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An Examination of Reinsurer Solvency – With Special Focus on India's GIC Re

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Abstract

Reinsurance mechanism helps insurance companies to manage their risks by sharing losses to the extent of a reinsured portfolio and helping them gain resilience. The element of reinsurance is critical not only for insurance companies for managing risks but also for the economy due to interconnectedness of the sector with the larger economy. Reinsurance thus becomes an important backbone of the industry. A reinsurer should therefore be of a sound financial health to offer such kind of protection and resilience (absorbing of losses) to ceding or primary insurance companies. This paper tries to examine the financial soundness of India's public sector reinsurer, the GIC Re, by studying some important variables that affect and impact its solvency. Analysing the data with the autoregressive distributed lag (ARDL) and bounds testing techniques model, the study finds that the combined ratio, operating profit, and liquidity are significant variables that have an impact on its solvency, thus providing important pointers for the reinsurance landscape in an emerging economic scenario.

Keywords: Solvency, Reinsurance, Risk, Insurance, Time Series

JEL Classification: G22, G52

Introduction and Background of the Study

Over the past several years, India has been on growth trajectory. As a result, India is poised for economic growth with the fundamentals improving and the insurance market significantly expanding across both the personal and commercial lines. Elango and Jones (2011) explain that growth for the insurance sector is dependent on factors such as the country rate of growth, GNI per capita, the level of interest rates, the country share of trade of goods, services, and ease of business and freedom that influences the insurance density.

The importance of insurance sector being immense for the emerging economy should also be supported with reinsurance adequacy (Dror & Wiechers, 2006). Reinsurance is the acceptance of a portion of the risk by the reinsurer for a premium to cover that risk. The purpose of reinsurance is management of risks faced by the primary insurers. Arrangements such as excess-of-loss, allows the primary insurance company to keep the portion of generally predictable losses while large and rarely occurring losses could be shared with reinsurance (Doron, 2010). The goals of reinsurance prominently include reducing the strain on an insurer's capital, extending coverage for large risks, and providing advisory services in critical areas such as underwriting, marketing, and pricing (CASACT, 2023). By reducing exposure, the reinsurance mechanism decreases the burden on regulatory capital for the primary insurance company (OECD, 2018). Additionally, reinsurance placements with admitted reinsurers[1] decreases regulatory capital requirements in some jurisdictions (Mankaï & Belgacem, 2016).

The study tries to fill the research gap for the insurance and reinsurance area in India by providing a perspective that a sound reinsurance system would be necessary for driving insurance growth for the country and to arrive at factors affecting the financial soundness of the reinsurer. The solvency aspect (Daykin, 1987) is thought to be a

[1] An admitted reinsurer is a substantially compliant reinsurer in a country but who has not taken out a license as a requirement.

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proper representative of financial soundness because of it being the ultimate test of viability. A reliable system of financial reporting for solvency monitoring is thus an essential regulatory tool (Falush, 1997). Since reinsurance is a business-to-business model it is very important that reinsurers are well efficient to provide capacity to insurers considering economic opportunities (Biener et al., 2017). Several researchers (Gatumel & Lemoyne de Forges, 2013; Park & Xie, 2014; Chen et al., 2020; Boonen & Jiang, 2023; Ugono et al., 2022;) have provided theories, models and discussion on risks that affect the reinsurer and highlighted the required oversight for the same to avert potential systemic risks in the insurance ecosystem. Such risks emanating for a reinsurer are counterparty risks, default risk, downgrading risk, etc. Although as per the Group of Thirty (2006), the systemic risks occurrence likelihood coming in the case of failure of reinsurance companies is low, the failures cannot be completely ruled out ever since the financial crisis of 2008 and events like the American Insurance Group failure.

In India, the public sector reinsurer the General Insurance Corporation Re (GIC Re) has been operating since 1972, and recently with the IRDAI regulations (2017), the regulator has allowed the foreign reinsurers to set up branches in India. However, the GIC Re continues to have the first right of refusal and enjoys a bigger market share yet and hence its financial soundness analysis is necessary. The report by the Reinsurance Expert Committee (2017) observes that the reinsurance mechanism constitutes an important process for the insurance industry, as it tries to improve the riskiness in portfolio of an insurer. Living in an increasingly risky world, just as insurance firms are being asked adequately to cover the growing risks, reinsurance businesses are being asked to reinsure them. In many ways, the (re) insurance sector continues to grow and adapt to a changing scenario.

