Does Enterprise Risk Management Enhance Insurers' Resilience? Empirical Evidence from the COVID-19 Pandemic Period

AUGUST | 2024

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Executive Summary

This empirical study examines the impact of the COVID-19 pandemic on insurers and investigates whether insurers with more sophisticated Enterprise Risk Management (ERM) frameworks have suffered fewer losses compared to those with less sophisticated frameworks. The study fills a gap in the existing literature by exploring the relationship between ERM sophistication and insurers' resilience during the pandemic.

Using a hierarchical linear model and an ERM score to measure the sophistication of insurers' ERM frameworks, the study analyzes financial data from listed insurers worldwide from 2017 to 2022. The findings reveal that insurers operating in jurisdictions with a severe pandemic impact experience lower Return on Equity (ROE) and Return on Assets (ROA) compared to insurers in jurisdictions with a milder impact. On average, insurers suffer a decline of 1.69% in ROE and 0.3% in ROA due to the pandemic.

However, the study demonstrates that a sophisticated ERM framework significantly mitigates the adverse effects of the pandemic. Insurers with sophisticated ERM frameworks experience a decrease of 1.4% and 0.3% in ROE and ROA, respectively, while insurers with less sophisticated ERM frameworks experience a decrease of 2.1% and 0.4% in ROE and ROA, respectively. These findings provide empirical evidence supporting the notion that implementing a sophisticated ERM framework enhances insurers' resilience during the pandemic period.

This study contributes to the understanding of the value of ERM in the insurance industry and provides insights that can inform insurers' risk management practices. By implementing sophisticated ERM frameworks, insurers can potentially reduce losses from future pandemics. Regulators can also benefit from this research by assessing the adequacy of insurers' pandemic reserves and promoting the implementation of sophisticated ERM frameworks.

Section 1: Introduction

ERM is a comprehensive approach to managing risk at the organizational level. Rather than relying on separate risk management processes within individual business units, ERM seeks to integrate all processes and activities across the entire firm's risk management system. This holistic approach allows organizations to identify and address risks in a more coordinated and strategic manner.

The adoption of ERM has been encouraged by regulatory bodies around the world. In 2011, the International Association of Insurance Supervisors (IAIS) introduced the Insurance Core Principle 16, which requires regulators to establish ERM requirements for insurers (IAIS, 2011). This recognition of the importance of ERM in the insurance industry has led to a widespread implementation of ERM practices by insurers globally. However, the level of sophistication in implementing ERM varies among insurers. Some organizations have fully embraced ERM and have integrated it into their decision-making processes and strategic planning. These organizations recognize the value of ERM in enhancing their risk management capabilities and improving overall performance. On the other hand, there are insurers that have only implemented ERM at a basic level, focusing primarily on compliance with regulatory requirements. These organizations may not fully appreciate the potential benefits of ERM beyond regulatory compliance and may not have fully integrated ERM into their business operations.

The effectiveness of ERM has been the subject of numerous studies since the early 2010s. One of the pioneering studies in this area provided evidence that implementing ERM enhances the firm value of U.S. insurers (Hoyt and Liebenberg, 2011). Since then, researchers have conducted studies to highlight various advantages of adopting ERM practices. For instance, Baxter et al. (2013) found that insurers with ERM frameworks experienced increased stock returns following a financial crisis. Malik et al. (2020) demonstrated that implementing ERM leads to improved firm performance. Perez-Cornejo et al. (2019) explored the link between ERM and corporate reputation, revealing that ERM implementation can enhance a firm's reputation. Eckles et al. (2014) discovered that insurers with ERM frameworks have a decreased cost of risk reduction. Lundqvist and Vilhelmsson (2018) found that ERM implementation is associated with a decreased default risk. Berry-Stolzle and Xu (2018) investigated the impact of ERM on the cost of capital, revealing a decrease for insurers with ERM frameworks. Sax and Andersen (2019) examined the relationship between ERM and financial leverage, finding that ERM implementation is associated with decreased financial leverage.

Despite the emerging consensus on the benefits of ERM, there is a dearth of empirical studies examining whether insurers with more sophisticated ERM frameworks have suffered fewer losses during the pandemic compared to those with less sophisticated frameworks. Anton and Nucu (2020), in their comprehensive review of hundreds of studies and articles on ERM, also did not identify any prior research on the effect of ERM on insurers' resilience. Therefore, this study aims to fill this gap by leveraging the exogenous shock caused by the pandemic to determine whether insurers with more sophisticated ERM frameworks have been more resilient to the adverse effects of the pandemic.

This study answers the following two research questions.

1. What has been the impact of the pandemic on insurers?
2. Have insurers with more sophisticated ERM frameworks suffered fewer pandemic-related losses than insurers with less sophisticated ERM frameworks?

These are timely and important questions. First, many analysts conclude that the pandemic has substantially increased insurers’ claim payments, dampened demand for new insurance policies, and generated investment losses for the portfolios held by insurers. The total losses to the worldwide insurance industry are estimated to be US$40–$60 billion (Sheehan, 2021), although no empirical evidence is provided to support this estimation. In addition, insurers have been able to mitigate the adverse impacts of the pandemic on their financial positions by increasing premium rates, decreasing shareholder dividends and discretionary policyholder profit-sharing, delaying share buy-backs, and adding pandemic exclusions to new insurance policies. Hence, the extent to which the pandemic has affected insurers' financial position is primarily an empirical question. Understanding the financial impact of the pandemic will help insurers to accurately price pandemic risk into their insurance products in the future and regulators to assess the adequacy of pandemic reserves set aside by insurers. Second, regulators worldwide generally agree that ERM is value-adding for insurers and have thus over the past decade been encouraging insurers to implement sophisticated ERM frameworks. Although previous studies focus on various advantages of ERM, none address how the level of sophistication of insurers' ERM frameworks has affected their resilience against the adverse effects of the pandemic. This study provides key new insights into the value of a sophisticated ERM framework and thereby lead to a broadening in the implementation of such frameworks by the industry, which may reduce insurers' losses from future pandemics.

