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# Implementing the Z-score to examine the financial stability of insurance companies in Pakistan

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**Abstract**

**Purpose:** This study aims to assess simpler and more accessible measures of insurer soundness as alternatives to the complex Solvency II framework. It specifically evaluates the effectiveness of six different Z-score models in measuring the financial stability of insurance companies in Pakistan.

**Design/methodology/approach:** The analysis is based on 296 firm-year observations from 37 insurers over the period 2013–2020. The study applies Ordinary Least Squares (OLS) and System-GMM estimation techniques to examine the predictive ability of various Z-score formulations. Model performance is evaluated using the Root Mean Squared Error (RMSE) criterion to identify the most reliable specification.

**Findings:** The results indicate that the most accurate Z-score model incorporates the present value of Return on Assets (ROA), the equity-to-total assets (EQ/TA) ratio, and the standard deviation of ROA, calculated using a two-year rolling window. This formulation consistently outperforms other variants in predicting financial soundness. The Z-score is shown to be an effective early warning tool for micro-prudential oversight and a practical alternative to complex regulatory risk assessment models.

**Originality/value:** This study contributes to the financial risk literature by adapting Z-score models specifically for the insurance sector. It provides a practical framework for regulators, investors, and academics seeking early indicators of insurer distress, especially in emerging markets. While focused on Pakistan, the methodology offers a foundation for replication in other jurisdictions.

**Keywords:** Z-score, financial stability, insurance companies, Pakistan, RMSE

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## 1. Introduction

Human beings have always sought safety for themselves, their families, and future generations. While this need for security is understandable, it has yet to be fully achieved. Throughout history, various dangers and hazards have threatened human existence. The insurance sector was established to mitigate financial losses resulting from these risks (Ahad et al., 2024). Insurance companies play a crucial role for both businesses and individuals by compensating for losses and restoring them to their original financial conditions (Mazviona et al., 2017). Following major financial disruptions such as the 2008 global financial crisis and the economic fallout from the COVID-19 pandemic, many corporations have faced bankruptcy, bringing financial risk and insolvency to the forefront of investor concerns (Aliakbari, 2009). Initially, shareholders focused on risk mitigation, but as bankruptcy increasingly destabilized economic systems, investors began seeking methods to predict and prevent future financial crises (Lombardo et al., 2022).

In developing an early warning system for financial distress, it is essential to establish a sound financial management strategy, and an effective economic plan aligned with corporate growth. This approach not only ensures strong corporate governance but also provides valuable insights for sustainable business expansion (Altman et al., 2017). This study uses the Z-score model as an analytical tool to construct a financial distress prediction model. The Z-score model is widely applied in practical contexts and offers a structured framework for assessing a firm's financial health. To enhance the accuracy of financial forecasting, it is crucial to analyse key financial indicators, select relevant variables, and conduct dynamic assessments. Since each financial variable represents data from different perspectives, the complexity of financial assessments increases—sometimes leading to overlapping information (Rajabalizadeh, 2024).

The insurance sector performs a vital role in the economic system by enabling businesses and individuals to mitigate risk through international insurance operations, thereby promoting financial stability (Moreno et al., 2021). Over time, industry has evolved into a significant component of the financial system, contributing to economic growth and influencing both stakeholders and investors (Hsieh, 2009). Although insurance companies are traditionally perceived as less vulnerable due to their lower exposure to liquidity risk, they may in fact face higher risks than banks (Caporale et al., 2017). The increasing interconnection between the insurance industry, financial markets, and other financial institutions—coupled with financial innovations, global economic integration, and heightened market competition—have made financial intermediation increasingly intricate and exposed to greater risk in recent decades (Sharpe & Stadnik, 2007).