Among other things and in line with Cummins and Nini (2002) this research aims to underline the reinsurance dynamics and their importance for the insurance industry. The study adds distinctly to the insurance / reinsurance sector literature by focusing exclusively on India and its national reinsurer the GIC Re by applying the ARDL model on its quarterly financial data from the year 2010–2020 obtained through its public disclosures. This study analyses solvency as a proxy of financial soundness and the factors that impact the same. It is expected that a financially sound and solvent reinsurer would be a reservoir of capacity for the insurance industry in the emerging economic environment and help the insurance companies to establish and lead properly. The paper is arranged as following - after providing a brief introduction and background of the study, the further sections delve into insights of GIC Re's financial performance followed by a review of literature, estimation of data through ARDL model and providing discussion on results as well as further directions.

A Brief Overview of GIC Re's Performance

The GIC Re had monopoly in the scenario of the Indian reinsurance sector till the year 2016. The IRDAI vide IRDAI Registration and Operations of Branch other than Lloyd's Regulations, 2015, permitted registering and reinsurance operation by branch offices of foreign based Reinsurers and coming in India and paving way for competition in the reinsurance sector. Further, on October 25, 2017, the GIC Re was listed on the stock exchange and is also among the top 15 largest global reinsurers (Datta, 2019). The mandatory cessions[2] placed with GIC Re were also reduced in a phased manner. Till 2006-2007, the mandatory cessions received from the direct insurers to GIC Re sustained at 20%. Further, they were gradually brought down to 15% in 2007-2008; thereafter to 10% in 2008–2013 and currently are at 5%. However, the GIC Re continues to hold a larger share of market of 80% and has a colossal presence backing up the Indian insurance sector (IRDAI Annual Report, 2020).

The gross premium income for GIC Re took a leap after the year 2015–16, largely supported by premiums through the agriculture reinsurance line of business. During the decade 2010–2020 the gross premium growth had been satisfactory, growing at a CAGR of 19.12%. For a reinsurance company, the gross premium earned is hailed as an important indicator of the company's overall financial health and success in the case of GIC Re too. A high level of gross premium is indicative that the company attracts portfolios for reinsurance and can generate a significant amount of revenue.

The incurred claims parameter measures the company's performance on the underwriting side, especially dealing

[2] Obligatory cession is to mandatorily cede to the reinsurer.

with risk management and losses; they represent a key outgo for the company. In the case of GIC Re, the average loss ratio during the period was 90.66%. The incurred claims are typically determined by estimating the likely amount of money that will be paid out on the claims that have been made against the policies the company has underwritten, based on several factors such as the nature and severity, the policy limits, and the terms and conditions of the policies.

The combined ratio is a measure of profitability for the company. It is calculated by adding the company's loss ratio plus its expense ratio and expressing the result as a percentage. In the case of GIC Re the combined ratio averaged to the tune of 100.61%. A ratio less than 100% indicates profitability and that the company is earning more in premiums than it is paying out in losses as well as expenses. A ratio of more than 100% indicates that the company is operating at a loss. A higher combined ratio may indicate that the company must depend on income from other sources, such as investments, etc., to meet the claims requirement.

The solvency ratio of GIC Re during the period of 2010–2020 had been volatile. Although it satisfied the mandatory solvency of 1.5% during all the periods, the GIC Re did experience a large dip in solvency in the year 2011–2012 owing to large outgoes on losses, it came down to 1.59% from 3.35% in the earlier year. It took another four years thereafter for GIC Re to regain its level back. By 2020, however, it had again been at a level that could simply comply with the statutory requirement, i.e., 1.53%.