In this study, empirical analysis was conducted using the hierarchical linear model and constructed an ERM score to measure the sophistication of insurers' ERM frameworks. The analysis focused on listed insurers worldwide from 2017 to 2022, utilizing financial data from the Thomson Reuters Datastream. The hierarchical linear model allowed an account for potential nesting effects, considering that insurers within the same country may exhibit more similarities than those from different countries. The model also incorporates controls for several factors that may influence performance, including leverage, insurer size, liquidity, market share, business diversification, and the type of insurance business. The findings of the study confirm that insurers operating in jurisdictions with a severe pandemic impact experience lower ROE and ROA compared to insurers in jurisdictions with a mild impact. On average, insurers suffer a decline of 1.7% in ROE and 0.3% in ROA due to the pandemic. However, the study also reveals that a sophisticated ERM framework substantially mitigates the adverse effects of the pandemic. The model also incorporates controls for several factors that may influence performance, including leverage, insurer size, liquidity, market share, business diversification, and the type of insurance business. In summary, this study provides empirical evidence supporting the notion that implementing a sophisticated ERM framework enhances the resilience of insurers during the pandemic period.

The remainder of this report is organized as follows. The hypothesis development is presented in section 2. The data, baseline empirical model, and choice of variables are discussed in section 3. Section 4 presents our empirical results and section 5 concludes the study.

Section 2: Hypothesis Development

The worldwide spread of COVID-19 since the beginning of 2020 has had a significant impact on the business of both life and health insurers, as well as property and casualty insurers. The effects of the pandemic have been far-reaching and have affected these insurers in various ways.

Life and health insurers, in particular, have faced challenges due to the substantial increase in medical and death claims. The pandemic has led to a surge in healthcare expenses, resulting in decreased profitability for these insurers. The higher number of claims has put a strain on their financial resources and has required them to allocate more funds towards fulfilling these claims. Furthermore, the pandemic has caused economic hardships, including rising unemployment rates, and falling incomes. This has led to a decrease in the demand for life insurance policies that include savings elements. With individuals facing financial difficulties, the priority for many has shifted towards meeting immediate needs rather than investing in long-term savings plans.

On the other hand, property and casualty insurers have also been impacted by the pandemic. They have experienced a substantial increase in event cancellation claims due to the postponement or cancellation of large-scale events such as the Tokyo Olympics, the Wimbledon tennis tournament, and numerous concerts. These insurers have had to bear the financial burden of reimbursing organizers for the losses incurred from these cancellations. Additionally, the measures taken to prevent the spread of the virus, such as lockdowns and restrictions on economic activities, have led to a reduced demand for various types of property and casualty insurance. Trade credit insurance, for example, has seen a decrease in demand as businesses face uncertainties and potential defaults. Travel insurance has also been affected as travel restrictions and concerns over safety have led to a decline in travel plans. Similarly, marine insurance has experienced reduced demand as global trade and shipping activities have been impacted by the pandemic.

In addition to the challenges faced by insurers due to the pandemic, they have also implemented various management actions to mitigate the adverse effects. One such action is the potential increase in premium rates for new and renewal business. This increase in rates helps insurers compensate for the costs associated with the higher number of pandemic-related claims. By adjusting the rates, insurers aim to maintain their profitability despite the increased claim burden. Insurers may have also introduced exclusions for certain claims in the policy terms of new products. These exclusions are designed to reduce the insurers' exposure to pandemic-related risks. By specifying which claims are not covered, insurers can better manage their liabilities and minimize potential losses associated with the pandemic. Furthermore, insurers have made adjustments in terms of shareholder dividends and policyholder profit sharing. These distributions are typically discretionary and can be reduced or stopped during times of economic downturn, such as the one caused by the pandemic. By conserving these funds, insurers have more flexibility in deploying resources to cope with the challenges posed by the pandemic. Lastly, insurers with share buyback programs may have postponed or suspended these programs to alleviate their financial burdens. Share buybacks involve repurchasing company shares from shareholders, which can put a strain on the company's finances. By postponing or suspending these programs, insurers can conserve their capital and allocate it towards managing the impacts of the pandemic.

Given these management actions taken by insurers, it is crucial to examine whether the pandemic has had an adverse effect on their operations and financial performance. This leads to the construction of Hypothesis 1, which aims to investigate the potential impact of the pandemic on insurers.

Hypothesis 1: Insurers’ performances have been adversely affected by the pandemic.

The researcher argues that a sophisticated ERM framework alleviates the adverse effects of the pandemic on insurers in several ways. Firstly, insurers with a sophisticated ERM framework can effectively manage risk at the firm level. For example, they can identify the mortality risk associated with their life insurance business and hedge this risk by increasing their exposure to the longevity risk of their annuity business. This means that when these insurers were impacted by the pandemic, they would have experienced increased death claims from their life insurance business but would have also benefited from reduced payouts through their annuity business. As a result, the overall financial positions of these insurers are better compared to those without sophisticated ERM frameworks who fail to hedge against mortality risk at the firm level. This argument is supported by the mortality and longevity risk-hedging strategies proposed by Lin and Tsai (2013).

Secondly, insurers may need to raise capital from the market after depleting their internal funds due to the challenges posed by the pandemic. Insurers with more sophisticated ERM frameworks tend to have better financial ratings and pay lower external financing costs. This is because rating agencies such as Standard & Poor's and A.M. Best explicitly evaluate insurers' ERM in their rating processes. Therefore, insurers with sophisticated ERM frameworks are in a better financial position compared to those with less sophisticated ERM frameworks. This argument aligns with the findings of Berry-Stolzle and Xu (2018) that ERM adoption reduces the cost of capital.

Thirdly, insurers with sophisticated ERM frameworks typically have lower financial leverage compared to insurers with less sophisticated ERM frameworks (Sax and Andersen, 2019). This means that they are less likely to exhaust their internal funds during the pandemic and are also less likely to require costly external capital. ERM enables managers to consider adverse situations with low predictability and high uncertainty. As a result, insurers with more sophisticated ERM frameworks tend to have larger equity cushions to handle unexpected adverse situations. Compared to insurers with less sophisticated ERM frameworks, insurers with more sophisticated ERM frameworks have lower levels of debt, resulting in lower interest expenses. This translates into higher flexibility and responsiveness during economically challenging times, such as those related to the pandemic. This argument is consistent with the findings of Lundqvist and Vilhelmsson (2018) that ERM reduces the volatility of cash flows and default risk.

Based on these arguments, Hypothesis 2 can be constructed as follows:

Hypothesis 2: The performances of insurers with more sophisticated ERM frameworks are less affected by the pandemic than the performances of insurers with less sophisticated ERM frameworks.

