate and the insurance capacity proxy. We also define $x_t=(r_t, c_t)'$ is a 2×1 vector of variables. We suppose that the data-generating process for underwriting profit, the interest rate, and the insurance capacity is an error correction version of VAR model as followed:

$$\Delta z_t = \alpha_0 + \Pi z_{t-1} + \sum_{i=1}^{n} \Psi_i \Delta z_{t-i} + u_t \tag{1}$$

where $z_t=(UP_t, r_t, c_t)'$ is a 3×1 vector of variables. $\Pi = \begin{bmatrix} \pi_{UP,UP} & \pi_{UP,x} \\ \pi_{x,UP} & \pi_{x,x} \end{bmatrix}$, is the long-term multiplier matrix of order 3×3, and Ψ_i is the short-term coefficient matrix. A critical assumption is that if 2×1 vector $\pi_{x,\,UP}=0$, there is at most one long-term relationship and the interest rate and the insurance capacity could be regarded as long-term forcing variables. Moreover, if $\pi_{x,\,UP}=0$ and $\pi_{x,\,x}=0$, then x_t is weakly exogenous for $\pi_{UP,\,UP}$. Such assumption is intuitively reasonable because the underwriting activity of insurance industry has seldom impacts on the macroeconomic system (e.g. movement of interest rate). Also, the current capacity, which is calculated by using *lagged* surplus, is not to be explained by the *current* underwriting profit. A testing procedure described by Pesaran and Pesaran (1997) can be utilized to ensure that there is a unique long-term relationship with the underwriting profits chosen as the dependent variable. Their bounds tests are based on error correction version of ARDL models without including current values of independent variables. When this assumption is tested to be valid, a *conditional* ECM[1] with difference of underwriting profits as the dependent variable becomes:

$$\begin{aligned} \Delta UP_t = \alpha_0 &+ \sum_{i=2}^{n} \Gamma_i \Delta UP_{t-i+1} + \beta_0 \Delta r_t + \sum_{i=2}^{n} B_i \Delta r_{t-i+1} + \phi_0 \Delta c_t + \sum_{i=2}^{n} \Phi_i \Delta c_{t-i+1} \\ &+ \theta_1 UP_{t-1} + \theta_2 r_{t-1} + \theta_3 c_{t-1} + \varepsilon_t. \end{aligned} \tag{2}$$

The *conditional* ECM represented as Eq. (2) is used as the basis of following cointegration testing procedure. This approach, which separates the long-term (level) relationship and short-term dynamics, could be applied to test the long-term relationship between the variables, irrespective of the order of the underlying variables ($I(0)$ or $I(1)$), even fractionally integrated (Cavanagh, Elliott, & Stock, 1995; Pesaran et al., 2001). Such outstanding characteristic is suitable for studying the underwriting activity in insurance industry because the underwriting profit is usually assumed to be stationary. Therefore, it cannot be utilized by traditional cointegration analysis. Unlike other cointegration techniques (e.g., Johansen's procedure) which require certain pre-testing for unit roots as well as underlying variables to be integrated of order one, the ARDL model provides an alternative test for examining long-term relationship. The unit root testing of variables (e.g. Haley, 1993, 1995) is no longer necessary. Such an important feature of this test reduces the degree of uncertainty arising from the pre-testing stage of each series in the analysis of levels relations (Kanas & Kouretas, 2005), which is an important issue in our case. Note also that the ARDL procedure allows for uneven lag orders, while the Johansen's VECM (Johansen, 1988) does not. Moreover, the ARDL analysis is still valid in small samples and can be reliably used to estimate and to test the cointegration relationship. (30–35 observations are still valid. see Agnese & Sala, 2009. Jalil, Feridun, & Ma, 2010) Small sample properties of the ARDL approach are superior to that of the Johansen's technique (Pesaran & Shin, 1999). Finally, for the error-correction representation (conditional ECM) of the corresponding ARDL model, only one error-correction term will be present, which avoids confusion from having multiple cointegration vectors.

According to Pesaran et al. (2001), to test the absence of any level relationships between UP_t, r_t and c_t requires the exclusion of the lagged level variables UP_{t-1}, r_{t-1} and c_{t-1}. Hence, the joint null hypothesis of interest in Eq. (2) is given by:

$$H_0 : \theta_1 = \theta_2 = \theta_3 = 0. \tag{3}$$

The alternative hypothesis is correspondingly stated as:

$$H_1 : \theta_1 \neq 0, \theta_2 \neq 0, \theta_3 \neq 0. \tag{4}$$

The *F*-test to test (3) is applied to examine the existence of a stable and long-term relationship. Note that the asymptotic distributions of the *F*-statistic are non-standard irrespective of the order of the underlying variables ($I(0)$ or $I(1)$). Since these asymptotic distributions are non-standard, Pesaran et al. (2001) provided bounds testing procedure which has two sets of asymptotic critical values. One set assumes all variables are $I(0)$ and the other assumes that all variables are $I(1)$. If the computed *F*-statistic falls

[1] See Boswijk (1994) for more interpretations of conditional ECM in detail.

Table 2
Descriptive statistics.

	Underwriting profit		Capacity proxy			Interest rate
	One minus combined ratio	One minus economic loss ratio	Relative wealth	De-trend relative wealth	Inverse Kenney ratio	3-Month T-bill rate
	$UP1_t$ (%)	$UP2_t$ (%)	G_t (%)	E_t (%)	K_t	r_t (%)
Mean	−1.3350	4.3898	2.5417	0.0007	0.8611	4.7716
Median	−0.5500	4.5534	2.1538	−0.0036	0.7939	4.4945
Maximum	9.2000	16.5652	4.5600	1.1181	1.4913	14.0133
Minimum	−16.1000	−14.9227	1.2660	−1.0779	0.4628	0.1350
Standard Deviation	6.2042	6.8561	0.9381	0.5426	0.2649	2.8267
Skewness	−0.4438	−0.5146	0.8047	−0.1574	0.9006	0.8851
Kurtosis	2.6397	2.8419	2.3617	2.1244	3.0029	3.8538
Jarque−Bera statistic	2.2939	2.6697	7.4941*	2.1640	8.1116*	9.6582**
Observations	60	60	60	60	60	60

Note: * denotes 5% level significance. ** denotes 1% level significance.

above upper limit of the bound critical value, then the null hypothesis is rejected which means the variables are cointegrated. Conversely, if the computed F-statistic falls below the lower bound critical value, then the variables are concluded to be non-cointegrated and the null hypothesis cannot be rejected. Finally, the case within the band would be inconclusive.