Some of the caution areas for GIC Re in today's time are the high volume coming from the agriculture reinsurance line of business and the GIC Re also experiencing a spurt in net claims which needs to be kept in check. The higher combined ratio means that the company must rely on investment income alone for operating profitability which may not be sustainable when macroeconomic conditions are not well suited. Therefore, from the sustainability viewpoint and from the viewpoint of the insurance-reinsurance sector interconnectedness, the GIC Re must overcome its financial weaknesses. Also, in the wake of higher losses still there has not been any drastic change in the retrocession[3] and risk retention strategies outlook of GIC Re over the past decade.

[3] Retrocession is a reinsuring of a risk by a reinsurer.

Literature Review

Reinsurer risk and distress research is becoming mainstream on a global level with the availability of data and application of new modeling techniques, some of the previous researches on GIC Re have made use of multi-discriminant and other methods to evaluate its financial performance (Bawa & Verma, 2017; Mukherjee et al., 2020). Other studies profusely cover the advanced world and include contributions on modeling different risks to which the interconnectedness of the sector is discussed and mathematical modeling of data (Asimit et al., 2013; Benard & Ludkovski, 2012; Tan & Weng, 2012). Biswas and Bhattacharya (2020) propound that the study of financial performance and soundness becomes essential because of dynamic changes in the economy. Melwani (2019) states that the internal financial determinants had significant impact on the measures of financial performance.

The products and coverages as well as the span of the insurance sector plays prominent role at the national levels. Prakash and Gupta (2014) reiterate that crop insurance can be an important parameter while dealing with problems such as food security. Dealing with such large schemes certainly requires a stronger reinsurer. Because of their systemic importance, the solvency of reinsurer is of paramount importance to not only for insurers but also to for the economy. In 2008 and 2009, among the top reinsurers, Swiss Re developed financial weakness and required capital injection which was done by Berkshire Hathaway. Although Munich Re well-maintained its rating but Berkshire Hathaway, due to some financial problems and losses in its banking activity, got downgraded by two rating agencies (Gatumel & Lemoyne de Forges, 2013). Reinsurer downgrading is viewed seriously, as contracts may contain unwinding clauses if the reinsurer's financial health deteriorates (Cummins & Weiss, 2010).

A solvent and capitalised reinsurer possesses a higher chance to pay all reinsured claims. Park and Xie (2014) make use of several important ratios such as combined ratio, reserves ratio to determine the reinsurer health, they further state that the downgrading of reinsurance companies increases the probability of impact of downgrading for counterparty primary insurers. Solvency has become a prime supervisory tool for regulators worldwide. More prominently the Swiss test of Solvency

(SST) and its implications have also been discussed by Eling et al. (2008). Chakraborty (2023) highlights the role of reinsurance, makes use of models such as Altman's 'Z' score to predict financial distress for GIC Re, and prescribes for significant improvements to avert distress. Agrawal and Patni (2019) make use of the 'Z' score for assessing the health of listed PSUs and find it to be an important tool to assess financial health.

Researchers such as Cheng and Weiss (2012), as also Li and Neilson (2015), and Ruml and Tippins (2016) have identified future insolvency indicators. According to them, the underwriting cycle, i.e., the fluctuations in business, is one of the most significant predictors with financially damaging impacts for the companies. Hopenhayn (1992) discusses an approach to harmonise the insurance sector, he states that regulatory controls must balance the capital requirements that tend to increase the cost of entry but this may result into limited choices for consumers and in contrast, lower barriers would result in higher insolvency rates as companies exit and enter with more frequency. As per AM Best (2020), China introduced the China Risk Oriented Solvency System (CROSS) for reinsurers with a view to increase capacity in the market. While operating in large sectors the goal of financial institutions should also be to foster reassurance and adopt risk management strategies for reduction of risk perception (Arora & Kaur, 2018).