Section 3: Data Collection and Empirical Frameworks

3.1 DATA DESCRIPTION

The study focuses on analyzing the performance of listed insurers worldwide during the period of 2017-2022. This time frame covers three years before the pandemic and three years during the pandemic, allowing for a comprehensive examination of the impact of the pandemic on insurers' performance. To ensure the accuracy and relevance of the analysis, only listed insurers classified under the "Life Insurance" and "Nonlife Insurance" categories by Thomson Reuters Datastream (Datastream) are included in the sample. This exclusion of firms outside the insurance industry helps to avoid potential bias caused by market and regulatory differences across industries. In addition, listed insurers that have no financial data available in Datastream and unlisted insurers are not examined in the sample due to the unavailability of their annual statements to the public. This exclusion is necessary as it would be challenging to construct their ERM Score without access to their annual statements. To further analyze the relationship between the ERM and various factors, additional data is collected. Macroeconomic data is obtained from the World Bank, pandemic-related data is sourced from Our World in Data, and insurers' characteristic data is gathered from Datastream. These datasets provide additional insights into the macroeconomic conditions, pandemic impact, and specific characteristics of the insurers. Finally, all the collected datasets are merged. The final sample consists of 2,425 firm-year observations from a total of 413 listed insurers across 62 jurisdictions. This diverse representation allows for a comprehensive analysis of insurers' performance and risk management practices on a global scale.

3.2 MEASURING SOPHISTICATION OF ERM

While most studies adopt one-dimensional proxies for ERM, this study follows Florio and Leoni (2017) to gauge the sophistication of ERM with a multi-dimensional measure that captures the joint effect of various aspects of ERM. Specifically, the ERM score is calculated by considering whether the insurer has designated a chief risk officer and established a risk committee, the frequency of the insurer’s risk assessment and reporting, the depth of the insurer’s risk assessment, and the methodology of the insurer’s risk assessment. The above ERM components are consistent with those stipulated in the ERM framework proposed by the Committee of Sponsoring Organizations of the Treadway Commission (COSO) (COSO, 2017), which is an international organization dedicated to the development of guidance on ERM, internal control, and fraud deterrence. Alternatively, the ERM Score proposed by Florio and Leoni (2017) is calculated by the following formula:

$$\text{ERM Score} = \text{CRO} + \text{Risk Committee} + \text{Frequency of Assessment} + \text{Frequency of Reporting} + \text{Depth of Assessment} + \text{Methodology of Assessment} \tag{1}$$

- *CRO:* This is a dummy variable that equals 1 if the insurer has designated a chief risk officer, and 0 otherwise. Having a dedicated chief risk officer indicates a higher level of commitment to risk management within the organization.

- *Risk Committee*: This is a dummy variable that equals 1 if the insurer has established a risk committee, and 0 otherwise. The presence of a risk committee suggests that the insurer has a formal structure in place to address risk-related issues.

- *Frequency of Assessment:* This is a dummy variable that equals 1 if the insurer performs risk assessments at least twice per year, and 0 otherwise. Regular and frequent assessments indicate a proactive approach to risk management.

- *Frequency of Reporting:* This is a dummy variable that equals 1 if the risk assessment results are reported to the insurer's Board of Directors at least twice per year, and 0 otherwise. Reporting the assessment results to the board ensures transparency and accountability in risk management practices.

- *Depth of Assessment:* This is a dummy variable that equals 1 if the insurer performs risk assessments at both the firm level and business unit level, and 0 otherwise. Assessing risks at multiple levels provides a more comprehensive understanding of the organization's risk profile.

- *Methodology of Assessment:* This is a dummy variable that equals 1 if the insurer performs both qualitative and quantitative risk assessments, and 0 otherwise. Using a combination of qualitative and quantitative methods ensures a more robust and comprehensive evaluation of risks.

As insurers need to disclose their risk management information in financial statements (Maingot et al., 2013), insurers' financial statements from 2017 to 2022 were downloaded and manually extract from these financial statements the information relevant to the six dummy variables in Equation (1). The ERM Score is then manually calculated for each listed insurer during the sample period. Unlike previous studies that rely on one-dimensional ERM proxies that reveal the effects of each ERM component, the multidimensional ERM Score in this study captures the overall effect of ERM.

3.3 EMPIRICAL FRAMEWORKS

To address potential nesting effects, such as insurers within the same country being more similar to each other than to insurers from other countries, a hierarchical linear model is employed as the empirical framework. This modeling approach has been utilized in previous studies within the fields of accounting and finance, such as the works of Li et al. (2013) and Chang et al. (2018). The hierarchical linear model allows for the separation of variation in the dependent variable (in this case, insurer profitability) that is caused by both country-specific and firm-specific independent variables. This is achieved by estimating Equations (2) and (3) using an iterative maximum likelihood algorithm.

Country level: $$\alpha_{jt} = a + \delta COVID_{jt} + \boldsymbol{\beta W_{jt}} + u_{jt} \tag{2}$$

Firm level: $$Profitability_{ijt} = \alpha_{jt} + \lambda \text{Sophisticated ERM framework}_{it} + \boldsymbol{\gamma X_{it}} + e_{ijt} \tag{3}$$

where i, j, and t denote the insurer, country, and time, respectively; $\mathbf{W_{jt}}$ and $\mathbf{X_{it}}$ are vectors of country- and firm-level control variables, respectively; $COVID_{jt}$ is the severity of COVID-19, which is measured by the logarithm of the number of confirmed COVID-19 cases per million people in country j at year t; $Profitability_{ijt}$ is a measure of the performance of insurers, which is gauged by return on equities and return on assets; Sophisticated ERM framework is a dummy variable that equals 1 if the ERM Score is higher than the median of 2; and u_{jt} and e_{ijt} allow the intercept to vary by country and firm, respectively.

The hierarchical linear model generally involves two levels: the firm level and the country level. At the country level, Equation (2) accounts for the impact of country-specific independent variables. At the firm level, Equation (3) captures the relationship between the dependent variable and the firm-specific independent variables. The iterative maximum likelihood algorithm is employed to estimate the model parameters, taking into consideration the hierarchical structure of the data. This algorithm iteratively adjusts the parameter estimates until convergence is achieved, maximizing the likelihood of the observed data given the model.

The estimated value of the coefficient of δ in the hierarchical linear model will provide insights into the impact of the pandemic on insurers' performances. If Hypothesis 1 is supported, indicating that the pandemic has had an adverse effect on insurers' performances, the coefficient δ should be negative and statistically significant. Additionally, the magnitude of the estimated δ will quantify the average impact of the pandemic on insurers' profitability.