Notice that there are two different forms of Eq. (2) separated by whether constant α_0 is restricted that only exist in cointegration space or not. If the constant is restricted that it only exists in the cointegration space, the joint testing hypotheses (3) and (4)have to be reconstructed. The joint testing hypotheses (5) and (6) would be:

$$H_0 : \theta_1 = \theta_2 = \theta_3 = \alpha_0 = 0. \tag{5}$$

The alternative hypothesis is correspondingly stated as:

$$H_1 : \theta_1 \neq 0, \theta_2 \neq 0, \theta_3 \neq 0, \alpha_0 \neq 0. \tag{6}$$

Furthermore, if the constant α_0 is unrestricted (i.e. not only exist in cointegration space), a null hypothesis $H_0^{UP}: \theta_1 = 0$ also has to be tested to ensure the existence of such long-term relationship. A similar bounds testing procedure (see Pesaran et al., 2001) is provided and the testing statistic is to be checked against a non-standard t-statistic table for critical values, which is much higher than the standard ones. Once the long-term relationship is determined by bounds testing procedure, the augmented autoregressive distributed lag model has to be estimated. According to Pesaran et al. (2001), it is allowable to differentiate lag lengths on the lagged variables UP_t, r_t and c_t in Eq. (2) to model without affecting the asymptotic results of bounds testing. Estimated by OLS, the maximum of lags (n) in Eq. (2) is retained to determine the optimal structure for the ARDL specification. The maximum of lags (n) is the order of lag when long term relationship has been found. We search across $(n+1)^3$ ARDL models spanned by the orders of lag (m, p, q) via Schwartz Bayesian Criterion (SBC).[2] The ARDL model is shown as follows:

$$\gamma(L, m)UP_t = \alpha_0 + \beta(L, p)r_t + \phi(L, q)c_t + \varepsilon_t \tag{7}$$

where

$$\begin{aligned}
\gamma(L, m) &= 1 - \gamma_1 L^1 - \ldots - \gamma_m L^m, \\
\beta(L, p) &= \beta_0 + \beta_1 L^1 + \ldots + \beta_p L^p, \\
\phi(L, q) &= \phi_0 + \phi_1 L^1 + \ldots + \phi_q L^q
\end{aligned}$$

and L is a lag operator such that $L^j l_t = l_{t-j}$. Notice that if the underwriting profit follows second-order autoregressive model (i.e. $m = 2$), the condition of cyclical phenomenon is the inequality as follows:

$$\gamma_1^2 + 4\gamma_2 < 0. \tag{8}$$

Take long term expectation on Eq. (7), we can obtain long term equilibrium of underwriting profit:

$$\overline{UP} = \alpha_0 / (1-\Gamma_1) + B_0 / (1-\Gamma_1)\bar{\bar{r}} + \Phi_0 / (1-\Gamma_1)\bar{\bar{c}} \tag{9}$$

where $\Gamma_1 = \sum_{i=1}^{m} \gamma_i, B_0 = \sum_{i=0}^{p} \beta_i \Phi_0 = \sum_{i=0}^{q} \phi_i$ and the coefficient, $\alpha_0/(1-\Gamma_1)$ is represented as long-term equilibrium constant of underwriting profit after controlling the variation of interest rate and capacity. The slope of interest rate and capacity when the

[2] Studies by Pesaran and Shin (1999) show that for small samples, the performance of Schwartz Bayesian Criterion is better than other criteria. We use the SBC criteria because our data are also small samples.

equilibrium achieved can be represented by $B_0/(1-\Gamma_1)$ and $\Phi_0/(1-\Gamma_1)$. By parameter rearranging procedure (See Patterson, 2000), the ARDL specification of Eq. (7) can be represented as:

$$\begin{aligned} UP_t &= \alpha_0 + (1-\gamma(L,m))UP_t + \beta(L,p)r_t + \phi(L,q)c_t + \varepsilon_t \\ &= \alpha_0 + \Gamma_1 UP_{t-1} - \sum_{i=2}^{m} \Gamma_i \Delta UP_{t-i+1} + B_0 r_{t-1} + \beta_0 \Delta r_t - \sum_{i=2}^{p} B_i \Delta r_{t-i+1} + \Phi_0 c_{t-1} + \phi_0 \Delta c_t - \sum_{i=2}^{q} \Phi_i \Delta c_{t-i+1} + \varepsilon_t. \end{aligned} \tag{10}$$

Subtract UP_{t-1} from both sides:

$$\begin{aligned} \Delta UP_t &= \alpha_0 - (1-\Gamma_1)UP_{t-1} - \sum_{i=2}^{m} \Gamma_i \Delta UP_{t-i+1} + B_0 r_{t-1} + \beta_0 \Delta r_t - \sum_{i=2}^{p} B_i \Delta r_{t-i+1} + \Phi_0 c_{t-1} + \phi_0 \Delta c_t - \sum_{i=2}^{q} \Phi_i \Delta c_{t-i+1} + \varepsilon_t \\ &= \alpha_0 - \sum_{i=2}^{m} \Gamma_i \Delta UP_{t-i+1} + \beta_0 \Delta r_t - \sum_{i=2}^{p} B_i \Delta r_{t-i+1} + \phi_0 \Delta c_t - \sum_{i=2}^{q} \Phi_i \Delta c_{t-i+1} \\ &\quad -(1-\Gamma_1)UP_{t-1} + B_0 r_{t-1} + \Phi_0 c_{t-1} + \varepsilon_t. \end{aligned} \tag{11}$$