- Reinsurer ratings are an important indicator of their financial health. Fitch, 2022, considers the factors that affect the rating decision for a reinsurer, the chief are the reinsurer's financial strength and solvency, which reflects ability to meet obligations to ceding insurers and policyholders. Rating agencies use various criteria and methodologies to assess the reinsurer's capital adequacy, earnings quality, risk management, liquidity, and leverage (S&P Global 2022). The technical reserves ratio measures the adequacy of reserves to cover future obligations. It is also called as technical reserves to net premium ratio. The technical reserves ratio is an important measure of an insurance company's financial strength and stability, as it indicates whether the company has sufficient reserves to pay out claims and meet its other obligations. In the technical reserves there is some part of reinsurance, if case of reinsurance defaults, it will cause large credit risk changes for the primary company (Cai et al., 2014; Wong, 2022). A higher technical reserve ratio is generally considered to be a sign of financial strength, as it indicates that the company has a larger cushion of reserves to protect against potential losses. A lower technical reserves ratio, on the other hand, may indicate that the company is at greater risk of financial difficulties if it experiences a large number of claims or other unexpected losses.

Since the purpose of solvency is to meet policyholder obligations it is a measure of financial strength, the rating agencies make use of key ratios to arrive and provide ratings. Indian rating agencies such as CRISIL (2023) and Care Ratings (2021) make use of key ratios for determining the ratings of insurance and reinsurance companies. The common among them as prescribed for general / non-life pertain to combined ratio and solvency ratio and entails assessment of liquidity profile. A high level of combined ratio, low liquidity and technical reserves would mean rating weaknesses. Deterioration in solvency levels as well as underwriting performance carry rating sensitivities which could lead to negative rating of the company. A higher gross premium is a desirable factor (Sen, 2012; Siddik, 2022) leading to superior financial performance in the insurance sector. In research on Indian insurance companies, Patel (2013) points out that one of the predictors - claims ratio, suggesting it had the likely sign and strongly suggestive of higher loss ratio which is damagingly contributing to the insurers' solvency.

The operating profit ratio is a measure of financial ratio that gauges the operational efficiency of a company and is calculated by dividing the company's operating profit by its revenue. In research by Chen and Hamwi (2000), the researchers find that the same is affected by ownership structure, size of the firm, and lines of insurance. This ratio is indicated through the percentage of the company's revenue that is left after accounting for business-related costs, such as the cost of goods sold, salaries, and other expenses. A higher operating profit ratio indicates that a company is more efficient at producing profit from its operations, while a lower operating profit ratio indicates that a company is less efficient on profit performance from its operations.

The liquidity ratio is an important indicator of a firm's financial strength and stability since it reflects if the company has enough liquid assets on hand to pay its short-term obligations. The reinsurer may face liquidity risk because of a mismatch between asset and liability management (ESRB, 2015). A lower liquidity ratio may indicate that the company is at greater risk of financial difficulties if it experiences a sudden increase in its short-term liabilities. The liquidity ratio measures the insurance company's capability to honour its liabilities and obligations in short-term.

Studies by Caporale et al. (2017) as well as Yakob et al. (2012) indicate that the parameter of liquidity has a negative and statistically important effect on the solvency. A reinsurance company's ability to fulfill commitments is aided by its liquidity. A reinsurer's liquidity is driven by factors such as the quality and quantity of holding money and investments that are easily realisable, diversified, and how strong are their operating cash flows. Kessler (2014) states that active asset-liability management approach is likely to reduce most of the liquidity mismatches. A high level of liquidity allows meeting the unpredicted cash requirements without distress sale of investments, which may result in significant realised losses due to temporary market fluctuations.

Sources of Data, Variables, and Methodology

Data Sources

The data is sourced from the quarterly public disclosures for the years 2010–2020 (Form NL 30- Analytical ratios) from the company's website.

Empirical Model

The literature examining reinsurer financial distress, counterparty risks, default risks and solvency risks consists of application of various models and use the Univariate Multiple Discriminant Analysis (UMDA), simulations and mathematical models**.** Other methods that have been utilised, include neural works (Brockett, 2006), cash flow simulation (Cummins, 1999), and the ruin approach model (Barth, 2000).