To further investigate the relationship between insurers' level of ERM sophistication and the impact of the pandemic on profitability, the samples will be divided into subgroups based on their ERM scores. The hierarchical linear model will be separately performed for each subgroup. If Hypothesis 2 is confirmed, suggesting that insurers with more sophisticated ERM frameworks experience a reduced impact from the pandemic, the estimated value of the coefficient of δ for the low-ERM-Score subgroup should be more negative than that for the high-ERM-Score subgroup.

To control for the effect of country and firm characteristics on insurers' profitability, an extensive literature review was performed on the determinants of profitability and include them as control variables in vectors W_{jt} and X_{it}. This is summarized and explained below.

Country Level Control Variables (W_{jt})

- *Anticipated inflation*: Inflation can have a significant impact on the demand for life insurance. Li et al. (2007) found empirical evidence that high anticipated inflation, as measured by average consumer price changes over 5 years, decreases the demand for life insurance. This is because inflation erodes the purchasing power of life insurance, which is expected to pay benefits decades away. With less insurance consumption, it is expected that insurers earn lower profits. Therefore, anticipated inflation is included as one of the control variables in the analysis to account for its potential influence on insurers' profitability.

- *Gross domestic product (GDP)*: Millo (2016) reports evidence supporting the claim that nonlife insurance is a normal good and that its consumption is associated with GDP. In other words, as GDP increases, the demand for nonlife insurance also tends to increase, which can have a positive impact on insurers' profits. To capture this relationship, the logarithm of GDP is controlled in the empirical model. This control variable helps account for the influence of GDP on insurers' profitability.

Firm Level Control Variables (X_{it})

- *Leverage*: Insurers' insolvency risk can impact their profitability. When insurers are perceived as more insolvent, policyholders may pay lower premium rates, which can adversely affect insurers' profitability (Sommer, 1996). To measure the insolvency risk of insurers, the capital asset ratio is commonly used as a control variable in empirical models (Pooser and Browne, 2018).

- *Insurer size*: Larger insurers tend to enjoy benefits from administrative efficiencies and economies of scale compared to smaller insurers. This suggests that larger insurers may have higher profitability. This relationship is supported by the findings of Born (2001), who reported a positive association between insurer size and profitability. In the empirical model, the logarithm of total assets is used as a measure of insurer size.

- *Liquidity:* Insurers with a shortage of cash may need to resort to costly external financing, especially during times of economic downturns such as the pandemic. As external financing can be expensive under such circumstances, it is expected that illiquid insurers will have lower profitability. The ratio of cash to total assets, as used by Pooser et al. (2017), is commonly used as a measure of liquidity in empirical models.

- *Market share:* Market leaders in the insurance industry often have more pricing power due to the tendency of policyholders to choose them as their insurance providers, influenced by herding behavior (Choi and Weiss, 2005). This suggests that market leaders may have higher profitability. In the empirical model, the ratio of premiums written by an insurer to the total premiums written by the market is used as a proxy for the insurer's market share.

- *Diversification*: The level of diversification among insurers can impact their profitability. Less diversified insurers tend to focus on their core business, where they have a comparative advantage, and this specialization can result in higher profitability compared to more diversified insurers. Shim (2011) found empirical evidence supporting this relationship. The ratio of non-insurance liabilities to total liabilities is often used as a measure of the degree of diversification in empirical models.

- *Insurer type*: The type of insurance that insurers underwrite, such as life or non-life insurance, can also impact their profitability. The business models and operations of life and non-life insurers differ, which can lead to differences in profitability. In the empirical model, a dummy variable called "insurer type" is used, with a value of 1 for life insurers and 0 for non-life insurers, to control for this factor.

Section 4: Empirical Results

4.1 DESCRIPTIVE STATISTICS

After collecting the macroeconomic data, pandemic-related data, insurers' characteristic data, and the ERM Score, the descriptive statistics of the final sample is presented in table 1. These descriptive statistics provide a summary of the key variables and help to understand the characteristics of the sample. It includes various measures such as mean, median, standard deviation, and quartiles for each variable. The performance measures are winsorized at the 5th percentile and 95th percentile to reduce the effect of possibly spurious outliers.

Table 1

SUMMARY STATISTICS

Variable	Percentiles					
	Mean	Std. dev.	25th	50th	75th	N
Panel A: Performance measures						
ROE (%)	8.625	11.843	3.663	9.379	15.132	2,425
ROA (%)	2.151	3.782	0.473	1.841	4.407	2,425
Panel B: COVID-19 measure						
Log (COVID-19 cases) (full sample)	4.865	5.190	0.000	0.000	10.545	2,425
Log (COVID-19 cases) (from 2020 to 2022)	9.591	2.784	8.575	10.538	11.517	1,230
Panel C: Country level control variables						
Anticipated inflation	2.694	3.058	0.774	1.776	3.638	2,425
GDP	25.893	6.961	26.428	26.949	28.850	2,425
Panel D: Firm level control variables						
Leverage	0.300	0.321	0.126	0.272	0.456	2,424
Insurer size	14.448	2.975	12.290	14.088	16.776	2,424
Liquidity	0.103	0.137	0.021	0.050	0.124	2,414
Market share (%)	0.591	1.345	0.021	0.113	0.580	2,203
Diversification	0.402	0.331	0.167	0.320	0.601	2,424
Insurer type	0.240	0.427	0.000	0.000	0.000	2,413
Panel E: ERM Sophistication						
ERM Score	2.563	1.509	1.000	2.000	4.000	2,425

This table presents the summary statistics of the variables used in the hierarchical linear model. The sample period is from 2017 to 2022, which covers the three years before the pandemic and three years after the start of the pandemic. Data on firm characteristics, macroeconomic factors, COVID-19, and ERM score are obtained from Thomson Reuters Datastream (Datastream), the World Bank, Our World in Data, and insurers' annual statements, respectively. All performance measures are calculated using firm-level data from Datastream. The variables are defined in appendix A.

As noted from table 1, the average ERM Score is 2.563 out of a 6-point scale, indicating that the overall level of sophistication in the implementation of ERM frameworks among insurers in our sample is not high. The median score of 2 suggests that more than half of the insurers have ERM frameworks that are not considered highly sophisticated. This implies that there is still significant room for improvement in the adoption and implementation of ERM practices worldwide.

The standard deviation of 1.509 indicates a moderate level of variation in ERM sophistication across insurers in our sample. The 25th percentile score of 1 and the 75th percentile score of 4 further highlight this variation, with some insurers having very basic or limited ERM frameworks, while others have more advanced and comprehensive systems in place. These findings suggest that there is a need for insurers to enhance their ERM capabilities to effectively identify, assess, and manage risks in a rapidly changing and complex operating environment.