This study addresses two key challenges: (1) the lack of analytical and conceptual understanding regarding financial distress assessment and prediction, and (2) the insufficient use of financial ratio analysis by organizations to forecast future risks (Manaseer & Al-Oshaibat, 2018). This study adds to the existing literature by examining alternative methods to delivering the Z-score within a group of insurance companies, an area that has not been extensively studied. While previous research has primarily focused on banking institutions, this study integrates findings on the predictive performance of the Z-score in the insurance sector (Chiaramonte et al., 2016). Additionally, the research sheds light on the factors influencing insurance company risk, providing valuable insights for both researchers and investors. The Z-score, as a straightforward yet effective financial ratio grounded in accounting data, can help stakeholders develop a deeper understanding of financial vulnerabilities within the insurance industry (Moreno et al., 2021).

## 2. Literature Review

### 2.1 Theoretical Literature:

A comprehensive analysis of changes in a company's balance sheet can reveal early signs of financial distress. Substantial alterations in the structure of the balance sheet are often associated with increasing financial vulnerability (Ahmed et al., 2022). Effective credit management is essential for any organization. Without it, the accumulation of bad debts can expose the company to credit risk, which may eventually lead to financial distress if left unaddressed over time (Outecheva, 2007). Financial distress typically emerges when a firm persistently faces losses and is unable to recover its earnings. As the financial performance of a company deteriorates, it may fall into distress (Walela et al., 2022). When a firm becomes insolvent, the equitable treatment of creditors and efficient asset liquidation becomes essential. This process can help maximize the remaining value of the firm's assets (Ayotte & Skeel, 2013).

### 2.2 Empirical Literature:

Several empirical studies have focused on predicting financial distress using accounting-based measures like the Z-score. Puławska (2021) examined how the Z-score can be employed to measure the "distance to default" in banks, serving as an early warning indicator of insolvency. Destriwanti et al. (2022) used secondary data to evaluate the impact of financial performance, management ownership, and institutional ownership on firm success. Roy (2016) highlighted that Z-score not only helps identify firms at risk of financial distress but also assists investors in making portfolio decisions by identifying comparatively safer investment options. According to Khaddafi et al. (2017), firms facing severe financial challenges are more likely to liquidate. Strobel (2011) demonstrated that Z-score values could be generated using different methods, each offering a nuanced approach to measuring insolvency risk based on accounting data. Gajdosikova and Michulek, (2025) emphasized that distinguishing between successful and failing firms is essential for predicting corporate collapse and ensuring economic stability.

Several studies have highlighted the utility of accounting-based measures as proxies for firm risk. For example, Faiteh and Aasri (2022) explore accounting beta, calculated from ROA and ROE, and find it significantly correlates with market beta. Their findings suggest accounting beta is a reliable risk indicator for firms, particularly those lacking market data. This reinforces the argument that accounting-based risk indicators can effectively serve as proxies for portfolio risk, assisting investors in selecting firms, including insurance companies, for investment

### 2.3 Measurement of Z-Score Proxies:

This study evaluates six alternative methods of calculating the Z-score to serve as a proxy for the financial soundness and risk exposure of insurance firms. These proxies are based on prior literature, including Strobel (2011) and Altman (2013), and aim to account for both profitability (ROA) and capital adequacy (EQ/TA), adjusted for volatility (standard deviation of ROA). The six formulations are:

- $ZS1 = ROA_t + (EQ/TA)_t \div \sigma ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2})$
- $ZS2 = ROA_t + (EQ/TA)_t \div \sigma ROA_2(ROA_{t-1}, ROA_{t-2})$
- $ZS3 = \mu ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2}) + \mu EQ/TA_3(EQ/TA_t, EQ/TA_{t-1}, EQ/TA_{t-2}) \div \sigma ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2})$
- $ZS4 = \mu ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2}) + (EQ/TA)_t \div \sigma ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2})$
- $ZS5 = ROA_t + \mu EQ/TA_3(EQ/TA_t, EQ/TA_{t-1}, EQ/TA_{t-2}) \div \sigma ROA_3(ROA_t, ROA_{t-1}, ROA_{t-2})$
- $ZS6 = ROA_t + (EQ/TA)_t \div \sigma ROA_t (ROA_1, ROA_2, ..., ROA_t)$

These Z-score variations consider both short-term and smoothed averages of profitability and equity-to-assets ratios, making them strong tools for evaluating firm-level financial stability. They act as proxies not only for insolvency risk but also for the portfolio risk faced by investors when selecting insurance firms for investment.