For the current study, the use of Time Series ARDL model is being used that describes the behaviour of a time-dependent variable. Time series models are used to analyse the past behaviour of a variable to make predictions about its future. The ARDL, also known as the autoregressive distributed lag model, is a type of econometric model that is used to analyse the long-run relationship between two or more time series data and is a generalisation of the popular autoregressive integrated moving average (ARIMA) model, and allows for both short-run and long-run effects in the relationship. The ARDL model is commonly used in the analysis of economic / financial data, and estimating long-run relationships in the analysis. The ARDL model is useful when we have a mix of variables that are stationary at levels and some that are stationary at the first difference.

The approach of analysing the model framework, i.e., the autoregressive distributed lag (ARDL) scores multiple advantages in comparison with traditional methodologies. Firstly, the ARDL discards the pre-requirement of all the variables in the model to be integrated of the similar order and allows application even when the variables are integrated of order such as one, or order zero or of a mixed order and in the situation of limited data sizes, the test is relatively more efficient. Lastly, the long-run estimates of the model are derived unbiasedly using ARDL (Harris & Sollis, 2003; Belloumi, 2014; Kripfganz & Schneider, 2016).

The number of variables and lags included in an ARDL model determines its specification. An ARDL model usually has at least two variables, the dependent and independent variables. Depending on the individual research, the model can include additional variables and lags. The time horizon determines the lags to be included in the model, with greater lags used to capture longer-term correlations between the variables. The type of the data being analysed dictates the functional form of the ARDL model.

The steps involved in estimating an ARDL model comprise organising the data in a time series format, with the variables of interest arranged in columns and the time periods arranged in rows. Next is to determine the appropriate lag structure, which involves selecting the number of lags to include and specifying their functional form. The third step is to test for stationarity, and to apply any necessary transformations (such as differencing or detrending) to make the data stationary. The fourth step is to estimate the ARDL model parameters by using a suitable estimation method, such as ordinary least squares (OLS) or estimation through maximum likelihood estimation (MLE). Lastly, the estimated parameters can be used to make predictions about future behaviour.

Because the ARDL model combines two time series regression models, it is important to discuss both the Autoregressive (AR) and the Distributed Lag components of the model. In contrast to linear regression, which normally works with cross-sectional data, time series regression works in two ways (Yobero 2017). The observations on a given unit over a period are likely to be associated and that the Time is naturally ordered. When the time series observations are shuffled, there is a risk of losing their most defining feature that is the possibility of dynamic interactions between variables considered. Given the dynamic relationship of time series data, in modelling relationships, three approaches are commonly used:

The first one is *Distributed Lag (DL) Model* with equation: yt = f(xt, xt−1, xt−2, …). The representation: (yt, xt), where xt−1, xt−2, etc., represent the values of x in previous periods. The model incorporates lagged effects due to considering prior periods. The second version is *Dynamic Model with Lagged Values* with equation: yt = f(yt−1, xt, xt−1, xt−2, …). It is combination of features and integrates a lagged dependent variable and lagged independent variables. It is known as Autoregressive Distributed Lag (ARDL) model, consisting of an autoregressive component and a distributed lag component. The third one is *Error Term Dependency Model* with equation: yt = f(xt) + et, et = g(et−1) and uses functions f(.) and g(.), incorporating linear functions later. The model introduces error term dependence over multiple periods, leading to serial correlation or autocorrelation in errors.

Long-Term and Short-Term Model Equation

The log transformed variables are used for estimating the model. Solvency ratio (l_sol) is our dependent variable (Table 1). The independent or explanatory variables are as follows: Gross Premium Growth Rate (l_gpgr), Combined Ratio (l_cr), Technical Reserves Ratio (l_tech), Operating Profit Ratio (l_oppr), Liquidity Ratio (l_liq)

$$l\_sol_t = a + \sum_{i=1}^{q1} a1l\_sol_{t-1} + \sum_{i=1}^{q2} a2\ l\_gpgr_{t-1} + \sum_{i=1}^{q3} a3l\_cr_{t-1} + \sum_{i=1}^{q4} a4l\_tech_{t-1} + \sum_{i=1}^{q5} a5l\_oppr + \sum_{i=1}^{q6} a6l\_liq + E_t$$

$$\Delta l\_sol_t = a + \sum_{i=1}^{q1} a1\Delta l\_sol_{t-1} + \sum_{i=1}^{q2} a2\Delta\ l\_gpgr_{t-1} + \sum_{i=1}^{q3} a3\Delta l\_cr_{t-1} + \sum_{i=1}^{q4} a4\Delta l\_tech_{t-1} + \sum_{i=1}^{q5} a5\Delta l\_oppr + \sum_{i=1}^{q6} a6\Delta l\_liq + a7\Delta E_{t-1} + E_t$$