4.2 PEARSON CORRELATION MATRIX

To provide a comprehensive overview of the relationships between all pairs of variables used in the study, the Pearson Correlation Matrix was constructed and is presented in table 2. This helps in understanding the interdependencies and associations between variables, which can provide valuable insights into the research topic.

Several observations can be made from table 2. Firstly, the ERM Score is positively related to ROE, indicating that insurers with more sophisticated ERM frameworks generate higher returns for their shareholders. This finding aligns with the results of Malik et al. (2020), which suggest that implementing ERM leads to improved firm performance. Secondly, the ERM Score is positively associated with insurer size and market share. This is not surprising, as larger insurers are expected to have more resources to implement more sophisticated ERM frameworks. Thirdly, the ERM Score is positively related to insurer type, implying that life insurers tend to have slightly more sophisticated ERM frameworks compared to non-life insurers.

However, it is important to exercise caution when interpreting the Pearson Correlation Matrix, as it only shows association, not causality. The impact of ERM on insurers, which are simultaneously affected by many factors, may be more nuanced than what the Pearson Correlation Matrix suggests. Therefore, further analysis using more robust empirical frameworks is conducted in the following subsections.

Table 2

PEARSON CORRELATION MATRIX

	ROE (%)	ROA (%)	Log(COVID-19 cases)	Anticipated inflation	GDP	Leverage	Insurer size	Liquidity	Market share	Diversification	Insurer type	ERM score
ROE (%)	1	0.700 (<.0001)	-0.059 (0.0034)	0.050 (0.0144)	-0.038 (0.0583)	-0.033 (0.1042)	0.137 (<.0001)	-0.088 (<.0001)	0.068 (0.0014)	-0.012 (0.5614)	0.028 (0.1674)	0.120 (<.0001)
ROA (%)	0.700 (<.0001)	1	-0.060 (0.0031)	0.075 (0.0002)	-0.041 (0.0439)	0.267 (<.0001)	-0.106 (<.0001)	0.000 (0.9807)	-0.065 (0.0024)	0.002 (0.9037)	-0.165 (<.0001)	-0.020 (0.3216)
Log(COVID-19 cases)	-0.059 (0.0034)	-0.060 (0.0031)	1	-0.008 (0.6861)	0.144 (<.0001)	-0.022 (0.2897)	0.084 (<.0001)	-0.007 (0.717)	0.002 (0.9385)	0.014 (0.5033)	-0.005 (0.8081)	-0.031 (0.1327)
Anticipated inflation	0.050 (0.0144)	0.075 (0.0002)	-0.008 (0.6861)	1	0.191 (<.0001)	0.066 (0.0012)	-0.365 (<.0001)	0.068 (0.0008)	-0.044 (0.0382)	0.087 (<.0001)	0.004 (0.8358)	-0.001 (0.9466)
GDP	-0.038 (0.0583)	-0.041 (0.0439)	0.144 (<.0001)	0.191 (<.0001)	1	0.025 (0.2241)	0.053 (0.0087)	-0.087 (<.0001)	-0.089 (<.0001)	0.040 (0.051)	-0.016 (0.431)	-0.092 (<.0001)
Leverage	-0.033 (0.1042)	0.267 (<.0001)	-0.022 (0.2897)	0.066 (0.0012)	0.025 (0.2241)	1	-0.352 (<.0001)	0.143 (<.0001)	-0.202 (<.0001)	0.047 (0.0204)	-0.216 (<.0001)	-0.208 (<.0001)
Insurer size	0.137 (<.0001)	-0.106 (<.0001)	0.084 (<.0001)	-0.365 (<.0001)	0.053 (0.0087)	-0.352 (<.0001)	1	-0.369 (<.0001)	0.307 (<.0001)	-0.143 (<.0001)	0.367 (<.0001)	0.355 (<.0001)
Liquidity	-0.088 (<.0001)	0.000 (0.9807)	-0.007 (0.717)	0.068 (0.0008)	-0.087 (<.0001)	0.143 (<.0001)	-0.369 (<.0001)	1	-0.045 (0.0362)	0.143 (<.0001)	-0.133 (<.0001)	-0.221 (<.0001)
Market share	0.068 (0.0014)	-0.065 (0.0024)	0.002 (0.9385)	-0.044 (0.0382)	-0.089 (<.0001)	-0.202 (<.0001)	0.307 (<.0001)	-0.045 (0.0362)	1	-0.074 (0.0005)	0.087 (<.0001)	0.182 (<.0001)
Diversification	-0.012 (0.5614)	0.002 (0.9037)	0.014 (0.5033)	0.087 (<.0001)	0.040 (0.051)	0.047 (0.0204)	-0.143 (<.0001)	0.143 (<.0001)	-0.074 (0.0005)	1	-0.047 (0.0204)	-0.152 (<.0001)
Insurer type	0.028 (0.1674)	-0.165 (<.0001)	-0.005 (0.8081)	0.004 (0.8358)	-0.016 (0.431)	-0.216 (<.0001)	0.367 (<.0001)	-0.133 (<.0001)	0.087 (<.0001)	-0.047 (0.0204)	1	0.115 (<.0001)
ERM score	0.120 (<.0001)	-0.020 (0.3216)	-0.031 (0.1327)	-0.001 (0.9466)	-0.092 (<.0001)	-0.208 (<.0001)	0.355 (<.0001)	-0.221 (<.0001)	0.182 (<.0001)	-0.152 (<.0001)	0.115 (<.0001)	1

This table presents the Pearson correlation matrix of the variables used in the hierarchical linear model. The p value for the test with hypothesis that the Pearson correlation equals to zero is reported in brackets. The sample period is from 2017 to 2022, which covers the 3 years before the pandemic and 3 years after the start of the pandemic. Data on firm characteristics, macroeconomic factors, COVID-19, and ERM score are obtained from Thomson Reuters Datastream (Datastream), the World Bank, Our World in Data, and insurers' annual statements, respectively. All performance measures are calculated using firm-level data from Datastream. The variables are defined in appendix A.

4.3 UNIVARIATE ANALYSIS

In this subsection, the researcher analyzes whether the COVID-19 pandemic has had a negative impact on insurers' performance and whether a sophisticated ERM framework can help improve their performance.