Notice that the Eq. (11) has the same structure as Eq. (2) except the orders of lag (m, p, q) is different. Allowing for differential lag lengths on the lagged variables, which is more general than the cointegration analysis of partial systems carried out by Boswijk (1994, 1995), does not affect the asymptotic results derived by Pesaran et al. (2001). Moreover, the error correction (EC) representation of Eq. (11) which involves the ECM term can be estimated by rearranging the original equation:

$$\begin{aligned} \Delta UP_t &= \alpha_0 - \sum_{i=2}^{m} \Gamma_i \Delta UP_{t-i+1} + \beta_0 \Delta r_t - \sum_{i=2}^{p} B_i \Delta r_{t-i+1} + \phi_0 \Delta c_t - \sum_{i=2}^{q} \Phi_i \Delta c_{t-i+1} \\ &\quad -(1-\Gamma_1)\{UP_{t-1} - [B_0/(1-\Gamma_1)]r_{t-1} - [\Phi_0/(1-\Gamma_1)]c_{t-1}\} + \varepsilon_t \\ &= \alpha_0 - \sum_{i=2}^{m} \Gamma_i \Delta UP_{t-i+1} + \beta_0 \Delta r_t - \sum_{i=2}^{p} B_i \Delta r_{t-i+1} + \phi_0 \Delta c_t - \sum_{i=2}^{q} \Phi_i \Delta c_{t-i+1} - (1-\Gamma_1)ECM_{t-1} + \varepsilon_t \end{aligned} \tag{12}$$

where $1-\Gamma_1$ represents the speed back to the equilibrium. Note that under the ARDL approach to cointegration, the existence of a unique valid long term relationship among variables, and hence a sole error-correction term, is the basis for estimation and inference. Short term relationship cannot be supported unless a unique and stable equilibrium relationship holds in significant statistical sense.

4. Empirical results

4.1. Pre-testing

Although the ARDL approach does not require pre-testing for unit roots, this study still conducts such testing to enhance the usefulness of the ARDL approach. This study investigates the orders of integration of each series through Augmented Dickey–Fuller (ADF) unit root test. Table 3 lists the results of testing the existence of unit roots of the data.

ADF test statistics suggest that all variables employed in this study are $I(1)$ except for underwriting profits. The overall results demonstrate that underwriting profits are most likely stationary, consistent with the findings of Choi et al. (2002) and Harrington and

Table 3
The ADF unit root test for various variables.

Variables	Levels	First difference
$UP1_t$	−2.9861(1)*	−6.4716(1)**
$UP2_t$	−3.3625(1)*	−6.2075(1)**
r_t	−2.4432(1)	−6.3863(1)**
G_t	−0.8854(1)	−5.5932(0)**
K_t	−1.6141(1)	−5.6951(0)*
E_t	−2.0726(1)	−5.5932(0)**

Notes:
1. $UP1_t$ denotes one minus combined ratio and $UP2_t$ as one minus economic loss ratio, G_t as relative wealth, K_t as inverse of Kenney ratio, E_t as de-trended relative wealth.
2. The augmented Dickey–Fuller regressions include an intercept but no trend.
3. The number of lags used for the ADF regressions are shown in parentheses.
4. * and ** indicate significantly at the 5% and 1% level, respectively.

Yu (2003). The inconsistency in the integration order of variables in this study supports to the use of the ARDL bounds approach rather than one of the alternative cointegration tests.

As mentioned in previous section, a critical assumption that has to be tested is there is at most one long-term relationship among variables. Consider the following two equations:

$$\Delta r_t = \alpha_0' + \sum_{i=2}^{n} \Gamma_i' \Delta UP_{t-i+1} + \sum_{i=2}^{n} B_i' \Delta r_{t-i+1} + \sum_{i=2}^{n} \Phi_i' \Delta c_{t-i+1} + \theta_1' UP_{t-1} + \theta_2' r_{t-1} + \theta_3' c_{t-1} + \varepsilon_t' \quad (13)$$

$$\Delta c_t = \alpha_0'' + \sum_{i=2}^{n} \Gamma_i'' \Delta UP_{t-i+1} + \sum_{i=2}^{n} B_i'' \Delta r_{t-i+1} + \sum_{i=2}^{n} \Phi_i'' \Delta c_{t-i+1} + \theta_1'' UP_{t-1} + \theta_2'' r_{t-1} + \theta_3'' c_{t-1} + \varepsilon_t''. \quad (14)$$

Notice that these equations have a similar structure as Eq. (2) except for that there are no current values involved as explanatory variables. That is because we do not know a priori what variables should be treated as forcing variables at this stage. Irrespective of whether variables are $I(0)$ or $I(1)$, a bounds testing procedure is provided to test following null hypotheses of long-term relationships[3]:

$$H_0' : \theta_1' = \theta_2' = \theta_3' = 0 \quad (15)$$

$$H_0'' : \theta_1'' = \theta_2'' = \theta_3'' = 0. \quad (16)$$

If hypotheses (15) and (16) are not being rejected, only one possible long-term relationship with underwriting profits is selected as the dependent variable. This study imposes the order of lag length (n) from 1 and calculates the F-statistic for the bounds test (Pesaran et al., 2001). The test results listed in Table 4 show that the null of the long-term relationship cannot be rejected when interest rate or capacity proxy are selected as dependent variables, even when the lag is increased to 3. Consequently, preliminary testing suggests the use of conditional ECM for the subsequent empirical analysis.