Table 1: Definitions of the Dependent and Independent Variables

Variable	*Definition*
Solvency Ratio	Ratio of the aggregate of the Available Solvency Margin (ASM) to the aggregate of Required Solvency Margin (RSM).
Gross Premium Growth	Growth rate calculated on basis of gross premium as compared to last year.
Combined Ratio	Aggregate of loss ratio and expense ratio and expressing the result as a percentage.
Technical Reserves Ratio	Additions of the reserve for risks unexpired plus deficiency premium reserves along with the reserve for claims (out-standing and including incurred and not reported as also incurred and not enough reported and arrived by dividing by net premium).
Operating Profit Ratio	Underwriting profit/loss plus investment income, all divided by net premium.
Liquidity Ratio	Ratio of Liquid assets to liabilities.

Results and Discussion

In the following section, we discuss the model estimation and results obtained in the process. For the time series model, it is important to check stationarity. The Augmented Dickey-Fuller (ADF) test was used for the same. The results are as appended below:

Unit Root Test

The use of data of time series for estimating parameters of economic relationships between variables is based on certain assumptions of the data series being stationary. The verification for stationarity becomes critical in this type of research. Using trend and intercept, Augmented Dickey-Fuller (ADF) we test it for the presence of unit roots. The test results presented as per Table 2, our study sample combines a mix of $I(0)$ and $I(1)$ series with the tests being consistent with the results on Gross Premium Growth, Technical Reserves Ratio and Operating Profit ratio is $I(0)$ while the results on Solvency, Combined Ratio and Liquidity are $I(1)$. The results express that the series are integrated of different order and the model variables can be used for analysis.

The Augmented Dickey-Fuller (ADF) test governs whether a time series data is stationar, i.e., whether the data has a constant mean, variance, and autocorrelation (throughout time) and is frequently easier to analyse and model over non-stationary data. The ADF test points to finding the optimum order of differencing necessary to make a time series data stationary and to test the null hypothesis that the data is non-stationary.

Table 2: Results of the Augmented Dickey Fuller Test

Variable	*At Levels*		*First Differences*		*Order*	*Remark*
	T Statistic	*Critical*	*T Statistic*	*Critical*		
Solvency Ratio	-2.389	-3.634	-6.974	-3.641	1 (1)	Stationary
Gross Prem Growth	-2.901	-3.634	-	-	1 (0)	Stationary
Combined Ratio	-1.739	-3.634	-6.488	-3.641	1 (1)	Stationary
Technical Reserves Ratio	-5.894	-3.634	-	-	1 (0)	Stationary
Operating Profit Ratio	-4.283	-3.634	-	-	1 (0)	Stationary
Liquidity	-2.695	-3.634	-6.642	-3.641	1 (1)	Stationary

Results of Bound Test

The ARDL bound test (also known as the bounds testing approach to cointegration), which is a statistical test for determining whether there is a long-run relationship existent between two or more time series data, i.e., cointegration, this refers to a situation where two or more time series data move together in the long-run, and tend to follow a common trend over time. The ARDL bound test is used to test the null hypothesis that there is no long-run relationship between the time series data, and to estimate the long-run coefficients of the relationship if it exists. The ARDL bound test is a widely used approach to testing for cointegration in time series analysis (Table 3). The F statistics obtained at 3.833 lie between the bounds at the 1 pc level of significance.

Table 3: ARDL Bounds Test

Model	*F Statistics*	*Lower Bound*	*Upper Bound*
Sol= f(gpgr+cr+tech+oppr+liq)	3.833	3.41	4.68

(At 1 pc level of significance).