To do this, the entire sample was divided into two subsamples: one representing the pre-pandemic period from 2017 to 2019, and the other representing the post-pandemic period from 2020 to 2022. This division allows a comparison of insurers' ROE and ROA during the two periods and an assessment of whether there was a decline in performance after the onset of the pandemic. The pre-pandemic subsample consists of 1,195 firm-year observations, while the post-pandemic subsample consists of 1,230 firm-year observations. By examining the differences in ROE and ROA between these two periods, we can gain insights into the potential impact of the pandemic on insurers' financial performance.

Additionally, the entire sample was divided into two further subsamples based on their ERM scores. Insurers with ERM scores higher than the median value of 2 are grouped into the high-ERM-Score subsample, while those with scores below or equal to 2 are grouped into the low-ERM-Score subsample. This division allows for an investigation into whether there are performance differences between insurers with more advanced ERM frameworks and those with less advanced ones. The high-ERM-Score subsample consists of 1,212 firm-year observations, while the low-ERM-Score subsample consists of 1,213 firm-year observations. By comparing the performance metrics of these two subgroups, we can assess the potential impact of having a sophisticated ERM framework on insurers' financial performance.

For detailed results and further information, please refer to tables 3 and 4.

Table 3

UNIVARIATE ANALYSIS OF THE PRE-PANDEMIC AND POST-PANDEMIC PERIODS

	Pre-pandemic (Years 2017 – 2019)		Post-pandemic (Years 2020 – 2022)			
	Mean	Sample size	Mean	Sample size	Mean difference	T-statistics of test for mean difference
ROE (%)	9.470	1,195	7.803	1,230	-1.667***	-3.47
ROA (%)	2.353	1,195	1.955	1,230	-0.398***	-2.60
Leverage	0.307	1,194	0.294	1,230	-0.013	-1.03
Insurer size	14.353	1,194	14.540	1,230	0.187	1.54
Liquidity	0.100	1,190	0.105	1,224	0.005	0.81
Market share (%)	0.590	1,089	0.592	1,114	0.002	0.04
Diversification	0.399	1,194	0.405	1,230	0.006	0.50

This table presents the results of the test for mean difference between the pre-pandemic and post-pandemic subsamples. Data on firm characteristics are obtained from Thomson Reuters Datastream (Datastream). All performance measures are calculated using firm-level data from Datastream. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in appendix A.

According to the findings in table 3, the mean ROE decreased from 9.470% in the pre-pandemic period to 7.803% in the post-pandemic period. Similarly, the mean ROA decreased from 2.353% to 1.955%. These decreases are statistically significant, indicating that the pandemic has had a negative impact on insurers' performance. Despite management actions taken to mitigate the adverse effects, such as reducing policyholder and shareholder dividends, increasing premiums, and postponing share buyback plans, the pandemic's impact cannot be fully offset. To visualize the impact of the pandemic on insurers' performance, please refer to figures 1 and 2, which display histograms and boxplots for ROE and ROA before and after the pandemic periods.

Figure 1

HISTOGRAMS AND BOXPLOTS OF ROE BEFORE AND AFTER THE PANDEMIC PERIODS

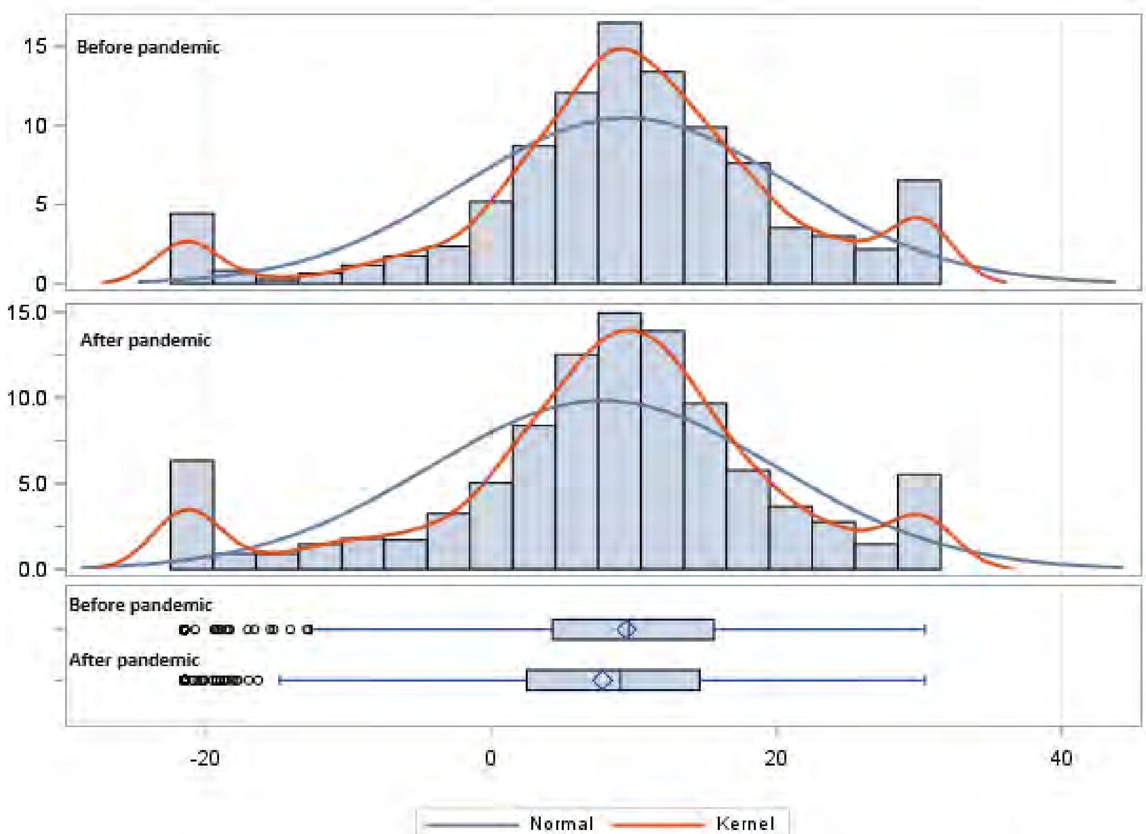

Figure 1 presents the histograms and boxplots for ROE before (i.e., 2017 – 2019) and after (i.e., 2020 – 2022) the pandemic periods. The blue and red lines in the histograms represent the normal and kernel density, respectively. As the ROE is winsorized at the 5th percentile and 95th percentile to reduce the effect of possibly spurious outliers, the density of ROE after winsorization is a bit higher in both tails.