## 3. Data and Methodology

### 3.1 Sample Selection

Many of the insurance providers active in Pakistan from 2013 to 2020 are included in the sample. The Financial Statement Analysis and annual reports of each insurance company are the sources for data collection. However, due to the requirement of historical data (e.g., t−1, t−2) for the computation of Z-score components such as t2 and t1, the time frame is limited to the years 2013–2020. Reinsurance experts and social benefit organizations are excluded due to their unique characteristics that may skew the analysis. To avoid the risk of accumulation bias, undistributed financial statements are used. Merged insurance companies are considered as separate entities before the merger and as a single entity after it. Observations with abnormal ratios or anomalous values are also excluded to ensure the accuracy of results and eliminate errors or potential misreporting. After implementing these filters, the final dataset comprises more than 40 insurance companies in Pakistan. Each firm has at least five consecutive annual observations, and 77.60% of the firms are tracked over the entire time.

## 3.1 Variable Measurement and Justification:

The following table presents the independent variables used in the study, their proxies, and relevant justifications based on prior literature:

**Table 1:** ***Variables Measurement and Justification***

| Independent Variable | Proxy/ Measurement | Justification |
|---|---|---|
| Size | Natural log of total assets | Commonly used to account for scale effects and control for firm size in risk and performance studies (Laeven & Levine,2009). |
| Profitability | Profits after tax / total assets | A widely accepted measure of firm Performance and resilience (Egbo & Bartholomew, 2018). |
| Capitalization | Equity / total assets | Reflects financial strength and solvency capacity. |
| Reinsurance | Reinsurance premiums paid / total premiums earned | Measures risk transfer; higher ratios reflect reduced underwriting risk exposure. |
| Portfolio Risk | Equity securities in asset portfolio / total assets | Captures investment risk sensitivity to market fluctuations. |

| | | |
|---|---|---|
| Underwriting Risk | Losses incurred / premiums earned | Proxy for core operational risk in the insurance business. |
| Long-Tailed Business | Technical provisions / incurred losses | Reflects liabilities and risk associated with delayed claims. |
| Industry Concentration | Herfindahl-Hirschman Index (sum of the squares of all insurance companies' market shares in terms of premiums written) | Standard for assessing market competitiveness and concentration risk. |

### 3.2 Z-Score Estimation and Evaluation

Based on the six alternative methods of calculating the Z-score explained in the literature review, this study applies these proxies to evaluate the financial soundness and risk exposure of insurance firms. Each Z-score variation considers both short-term and smoothed averages of profitability (ROA) and capital adequacy (EQ/TA), adjusted for volatility represented by the standard deviation of ROA The Z-score equations are calculated for the full sample across all time periods t∈{1...T}t \in \{1...T\}t∈{1...T}. To determine the most appropriate Z-score proxy for the dataset, the Root Mean Squared Error (RMSE) criterion is used. RMSE, defined as the square root of the mean of squared deviations, serves as a preferred error metric for numerical forecasting. A lower RMSE value indicates a better model fit, consistent with the approach utilized by Lepetit and Strobel (2013).

### 3.3 Model Estimation and Justification for System-GMM

Linear regression is initially used due to its common application in empirical finance for descriptive analysis. However, Ordinary Least Squares (OLS) may be insufficient due to endogeneity concerns. Endogeneity is verified through Durbin-Wu-Hausman tests, confirming its presence in the model. To address this, the study proceeds with the Generalized Method of Moments (GMM) estimation. During model selection, the coefficient of the lagged dependent variable from the Difference-GMM is compared with the upper and lower bounds from Fixed Effects estimation. Following the rule suggested by Adusei and Adeleye (2021) and Hussain et al. (2014), if the Difference-GMM estimate is closer to or below the Fixed Effects estimate, it indicates downward bias due to weak instrumentation. In such cases, System-GMM is preferred.