Long Run Test ARDL Regression

The ARDL long run relationship model has an R squared value of 0.7573 implying that the regressors are capable to explain 75 pc variation in the dependent variable. The model provides evidence that in the long-run variables such as combined ratio, operating profit and liquidity are the significant determinants of reinsurer's solvency (Table 4). A percent rise in the combined ratio leads to a decrease of -.7860 in the solvency margin, whereas a unit increase in operating profit improves the margin by .1034 percent. A percent increase in liquidity is expected to improve the solvency ratio by .88 pc. Thus, by taking care of the parameters discussed, the GIC Re can increase its chances of a more improved standing on solvency as well as rating criteria.

Table 4: Long Run Test ARDL Regression (1,1,1,4,0,1) Dependent Variable - Solvency Ratio

No of Obs	40	*F (13,26)*	6.24	
Prob > F	0.0000	*R Squared*	0.7573	
Adj R Squared	0.6359	*Log Likelihood*	20.1867	
Root MSE	0.1812			
Regressor	*Coefficient*	*SE*	*T-Ratio*	*Probability*
l_sol L1	.546373*	.1137718	4.80	0.000
l_gpgr	.0219824	.033767	0.65	0.521
L1	.0109332	.0353564	0.31	0.760
l_cr	-.7860679**	.3310592	-2.37	0.025
L1	.8654878**	.3209264	2.70	0.012
l_tech	.141849	.0915255	1.55	0.133
L1	.1165039	.0831035	1.40	0.173
L2	.0207348	.0803362	0.26	0.798
L3	.1054656	.0717693	1.47	0.154
L4	-.0603575	.0855532	-0.71	0.487
l_oppr	.1034782**	.0428253	2.42	0.023
l_liq	.888987*	.2792356	3.18	0.004
L1	-.7791275**	.2996004	-2.60	0.015
_cons	-2.618073	1.780939	-1.47	0.154

(* = Significant at 1 pc level, ** = Significant at 5 pc level).

Thus, in the long-run the combined ratio, operating profit, and liquidity are significant factors affecting the solvency margin.

ECM - Error Correction Model Results

In the ECM, the R squared is at value of 0.7447 meaning that the regressors are able to explain 74 pc variations in the dependent variable. In Table 5, the results of the model pertain to the error correction.

Table 5: Error Correction Model (ECM) Results

Short Run Test ARDL Regression (1,1,1,4,01) Dependent Variable - Solvency Ratio				
No of Obs	40	*R Squared*	0.7447	
Root MSE	0.1812	*Adj R Squared*	0.6171	
		Log Likelihood	20.1867	
Regressor	*Coefficient*	*SE*	*T-Ratio*	*Probability*
Adj				
l_sol L1	-.456271*	.1137718	-3.99	0.000
LR				
l_gpgr	.0725609	.0783583	0.93	0.363
l_cr	.1750776	.5408537	0.32	0.749
l_tech	.7146725	.4702426	1.52	0.141
l_oppr	.2281129**	.1025397	2.22	0.035
l_liq	.2421803	.7395539	0.33	0.746
SR				
l_cr D1	-.8654879*	.3209264	-2.70	0.012
l_liq D1	.7791275*	.2996004	2.60	0.015
_cons	-2.618073	1.780939	-1.47	0.154

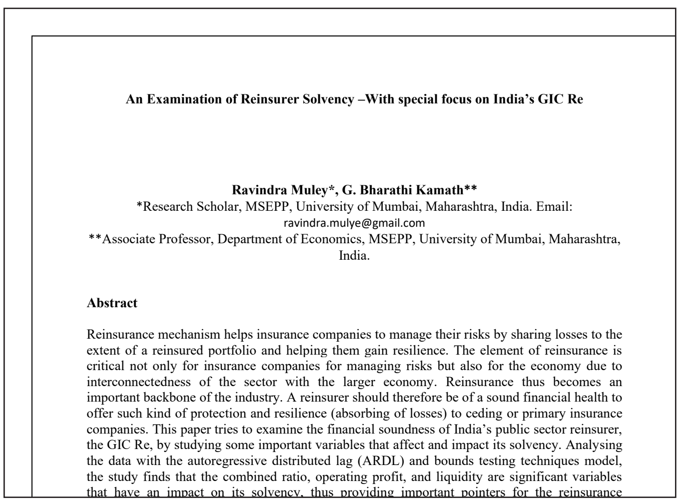
(* = Significant at 1 pc level, ** = Significant at 5 pc level).