Figure 2

HISTOGRAMS AND BOXPLOTS OF ROA BEFORE AND AFTER THE PANDEMIC PERIODS

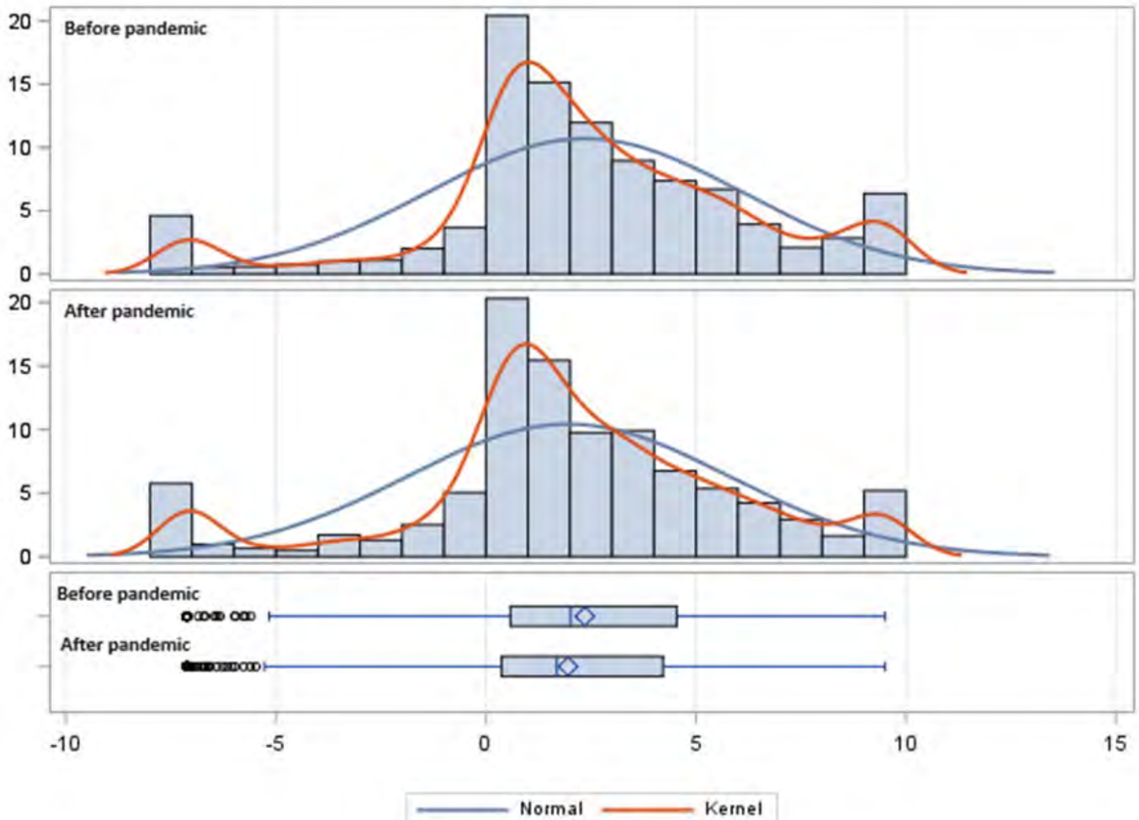

Figure 2 presents the histograms and boxplots for ROA before (i.e., 2017 – 2019) and after (i.e., 2020 – 2022) the pandemic periods. The blue and red lines in the histograms represent the normal and kernel density, respectively. As the ROA is winsorized at the 5th percentile and 95th percentile to reduce the effect of possibly spurious outliers, the density of ROA after winsorization is a bit higher in both tails.

As shown in table 4, insurers with more sophisticated ERM frameworks have an average ROE of 10.241%, which is higher than the average ROE of 7.009% for insurers with less sophisticated ERM frameworks. The mean difference of 3.232% is also statistically significant. However, there is no significant difference in ROA between insurers with more and less sophisticated ERM frameworks. It is worth noting that insurers with sophisticated ERM frameworks tend to differ in firm characteristics, such as size, market share, leverage, and focus on underwriting insurance business. These differences may contribute to the performance disparity between the two groups. To visualize the impact of sophisticated ERM frameworks on insurers' performance, please refer to figures 3 and 4, which display histograms and boxplots for ROE and ROA for the high-ERM-Score and low-ERM-Score subsamples.

Table 4

UNIVARIATE ANALYSIS OF THE HIGH-ERM-SCORE AND LOW-ERM-SCORE SUBSAMPLES

	Low-ERM-score subsample		High-ERM-score subsample			
	Mean	Sample size	Mean	Sample size	Mean difference	T-statistics of test for mean difference
ROE (%)	7.009	1,213	10.241	1,212	3.232***	6.78
ROA (%)	2.222	1,213	2.080	1,212	-0.142	-0.93
Leverage	0.364	1,212	0.237	1,212	-0.127***	-9.88
Insurer size	13.385	1,212	15.511	1,212	2.126***	18.82
Liquidity	0.135	1,209	0.071	1,205	-0.064***	-11.77
Market share (%)	0.293	1,037	0.855	1,166	0.562***	10.01
Diversification	0.454	1,212	0.351	1,212	-0.103***	-7.76

This table presents the results of the test for mean difference between the low-ERM-Score and high-ERM-Score subsamples. Data on firm characteristics are obtained from Thomson Reuters Datastream (Datastream). All performance measures are calculated using firm-level data from Datastream. ERM scores are constructed according to the information disclosed in insurers' annual statements. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in appendix A.