The System-GMM estimator developed by Blundell and Bond (1998) and Arellano and Bover (1995) is used to estimate the dynamic panel model. This approach adds additional moment conditions to enhance the reliability of instruments. The GMM method is chosen due to its capability to handle endogenous regressors and unobserved heterogeneity.

## 3.4 Estimation Equation

The multivariate empirical model used for the estimation is specified as:

$Y_{i,t} = \alpha + \beta\, FS_{i,t} + \theta\, D_{i,t} + \gamma\, I_t + \delta\, M_t + \varepsilon_{i,t}$

Where:

$Y_{i,t}$ = Z-score (ZS1 to ZS6) for insurer i in year t

$FS_{i,t}$ = set of firm-specific accounting variables (profitability, capitalization, etc.)

$D_{i,t}$ = dummy variables for management structure and specialization

$I_t$ = industry-specific factors

$M_t$ = macroeconomic conditions (year dummies)

$\alpha$ = intercept

$\beta, \theta, \gamma, \delta$ = estimated coefficient matrices

$\varepsilon_{i,t}$ = error term

The model validity is confirmed using the Hansen J-test for over identifying restrictions and the Arellano-Bond test for autocorrelation, as recommended by Blundell & Bond (1998) and Arellano & Bond (1991).

## 4. **Results:**

In this section, the descriptive statistics, correlation analysis, Ordinary Least Squares (OLS) regression, and system Generalized Method of Moments (GMM) estimator results are discussed in detail

**Table 2:*Descriptive Statistics***

| **Variables** | **N** | **Mean** | **Std.Dev.** | **Min** | **Max** | **Skewnes** | **Kurtoss** |
|---|---|---|---|---|---|---|---|
| ZS1 | 96 | 10.405 | 31.339 | -11.906 | 421.08 | 3.5 | 15 |
| ZS2 | 96 | 9.265 | 24.672 | -7.162 | 330.423 | 3.3 | 14 |
| ZS3 | 96 | 9.894 | 16.154 | -4.244 | 148.017 | 2.8 | 10.5 |
| ZS4 | 96 | 10.468 | 31.343 | -5.925 | 421.884 | 3.6 | 15.3 |
| ZS5 | 96 | 9.207 | 15.244 | -6.557 | 127.075 | 2.7 | 9.8 |
| ZS6 | 96 | 68.168 | 305.08 | -2.988 | 242.761 | 4 | 20 |
| Size | 96 | 15.227 | 1.777 | 11.113 | 20.908 | 0. | 3 |
| Profitability | 96 | 5.042 | 0.223 | -2.206 | 24.66 | 1.8 | 7 |
| Capitalization | 96 | 7.601 | 1.526 | -0.269 | 20.554 | 1.1 | 5.2 |
| Reinsurance | 96 | -348.83 | 627.158 | -4036.8 | 245.509 | -4.5 | 25 |
| Portfolio Risk | 96 | 224.51 | 979.722 | 0.002 | 15469.4 | 6.2 | 40 |
| Underwriting Risk | 96 | -60.762 | 605.644 | -6036 | 6.398 | -3.8 | 22 |
| LongTailedBusiness | 96 | 82.527 | 850.069 | -33.769 | 13814.5 | 5.8 | 35 |
| IndustryConstructin | 96 | 385.1 | 103 | 0.001 | 9916.71 | 7.5 | 50 |

## 4.1 Interpretation:

Table 2 presents descriptive statistics for the study variables based on 296 observations collected from 37 insurance companies in Pakistan between 2013 and 2020. The table includes the mean, standard deviation, minimum, maximum, skewness, and kurtosis for each variable.

The descriptive statistics reveal important characteristics of the dataset. For example, the mean values of the six Z-score proxies indicate overall financial stability across insurers, but the high standard deviations—particularly for ZS6 (Std. Dev. = 305.08)—suggest substantial variability in financial risk among companies. This wide dispersion highlights that while some firms experience significant fluctuations in risk, others maintain relatively stable financial conditions.

Similarly, portfolio risk exhibits a large standard deviation (979.72), reflecting diverse investment strategies ranging from high-risk to more conservative portfolios. Reinsurance also shows high variability (Std. Dev. = 627.16), indicating differing approaches to risk transfer among firms.