4.2. Estimation

Based on the conditional ECM (Eq. 2), hypotheses (3)–(6) have to be tested using the bounds test (Pesaran et al., 2001). This study imposes the order of lag length (n) from 1 and calculates the F-statistic. When the null hypothesis is rejected, the increasing order of lag length is immediately stopped, and the existing order is retained as the maximum lag for ARDL estimation. The results for the cases involving both restricted and unrestricted constant are listed in Table 5.

Table 5 shows that the null hypothesis maintaining nonexistence of the long-term relationship is rejected for whole industry underwriting profits when the order of lag length equals to 1. Furthermore, the null hypothesis is rejected when the F statistic significantly exceeds the critical values at the 1% level. Therefore, the estimation process stops increasing order of lag and retains this order of lag ($n=1$) when estimating ARDL models. The significant results support the existence of a long-term profit underwriting equation, regardless of whether the underlying variables are $I(0)$ or $I(1)$. Therefore, merely considering short-term determination (e.g. capacity constraint hypothesis) is definitely insufficient to explain underwriting profit dynamics.

While obtaining the maximum order of lag ($n=1$), one of eight ($=(1+1)^3$) ARDL models must be selected using Schwartz Bayesian Criterion (SBC) during the second stage. Table 6 then lists the diagnostic statistics used in ARDL estimation. The adjusted ${R^2}_s$ for all six models exceeds 0.65. The computed F-statistics clearly reject the null hypothesis that all regressors have zero coefficients, suggesting that the ARDL model fits the data reasonably well. Furthermore, diagnostic testing is statistically insignificant for all six ARDL models, suggesting no misspecification. Notably, when de-trended relative wealth E_t is defined as the capacity proxy, it implicitly implicates a linear trend is in the underwriting profit equation.

For more confidence specification, this study also compares the findings against the lag structure generated from the ADF test. Table 3 shows that the DGP of underwriting profits, interest rate, and capacity are all ADF(1) ≡ AR(2), meaning that the lag length for ARDL estimation is ARDL(2, 2, 2). Table 7 lists the results of Akaike information criterion (AIC), SBC and Hannan–Quinn criterion (HQC) for the two methods of lag structure selection. Generally, the lag results presented in this study are all superior to ARDL(2, 2, 2).

Furthermore, to ensure the lag structure is reliable, this study also conducts a "general-to-specific" approach in model selection.[4] This study begins with orders of lag (m, p, q) equal to (2, 2, 2) and then conducts likelihood ratio test for zero restrictions. This study directly tests the restrictions and also checks that the residuals are not violated in the restricted models by diagnostic testing. Furthermore, this study uses a nested testing structure, which is a sequential testing procedure. Within each nest, each model is a special case of the preceding cases, obtained by imposing relevant zero restrictions. The final optimal lag structure determined by the general-to-specific approach is the same as the lags selected via ARDL estimation. This consistency of findings enhances the credibility of the model selection. Table 8 lists one path of model reduction process.

[3] See pp. 304–306 in Pesaran and Pesaran (1997) for more details.
[4] See Hendry (2000) for a brief review.

Table 4
Statistics for testing existence of long term forcing variables.

Dependent variable					
Difference of interest rates			Difference of capacity proxies		
	Orders of lag n	F-statistic		Orders of lag n	F-statistic
Model (r_t |$UP1_t$,G_t)	1	2.5750	Model (G_t|$UP1_t$, r_t)	1	1.0813
	2	3.2597		2	0.5413
	3	2.6546		3	0.3635
Model (r_t|$UP1_t$,K_t)	1	3.4871	Model (K_t|$UP1_t$, r_t)	1	1.6930
	2	4.0147		2	0.5381
	3	2.7628		3	0.3595
Model (r_t|$UP1_t$,E_t)	1	3.2189	Model (E_t|$UP1_t$, r_t)	1	2.1674
	2	2.4285		2	1.0377
	3	1.8956		3	0.3339
Model (r_t|$UP2_t$,G_t)	1	2.8739	Model (G_t|$UP2_t$, r_t)	1	1.0481
	2	2.2981		2	0.5676
	3	1.3972		3	0.3332
Model (r_t|$UP2_t$,K_t)	1	3.2937	Model (K_t|$UP2_t$, r_t)	1	1.8015
	2	2.2158		2	0.5556
	3	1.1282		3	0.3491
Model (r_t|$UP2_t$,E_t)	1	3.1182	Model (E_t|$UP2_t$, r_t)	1	2.2931
	2	2.8126		2	1.0390
	3	1.0953		3	0.9835

Notes:
1.* and ** indicate significantly at the 5% and 1% level, respectively.
2. Critical value bounds of F statistics is (5.15, 6.36) at the 1% level.
3. Critical value bounds of F statistics is (3.79 4.85) at the 5% level.

Table 5
Results of bounds tests for whole industry.

	Orders of lag n	Restricted	Non-restricted	
		F-statistic	F-statistic	t-statistic
Model ($UP1_t$ |r_t, G_t)	1	8.0416*	10.7196*	−4.9507*
Model ($UP1_t$ |r_t, K_t)	1	7.9544*	9.9327*	−4.8104*
Model ($UP1_t$ |r_t, E_t)	1	9.0753*	12.0725*	−4.3926*
Model ($UP2_t$ |r_t, G_t)	1	7.4391*	9.9063*	−4.9848*
Model ($UP2_t$ |r_t, K_t)	1	6.9391*	9.2401*	−4.6992*
Model ($UP2_t$ |r_t, E_t)	1	8.4226*	11.1988*	−4.3895*

Note:
1.* indicates significantly at the 1% level.
2. For restricted intercept case, critical value bounds of F statistics is (4.13, 5.00) at the 1% level.
3. For unrestricted intercept case, critical value bounds of F statistics is (5.15, 6.36) at the 1% level. Critical value bounds of t statistics is (−3.43,− 4.10) at the 1% level.