Table 6: Post Estimation Tests

		Heteroskedasticity	*Autocorrelation*	
Specifications	*Ramsey Reset*	*Bruesch Pagan*	*Bruesch Godfrey*	*Durbin Watson*
Stat	3.92	11.040	2.003	2.25
P-Value	0.0166	0.0040	0.1570	

The results reported in Table 6 indicate no challenges such as that of misspecification, or challenge of heteroscedasticity, autocorrelation of higher-order, or normality.

To investigate whether for the long run, the relationships are stable, we examine the stability of the model using the test procedures of a plot of cumulative sum of recursive residuals (CUSUM) and the test procedures of cumulative sum of squares of recursive residuals (CUSUMSQ), and plotted against the break points. The stability is indicated when the plot lies in the 5% range level of significance, in our case the plots exhibit that the model stability and the graph lying within 5% boundary levels (Fig. 1).


An Examination of Reinsurer Solvency –With special focus on India's GIC Re

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Abstract

Reinsurance mechanism helps insurance companies to manage their risks by sharing losses to the extent of a reinsured portfolio and helping them gain resilience. The element of reinsurance is critical not only for insurance companies for managing risks but also for the economy due to interconnectedness of the sector with the larger economy. Reinsurance thus becomes an important backbone of the industry. A reinsurer should therefore be of a sound financial health to offer such kind of protection and resilience (absorbing of losses) to ceding or primary insurance companies. This paper tries to examine the financial soundness of India's public sector reinsurer, the GIC Re, by studying some important variables that affect and impact its solvency. Analysing the data with the autoregressive distributed lag (ARDL) and bounds testing techniques model, the study finds that the combined ratio, operating profit, and liquidity are significant variables that have an impact on its solvency, thus providing important pointers for the reinsurance

Fig. 1: CUSUM Plot

Policy and Research Implication

This research paper tries to provide a basis for understanding important drivers of solvency of GIC Re both in the long and short-run using the autoregressive distributed lag model for the time series data. The findings of this empirical analysis have important implication and pointers to critical areas that impact the reinsurer's solvency. The study identifies solvency as an elixir for a healthy and growing insurance industry, much needed in the emerging economic scenario. At the same time, the operational quality of the reinsurer can be seen as a provider of additional capacity much needed for the insurance sector to grow amid a competitive scenario. As evidenced from the model, the combined ratio, operating profit, and liquidity are significant factors impacting the solvency of GIC Re.

The study also highlights the importance of financial soundness of the reinsurance company which is of prominence for the insurance sector. The research also highlights the need of a vibrant reinsurance scenario and the associated dynamics. The findings are also important for new reinsurance companies entering the market. Reinsurance becomes an important backbone more prominently for General Insurers who play a critical role in providing resilience to other sectors of the economy and for Life Insurance companies thinking of bringing in new and innovative products.

The research on the topic concerning reinsurer solvency opens possibilities for examining it with other variables important from the reinsurance point of view. The future of the insurance and reinsurance sectors in India will be full of opportunities and hence, companies need to gear up properly.

Conclusion and Recommendations

We believe that the results of this research are of potential importance for the reinsurance sector not only locally but also globally. Given the need for sound financial management for reinsurance, the research tries to underpin the drivers of solvency which is very important from being competitive, reputational and adherence in terms of governance aspect. The study concludes that a reinsurer needs to control combined ratio (loss plus expenses ratio), enhance operating profit, and take care of liquidity which are the important factors from solvency point of view. The study has important implications for the reinsurance market in India and similar emerging economies in the world, the main contribution of the study lies in providing and discussing a background of issues concerning development of insurance market, the important role played by reinsurance, and its strategic importance in an emerging scenario.

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