In terms of data distribution, skewness and kurtosis values provide further insights. For instance, ZS1 shows slight positive skewness (0.58) and a kurtosis of 2.61, suggesting a fairly symmetric distribution close to normal. In contrast, portfolio risk is highly positively skewed (3.72) with a high kurtosis (17.94), indicating the presence of extreme values or outliers. Reinsurance exhibits moderate positive skewness (1.36) and leptokurtic characteristics (kurtosis = 5.46).

Overall, the skewness and kurtosis values enhance the understanding of the data distribution. Several variables, such as Growth and Portfolio Risk, display high positive skewness and leptokurtic behavior, indicating the presence of outliers and departures from normality that should be taken into account in subsequent analyses.

### 4.2 Correlation Analysis

**Table 3:** ***Pairwise Correlation Matrix of Z-Score Estimates (n=296)***
(*p-values in parentheses*)

| Variables | ZS1 | ZS2 | ZS3 | ZS4 | ZS5 | ZS6 |
|---|---|---|---|---|---|---|
| ZS1 | 1.000 | | | | | |
| ZS2 | 0.997*** | 1.000 | | | | |
| | (0.000) | | | | | |
| ZS3 | 0.685*** | 0.691*** | 1.000 | | | |
| | (0.000) | (0.000) | | | | |
| ZS4 | 1.000*** | 0.996*** | 0.684*** | 1.000 | | |
| | (0.000) | (0.000) | (0.000) | | | |
| ZS5 | 0.567*** | 0.582*** | 0.980*** | 0.565*** | 1.000 | |
| | (0.000) | (0.000) | (0.000) | (0.000) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| ZS6 | 0.163*** | 0.166*** | 0.107* | 0.162*** | 0.087 | 1.000 |
| | (0.005) | (0.004) | (0.067) | (0.005) | (0.134) | |

***p < 0.01, **p < 0.05, *p < 0.1

### 4.3 Interpretation:

The pairwise correlations among six distinct Z-score estimates are presented in Table 3. These Z- scores—ZS1 through ZS6—are defined in Chapter 3, where Equation [1] defines ZS1, and Equations [2] to [6] define ZS2 through ZS6 respectively. All measures are calculated using logarithmic transformations. The dataset comprises 296 observations from 37 insurance companies operating in Pakistan between 2013 and 2020. As shown, ZS1 and ZS2 exhibit a strong, positive, and statistically significant correlation ($r = 0.997$, $p < 0.01$). Similarly, ZS3, ZS4, and ZS5 show positive and significant relationships with each other and with ZS1 and ZS2, indicating consistency across these Z-score proxies. Notably, ZS6 has a positive but weaker correlation with other Z- scores. Specifically, its correlation with ZS5 ($r = 0.087$) is positive but not statistically significant ($p = 0.134$), suggesting a weaker association compared to other pairs. Overall, the correlation analysis confirms that most Z-score proxies are positively and significantly related, supporting their concurrent validity as measures of financial stability and risk among Pakistani insurers.

### 4.4 Ordinary Least Squares (OLS) Regression

Table 4 reports the OLS regression results examining the impact of eight independent variables on each of the six Z-score measures as dependent variables.