Table 6
Diagnostic statistics of ARDL estimations.

Dependent variable	$UP1_t$(%)			$UP2_t$(%)		
Capacity proxy	G_t	K_t	E_t	G_t	K_t	E_t
ARDL (m, p, q)	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,1,0)	ARDL (1,1,0)
$\overline{R^2}$	0.7027	0.7440	0.7126	0.6536	0.6717	0.6713
F-statistic	43.3458**	39.2401**	45.4593**	25.4449**	27.6208**	27.6219**
DW-statistic	1.8713	1.8627	2.0622	1.7532	1.8235	1.9587
Durbin's h-statistic	0.6214	0.6706	−0.2940	1.3286	0.8962	0.2050
Serial correlation ~ $\chi(1)$	0.3908	0.3606	0.0956	1.6377	0.6823	0.0341
RESET test~ $\chi(1)$	0.8959	0.4356	0.2884	0.4625	0.1364	0.3259
Heteroscedasticity ~ $\chi(1)$	0.7244	0.2034	0.5192	2.3151	2.4686	2.4178

Note: * and ** indicate significantly at the 5% and 1% level, respectively.

Table 7
Comparison of two methods for the lag length selection in ARDL estimation.

Panel A. Lags structure selected by SBC when the maximum lag equal to 1						
Dependent variable	$UP1_t$(%)			$UP2_t$(%)		
Capacity proxy	G_t	K_t	E_t	G_t	K_t	E_t
ARDL (m, p, q)	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,1,0)	ARDL (1,1,0)
AIC	5.3814	5.2644	5.3476	5.7741	5.7198	5.7119
SBC	5.5222	5.4418	5.4885	5.9502	5.8985	5.8795
HQC	5.3463	5.3345	5.4026	5.8022	5.7723	5.7488
Panel B. Lags structure selected by ADF test for each series						
Dependent Variable	$UP1_t$(%)			$UP2_t$(%)		
Capacity proxy	G_t	K_t	E_t	G_t	K_t	E_t
ARDL (m, p, q)	ARDL (2,2,2)	ARDL (2,2,2)	ARDL (2,2,2)	ARDL (2,2,2)	ARDL (2,2,2)	ARDL (2,2,2)
AIC	5.4310	5.3933	5.3897	5.8850	5.8367	5.8612
SBC	5.7508	5.7140	5.7094	6.2047	6.1573	6.1809
HQC	5.5561	5.5198	5.5142	5.9769	5.9553	5.9713

Note: m, p and q denote the lag length of the underwriting profits, interest rate and the capacity, respectively.

Table 8
The testing results of general-to-specific approach for ARDL model.

Model reduction process	Capacity proxy		
	G_t	K_t	E_t
Panel A. The dependent variables using $UP1_t$			
(2,2,2)→(2,1,1): $\chi(2)$	0.2146	0.9010	0.5510
(2,1,1)→(1,1,1): $\chi(1)$	0.8863	0.4647	0.0019
(1,1,1)→(1,1,0): $\chi(1)$	0.6825	0.2037	0.4291
(1,1,0)→(1,0,0): $\chi(1)$	3.2197	6.4026*	3.1314
(1,0,0)→(0,0,0): $\chi(1)$	48.1798**	–	61.5381**
Panel B. The dependent variables using $UP2_t$			
(2,2,2)→(2,1,1): $\chi(2)$	0.0148	1.2170	0.4039
(2,1,1)→(1,1,1): $\chi(1)$	1.5798	0.7624	0.1091
(1,1,1)→(1,1,0): $\chi(1)$	0.8036	0.2150	0.3073
(1,1,0)→(1,0,0): $\chi(1)$	9.9531**	10.5804**	12.9291**

Notes:
1. The numbers listed in this table indicate the likelihood ratio test (LR-test) statistic.
2. The critical value of the LR test statistics with 1 (2) degree(s) of freedom at the 5% significance level is 3.84 (5.99). The critical value of the LR test statistics with 1 (2) degree(s) of freedom at the 1% significance level is 6.63 (9.21).
3.* and ** indicate significantly at the 5% and 1% level, respectively.

Particularly, this study covers a longer period (half a century), and thus structural stability must be carefully examined. The CUSUM tests of the model stability show that the cumulative sum of residuals lie within the critical band of the 95% confidence level. Indeed the residuals follow a central path indicating high parameter stability (see Figs. 1 and 3). The CUSUM of squares test also reveals that the cumulative sum of the squares of recursive residuals remains roughly within the 95% confidence critical band (see Figs. 2 and 4). These results suggest that the model parameters are stable over the entire sample period.

The dynamic relationship between underwriting profits and other variables requires an estimation method designed to deal with the specific problems associated with the inclusion of lagged dependent variables. After controlling interest rate and capacity proxy, the underwriting profits of the whole industry follow the AR(1) process at the 1% significance level, demonstrating that the first lagged underwriting profit has strong explanatory power during the current period underwriting profit, whereas the coefficient on the second lagged underwriting profit has negligible explanatory power. The improved financial pricing hypothesis developed by Cummins and Outreville (1987), notes that two lags exist in the insurance industry and in combination they can generate an AR(2) process of underwriting profits. The information lag, which is common to the insurance industry, includes the data collection lag, regulatory lags or policy renewal lags. Meanwhile, the reporting lag results from the annual financial reporting routine of insurance companies. They suggest that the AR(2) process is effective in data generation and the inequality (8) must be satisfied to generate an insurance cycle. The existing literature (e.g. Niehaus & Terry, 1993; Lamm-Tennant & Weiss, 1997; Fung et al., 1998; Harrington & Yu, 2003) adopted the same DGP assumption. The results presented in this study provide a more reliable explanation with statistically recognizing and suggest that after controlling relevant variables, the AR(1) process is sufficient for modeling the dynamics of underwriting profits at the industry level.