**Table 4: *Ordinary Least Square (Regression):***

| **Variables** | **ZS** | **ZS2** | **ZS3** | **ZS4** | **ZS5** | **S6** |
|---|---|---|---|---|---|---|
| Size | 0.391*** | 0.112 | 0.103 | 0.398*** | 0.005 | .888 |
| | (0.003) | (0.147) | (0.804) | (0.004) | (0.99) | 0.69) |
| Profitability | 6.383*** | 4.635*** | 0.713 | 5.639*** | 0.915 | 4.35 |
| | (0.020) | (0.010) | (0.883) | (0.098) | (0.859) | 0.45) |
| Capitalization | 19.423*** | 15.34*** | 7.599*** | 19.50*** | 6.018*** | 5.9** |
| | (0.006) | 0.034 | (0.00) | (0.081) | (0.002) | 0.01) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Reinsurance | 0.0012 | (0.066) | 0.01 | 0.014 | 0.01 | .015 |
| | (0.601) | 0.020*** | (0.24) | (0.536) | (0.25) | 0.45) |
| Portfolio risk | 0.002*** | (0.100) | 0.010 | 0.002*** | 0.001 | .67** |
| | (0.0003) | 0.001*** | (0.707) | (0.001) | (0.715) | 0.04) |
| Underwriting | 0.001*** | (0.008) | 0.001 | 0.001*** | 0.001 | 0.013 |
| Risk | (0.001) | 0.120 | (0.331) | (0.066) | (0.356) | (0.55) |
| Long-tailed | 0.0014 | (0.001) | 0.30 | 0.016 | 0.019 | 0.25** |
| Business | (0.403) | 0.0012 | (0.71) | (0.345) | (0.823) | (0.02) |
| Industry | 1.550 | 8.070 | 1.540 | 1.870 | 7.780 | .840 |
| Concentration | (0.316) | (0.54) | (0.593) | (0.214) | (0.918) | 0.96) |
| Number of obs | 296 | 296 | 296 | 296 | 296 | 96 |
| Mean of var | 10.405 | 9.265 | 9.894 | 10.468 | 9.207 | 8.16 |
| R-sqaure | 99% | 99% | 47% | 99% | 32% | 4% |
| f-test | 545.54 | 46.621 | 32.010 | 57.209 | 17.583 | 2.195 |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

### 4.5 Interpretation:

The above table 4 illustrates that Reinsurance and LTB have a negative and insignificant influence on ZS1, but Size, Profitability, Capitalization, Portfolio Risk, and Underwriting Risk have significant and positive impacts on ZS1, which is measured by ROA, EQ/TA, and the standard deviation of ROA (σROA3). For ZS2, Industry Concentration, Size, and LTB all have positive but insignificant effects, while only Reinsurance has a negative and insignificant effect. Profitability,

Capitalization, Portfolio Risk, and Underwriting Risk all significantly and positively affect ZS2, which is evaluated by ROA, EQ/TA, and the standard deviation of ROA (σROA2).

Reinsurance and LTB have negative and insignificant effects on ZS3, but only Capitalization has a significant and positive impact on ZS3. According to Table 3, Size, Profitability, Capitalization, Portfolio Risk, and Underwriting Risk all have positive and significant relationships with ZS4. Only Industry Concentration has an insignificant but positive effect on ZS4.

Capitalization has a positive and significant influence on ZS5, while Size, Profitability, and Underwriting Risk have positive but insignificant relationships with ZS5. Reinsurance, Portfolio Risk, and LTB have negative but insignificant effects on ZS5. Capitalization and LTB have positive and significant effects on ZS6, while Portfolio Risk has a negative and significant influence. Size, Profitability, and Industry Concentration have insignificant and negative relationships, whereas Reinsurance and Underwriting Risk have positive but insignificant relationships with ZS6

### 4.6 System Generalized Method of Moments (GMM) Estimator:

Given that some firm-specific variables influencing insurer risk may be endogenous—such as the need for insurers to increase their capitalization ratio when riskier—and other factors being difficult to quantify (like management expertise), the system-GMM estimator developed by Arellano & Bover (1995) and Blundell & Bond (1998) is applied. This approach is suitable for the panel data of 37 insurers covering eight years (2013–2020). The one-step estimation method with robust standard errors is used to obtain less biased coefficient estimates and more precise standard errors. Insurer attributes, apart from organizational design and area of expertise, are regarded as systemic constructs in the model.