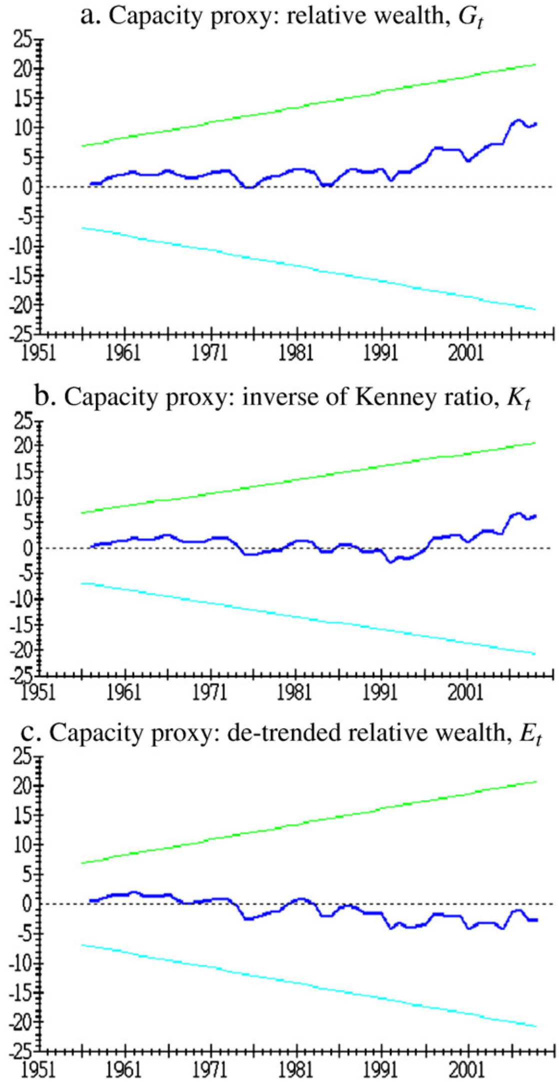

Fig. 1. Plots of cumulative sum of recursive residuals for underwriting profit ($UP1_t$) equation. (The straight lines represent critical bonds at 5% significant).

Another implication of AR(1) process in our estimation results is that it reveals Koyck form of geometric lag model.[5] In practice, incurred loss at a given year includes paid loss and unpaid loss.[6] Underwriting profits are realized in part at current year because of parts of current loss been paid, thus, is related to current interest rates and current capacity. Unpaid loss, on the other hand, relies on estimation from previous year's loss ratio because of information lag. Therefore, current underwriting profits are also related to lagged underwriting profits and the effects of past impact of interest rates and capacity will persist at a declined rate based on the autoregressive effect of lagged underwriting profits. These features ensure that the impact of changes in the current and the preceding periods is bigger than the impact of change of earlier periods, which is consistent with the assumptions of Koyck's geometric lag scheme.

Evidence from this study indicates that a visible cyclical pattern of underwriting profits can be explained as dynamic feedback to the long-term equilibrium, rather than modeling as a predetermined AR(2) process. Following the ECM inference, which reinforces the findings of insurance cycle dynamics, the long-term and short-term implications can be modeled together within ARDL modeling. The specification of underwriting profits must be further explored for both long term equilibrium and short term dynamics. The static long-term model and the error correction representation of the corresponding ARDL model are reported in Tables 9 and 10.

The error correction coefficient is significantly negative for all six models indicating a long-term relationship between underwriting profits and capacity. Earlier studies focused on analyzing the short-term relationship because of the stationary characteristic of underwriting profits. For *UP1*, interest rate is negatively related with underwriting profits in both long- and short-term, as expected. For *UP2*, which is defined as 1-ELR, the negative long-term relationship between underwriting profits and interest rate remain, but become

[5] See Koutsoyiannis (1977) for more details about Koyck's transformation and modified Koyck's transformation.

[6] At whole industry level, more than 43% incurred loss are paid at the current year and unpaid loss will gradually be paid out in subsequent years at a declined pattern. See Winter (1994).

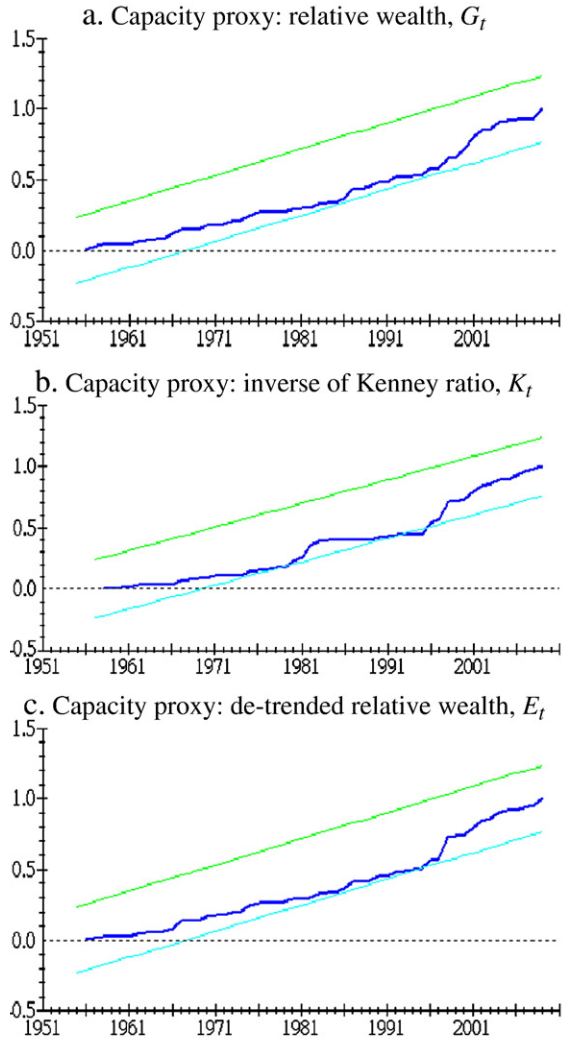

Fig. 2. Plots of squares of recursive residuals for underwriting profit ($UP1_t$) equation. (The straight lines represent critical bonds at 5% significant).

insignificantly positive in the short-term.[7] Such findings are consistent with Choi et al. (2002), who identified a negative relationship between interest rate changes and ELR. Choi et al. explained this relationship as reflecting the definition of ELR, in which interest rate is used to build or measurement errors are captured.

In the short-term, models indicate that underwriting profits and capacity proxy are negatively related, which is consistent with the prediction of the capacity constraint model as identified in earlier studies. Interestingly, the proposed models show a negative long-term relationship between underwriting profits and all three capacity proxies. These results contradict the implication of the generally accepted capacity constraint hypothesis because capacity constraint hypothesis, which only focuses on short-term determinant nature. Choi et al. (2002) conclude that the financial quality hypothesis, option pricing approach and economic pricing hypothesis are inconsistent with the results of unit root tests because the ELR series is $I(0)$ and the capacity proxy is $I(1)$. Higgins and Thistle (2000) also suggest that underwriting profits do not depend on capacity in the long-term. In contrast, the findings of the present study are substantially consistent with the economic pricing hypothesis, which implies a strictly negative relationship between underwriting profits and capacity proxy in both the short- and long-term. A critical feature of the economic model is that insurance companies are assumed to be risk averse. The insurance company acts as if it is a risk-averse expected utility maximizing firm. Risk-averse firms under uncertainty require strictly positive profits, and in the long-run equilibrium position, can regard such a profit as reward to risk-bearing. (See Sandmo, 1971) A decrease in price will make firms leave the market. The insurance industry-wide uncertainty, for example, includes unexpected catastrophic events, uncertain demand of insurance, unforeseen changes in tort law or regulation reform, higher-than-expected cost inflation and uncertain settlement (both in time and amount) of long-tailed claims. Such uncertainty is usually costly or unavailable to diversify or hedge, thus, need to acquire risk premium. Lower surplus or capacity increases risk perception of insurance companies. According to Choi et al. (2002), under this economic model, risk premium is decreasing in the amount of surplus.

[7] For the case of capacity proxy G_t the coefficient of changes of interest rates is significantly positive at a marginal 10% level.

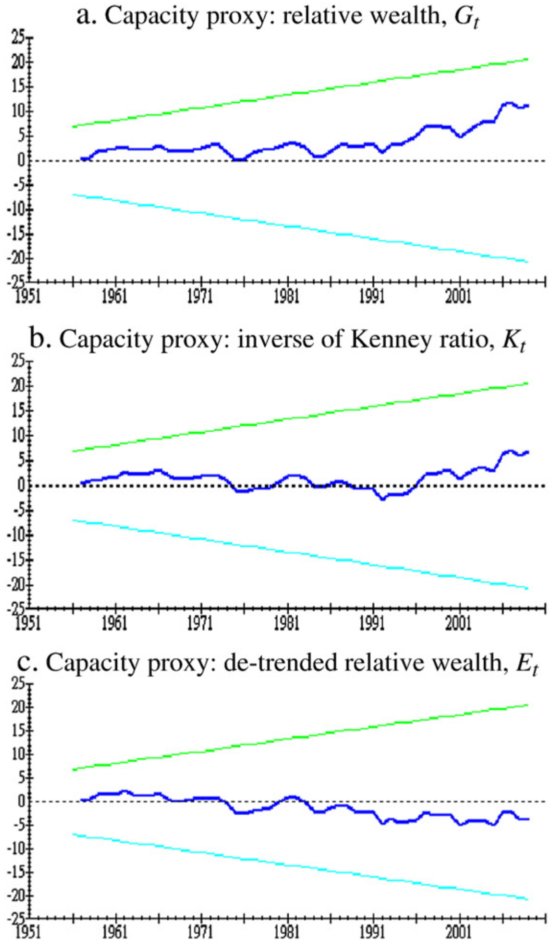

Fig. 3. Plots of cumulative sum of recursive residuals for underwriting profit ($UP2_t$) equation. (The straight lines represent critical bonds at 5% significant).

Such a point of view is supported based on empirical evidence from this study.[8] The results demonstrate that the supply effect dominates the U.S. insurance market at the whole industry level.

5. Conclusion

The main contribution of our study is exploring the long-term relationships related to underwriting profits, an area that was previously not possible to examine owing to inconsistent integration order. This study presents a more flexible means of portraying the pattern of underwriting profits, and provides an econometric base for describing insurance cycle dynamics. Empirical comparisons of five alternative models of underwriting profits are carried out to support the economic pricing hypothesis. Another contribution is finding significantly negative long-term relationship between underwriting profits and capacity proxy, which indicates that the capacity constraint hypothesis may not be enough to reveal the whole picture of underwriting profit dynamics. The empirical evidence strongly suggests that the supply effect, which can be reflected by the pricing strategies of risk-averse insurance companies or suppliers, has dominated the U.S. insurance market for the last half century.

Considering the uncertainty in the time series properties of the variables in question, this study proposes ARDL modeling as an appropriate approach for examining the existence and causes of U.S. insurance cycles. Rather than being structured by the predetermined second-order process (i.e. AR(2)), the tendency to return to the long-term equilibrium explains the cyclical pattern of underwriting profits reasonably well. The predetermined second-order process DGPs has been replaced by more flexible ARDL models. The results of this study provide clear and reliable answers that are statistically significant to capture the equilibrium of insurance markets and represent their short-term dynamics via error correction.