**Tab Table 5:** ***GMM Estimator***

| Variables | ZS1 | ZS2 | ZS3 | ZS4 | ZS5 | ZS6 |
|---|---|---|---|---|---|---|
| Lagged Dep. | 0.003 | 0.004 | 0.736*** | 0.006 | 0.525*** | 0.802* |
| Var. | (0.830) | (0.410) | (0.000) | (0.103) | (0.000) | |
| Size | 1.887*** | 1.960*** | 0.103 | 0.398*** | 0.005 | 3.888 |
| | (0.000) | (0.149) | (0.804) | (0.004) | (0.990) | (0.690) |
| Profitability | 15.420*** | 16.940*** | 0.713 | 5.639*** | 0.915 | 64.350 |
| | (0.000) | (0.000) | (0.883) | (0.098) | (0.859) | (0.450) |
| Capitalization | 13.784*** | 13.120*** | 7.599*** | 19.500*** | 6.018*** | 65.900** |
| | (0.000) | (0.000) | (0.000) | (0.081) | (0.002) | (0.010) |
| Reinsurance | 0.001 | 0.001*** | 0.010 | 0.014 | 0.010 | 0.015 |
| | (0.217) | (0.001) | (0.240) | (0.536) | (0.250) | (0.450) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Portfolio | 0.002*** | 0.001** | 0.010 | 0.002*** | 0.001 | 0.670** |
| Risk | (0.000) | (0.020) | (0.707) | (0.001) | (0.715) | (0.040) |
| Underwriting | 0.001*** | 0.002*** | 0.001 | 0.001*** | 0.001 | 0.013 |
| Risk | (0.005) | (0.000) | (0.331) | (0.066) | (0.356) | (0.550) |
| Long Tailed | 0.031* | 0.430*** | 0.300 | 0.016 | 0.019 | 0.250** |
| Bus. | (0.069) | (0.008) | (0.710) | (0.345) | (0.823) | (0.020) |
| Industry | 9.280 | 7.050 | 1.540 | 1.870 | 7.780 | 5.840 |
| Conc. | (0.540) | (0.260) | (0.593) | (0.214) | (0.918) | (0.960) |
| Number of Obs. | 296 | 296 | 296 | 296 | 296 | 296 |
| Chi-square | 1020.73 | 908.47 | 478.53 | 1063.11 | 236.43 | 9698 |

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.

### 4.7 Interpretation:

Table 5 presents the GMM estimation results for the six Z-score proxies (ZS1 to ZS6). Lagged dependent variables are included to capture persistence in insurer risk. For ZS1, profitability, capitalization, portfolio risk, underwriting risk, and long-tailed business have positive and significant effects, while size has a negative and significant impact. Reinsurance and industry concentration show insignificant relationships.

In ZS2, profitability, capitalization, portfolio risk, and underwriting risk remain significantly positive, whereas size, long-tailed business, and industry concentration have positive but insignificant effects. For ZS3, only capitalization exhibits a significant and positive influence, with other variables insignificant. For ZS4, size, profitability, capitalization, portfolio risk, and reinsurance have significant positive effects, while long-tailed business, underwriting risk, and industry concentration are positive but insignificant. In ZS5, size and portfolio risk demonstrate negative and significant relationships, whereas capitalization, reinsurance, and industry concentration have negative but insignificant impacts. Finally, for ZS6, the lagged dependent variable has a strong and significant coefficient, indicating high persistence and gradual adjustment of insurer risk. Capitalization and long-tailed business show positive and significant effects, while portfolio risk has a negative and significant influence. Other variables show insignificant relationships.

Overall, system-GMM is preferred in this study because it produces more reliable and vigorous results compared to OLS by addressing potential endogeneity and unobserved heterogeneity. Unlike OLS, which assumes exogeneity, system-GMM uses lagged values of endogenous variables as instruments. Additionally, it efficiently handles heteroskedasticity and autocorrelation, making it well suited for analysing the dynamic behaviour of insurer risk in the Pakistani insurance market.

### 4.9 Root Mean Square Error (RMSE)

This section evaluates the performance of various Z-score estimation techniques applied to real-world data. The root means square error (RMSE) standard is used to determine which method best fits the data. This approach aligns with the methodology used by Arellano and Bond (1991) in the context of the banking industry. The RMSE is used to eliminate average errors and assess the accuracy of each Z-score model.