[8] Some studies assume risk-averse insurers. Froot and O'Connell (1996) examine insurance-market equilibrium in a setting where both insurers and insurance buyers are effectively risk averse. Their empirical results show that the industry-wide level of financial slack in the reinsurance sector is estimated to be significantly negative with the price. Gron and Winton (2001) extend their model in non-life insurance market allowing for risk overhang from insurers' past decisions. See Froot and O'Connell (1996) and Gron and Winton (2001).

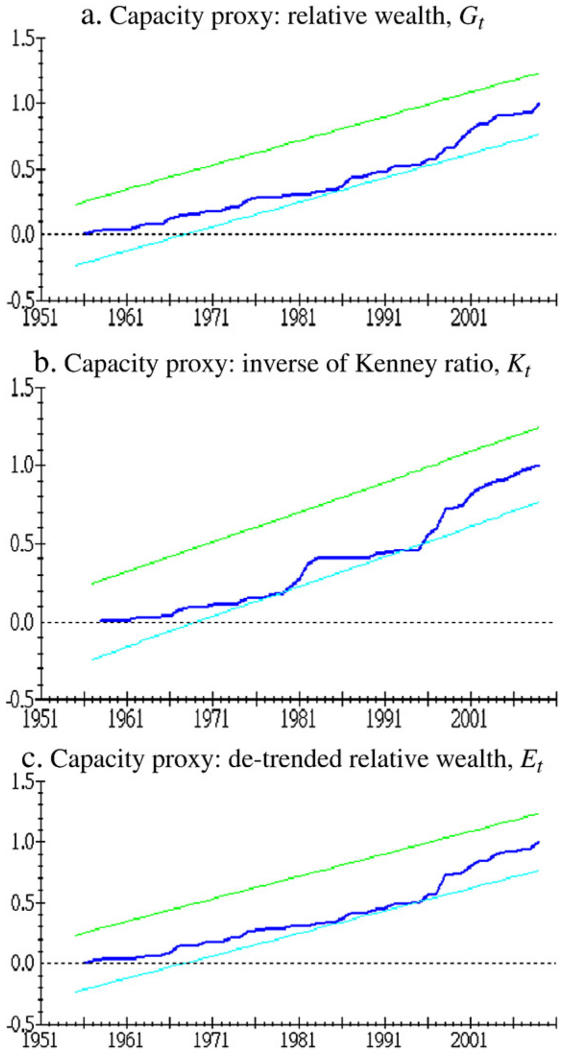

Fig. 4. Plots of squares of recursive residuals for underwriting profit ($UP2_t$) equation. (The straight lines represent critical bonds at 5% significant).

ARDL modeling has implications for forecasting. In the short term, underwriting profits can be essentially viewed as a risk premium plus a disequilibrium component which is represented as a conditional error correction term. One step ahead forecasting can be generated using the error correction model to predict underwriting profits in the coming year. Such dynamic forecasting can also help actuaries to determine an appropriate underwriting profit loading.

More comprehensive future studies could incorporate alternative risk management activities, such as retention, self-funding, captives, large dollar deductible policies and residual markets. During the late 1980s, increasing costs of U.S. Worker Compensation insurance, exacerbated by large residual market loads in many jurisdictions, led numerous employers to adopt alternative risk transfer

Table 9
Estimated long term effects of ARDL model.

Dependent variable	$UP1_t$(%)			$UP2_t$(%)		
	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,0,0)	ARDL (1,1,0)	ARDL (1,1,0)	ARDL (1,0,0)
Constant	17.0040** [5.6082]	20.9770** [5.5398]	15.5756* [7.2488]	22.9966** [4.9129]	29.6995** [6.5806]	20.3837** [5.6869]
r_t	−1.8993** [0.5684]	−2.1951** [0.4767]	−3.6291** [1.1842]	−1.3225** [0.4792]	−1.7007** [0.5570]	−3.1374** [1.1485]
G_t	−3.7286** [1.3134]	–	–	−4.3725** [1.3597]	–	–
K_t	–	−13.9482** [4.6044]	–	–	−18.7242** [5.5115]	–
E_t	–	–	−13.0960* [6.2727]	–	–	−14.1388** [5.2611]

Notes:
1.* and ** indicate significantly at the 5% and 1% level, respectively.
2. Numbers in parentheses are standard errors.

Table 10
Error correction representation of ARDL model.

Dependent variable	$\Delta UP1_t$(%)			$\Delta UP2_t$(%)		
	ARDL(1,0,0)	ARDL(1,1,0)	ARDL(1,0,0)	ARDL(1,1,0)	ARDL(1,1,0)	ARDL(1,1,0)
Constant	5.7164** [1.8400]	8.5909** [2.0839]	3.4597** [1.0482]	10.5288** [2.4782]	12.8718** [2.7581]	6.5386** [1.4009]
ECM_{t-1}	−0.3362** [0.0789]	−0.4095** [0.0804]	−0.2221** [0.0758]	−0.4578** [0.0912]	−0.4334** [0.0851]	−0.3208** [0.0824]
Δr_t	−0.6385** [0.1761]	−0.2812 [0.3246]	−0.8061** [0.1972]	0.7144 [0.4175]	0.6096 [0.4084]	0.5361 [0.4112]
ΔG_t	−1.2535* [0.5290]			−2.1009** [0.6548]		
ΔK_t		−5.7123** [1.7763]			−8.1151** [2.2606]	
ΔE_t			−2.9089** [1.0489]			−4.5354** [1.2625]
$\bar{R}^2$	0.3401	0.4063	0.3276	0.3710	0.4042	0.4043
F-statistic	9.8004**	12.0313**	8.9913**	10.6143**	12.2310**	12.2138**
DW-statistic	1.8713	1.8627	2.0622	1.7573	1.8235	1.9587

Notes:
1.* and ** indicate significantly at the 5% and 1% level, respectively.
2. Numbers in parentheses are standard errors.

techniques, such as group self-insurance and large dollar deductible policies. It will be interesting to concentrate on determining whether such activities increase demand elasticity in relation to insurance price.

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