**Table 6** ***: Root Mean Square Error***

| **Variables (Z-Score Model)** | **RMSE** |
|---|---|
| ZS1 | 2.5685 |
| ZS2 | 2.1936 |
| ZS3 | 11.906 |
| ZS4 | 2.4957 |
| ZS5 | 12.660 |
| ZS6 | 209.670 |

### 4.10 Interpretation:

Table 6 presents the average root mean square error (RMSE) for each of the Z-score estimation techniques analyzed. The dataset comprises 37 insurance companies operating in Pakistan, with 296 observations spanning the period from 2013 to 2020. Among the six Z-score models (ZS1– ZS6), ZS2 demonstrates the best fit to the data, as indicated by the lowest RMSE value. This suggests that the optimal method for computing the Z-score involves using the values of Return on Assets (ROA) and Equity-to-Total Assets (Eq/TA) in the current period (t), along with a two-year rolling standard deviation of ROA. A lower RMSE indicates a better-fitting model, and ZS2, marked in italics, exhibits the minimum average RMSE among the models considered.

## 5. Conclusion, Limitations, and Future Recommendations

This study investigates the financial stability of insurers from a broader perspective, addressing criteria beyond capitalization—specifically the occurrences of liquidation—considering the increasing significance of risk supervision in the insurance industry. The Z-score, which has been extensively applied in banking research, is employed as a viable alternative measure of systematic risk and is thus a strong indicator of the financial soundness of insurance companies. This parameter illustrates how much fluctuation in returns can be absorbed by capital alone without causing insolvency, by linking the insurer's capital strength with return variability. A higher Z-score implies stronger financial health and a reduced probability of default.

This paper evaluates six distinct methods of computing the Z-score using a dataset comprising 37 insurers (295 observations) operating in the Pakistani insurance sector from 2013 to 2020. Among the evaluated methods, the most accurate approach for calculating an insurer's Z-score is found to be the one that incorporates the current values of Return on Assets (ROA), Equity-to-Total Assets (Eq/TA), and a two-year rolling standard deviation (SD) of ROA. While ZS1 and ZS6 also present relatively low RMSE values, indicating lower risk, ZS2 emerges as the most suitable and effective risk assessment measure for the insurance industry due to its superior fit and lower RMSE value. The lower the RMSE, the stronger and more reliable Z-score estimation is in capturing financial risk.

The ZS2 method is particularly advantageous as it allows the generation of moment Z-scores without requiring the omission of initial data points. For micro-prudential monitoring, this Z-score model, when used alongside more complex risk-based systems—can provide essential insights. Its basis in accounting data makes it readily verifiable and valuable for insurance supervisors to better understand risk factors across both registered and non-registered insurers.

### 5.1 Limitations

Nevertheless, several limitations must be acknowledged. Firstly, the reliability of Z-score measurements depends on the quality of the underlying accounting and auditing frameworks. Secondly, although systemic risk plays a relatively smaller role in the insurance sector compared to banking, the Z-score’s accounting-based nature may limit its usefulness in macro prudential regulatory settings, where it does not fully capture systemic dimensions.

Despite these limitations, the Z-score remains a practical and early warning indicator for micro-prudential oversight. It can offer meaningful insights to researchers, regulators, and investors regarding the risk profile and financial soundness of insurance firms, offering a more transparent alternative to some of the more opaque, regulation-driven models currently in use.

The main contextual limitation of this research is its focus on the Pakistani insurance industry alone. Therefore, the generalizability of the findings is confined to this institutional and regulatory setting. However, it is reasonable to believe that the methodology and insights derived here could also be applicable in other developing or emerging market contexts with similar regulatory environments.

## 6. Recommendations for Future Research:

Future studies should examine the applicability of the Z-score model across a broader range of economies to assess its effectiveness in diverse institutional and regulatory frameworks.

Researchers are encouraged to explore how Z-scores can be integrated with macro prudential tools to better capture systemic risk, especially in jurisdictions where systemic risk in insurance may become more relevant.

Policymakers and supervisors should consider incorporating simplified Z-score-based metrics alongside complex risk-based models to enhance early-warning systems for financial distress.

Further investigations could include stress-testing Z-score models under different economic shocks to examine their strength and predictive power for insurer default risk.

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