Figure 3
HISTOGRAMS AND BOXPLOTS OF ROE FOR THE HIGH-ERM-SCORE AND LOW-ERM-SCORE SUBSAMPLES

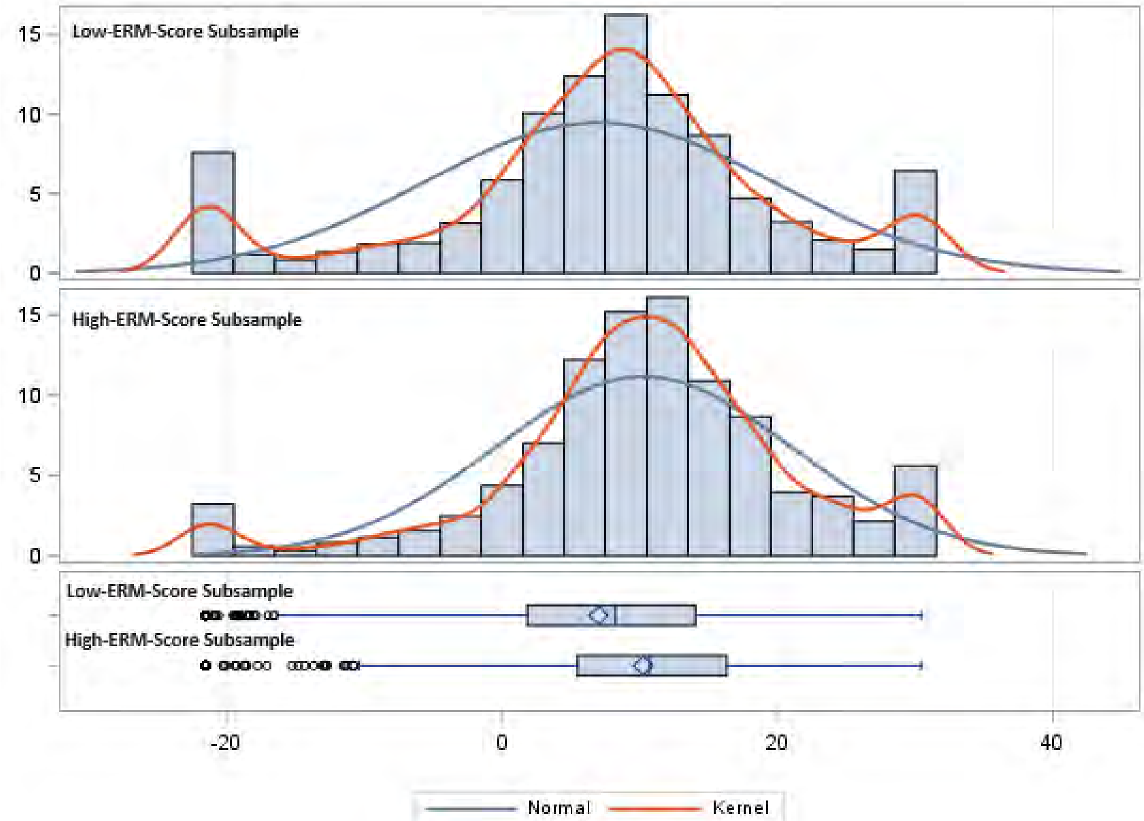

Figure 3 presents the histograms and boxplots for ROE for the high-ERM-Score and low-ERM-Score subsamples. The blue and red lines in the histograms represent the normal and kernel density, respectively. As the ROE is winsorized at the 5th percentile and 95th percentile to reduce the effect of possibly spurious outliers, the density of ROE after winsorization is a bit higher in both tails.

Figure 4

HISTOGRAMS AND BOXPLOTS OF ROA FOR THE HIGH-ERM-SCORE AND LOW-ERM-SCORE SUBSAMPLES

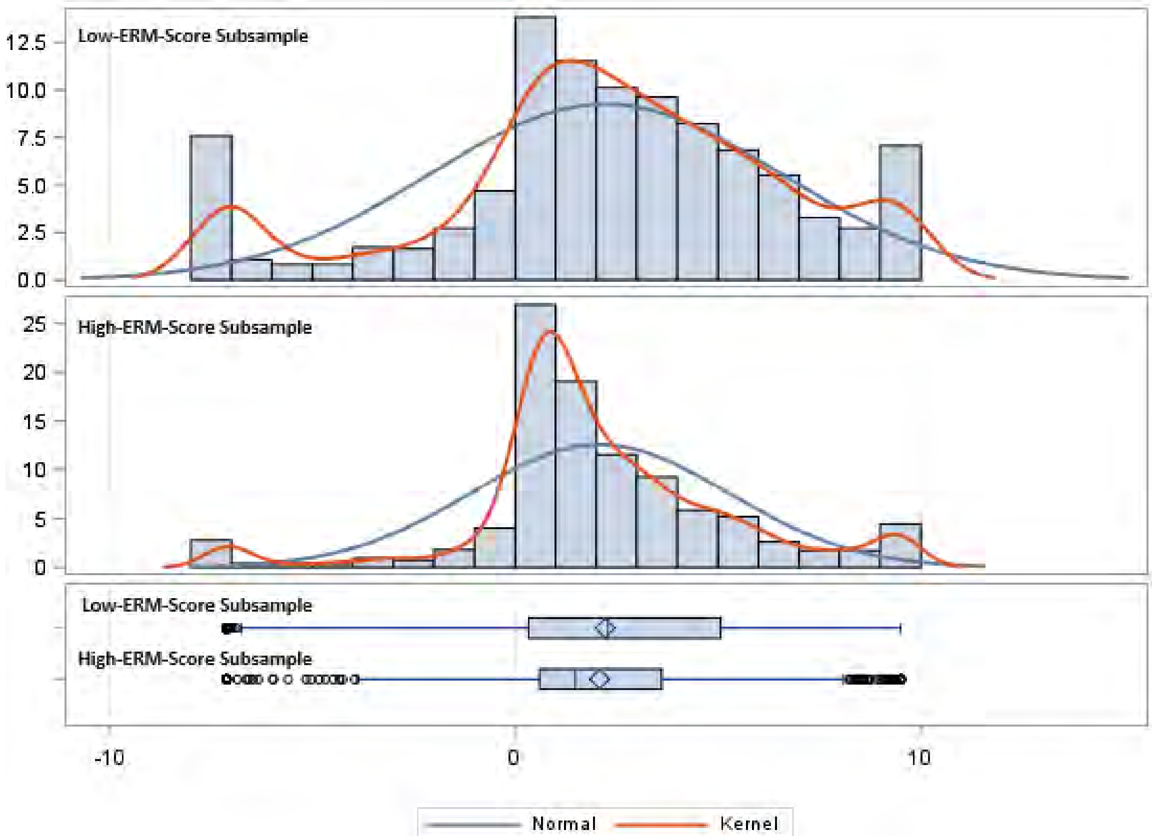

Figure 4 presents the histograms and boxplots for ROA for the high-ERM-Score and low-ERM-Score subsamples. The blue and red lines in the histograms represent the normal and kernel density, respectively. As the ROA is winsorized at the 5th percentile and 95th percentile to reduce the effect of possibly spurious outliers, the density of ROA after winsorization is a bit higher in both tails.

It is important to interpret these results with caution. Firstly, the impact of the pandemic may vary across different jurisdictions, so assuming a homogeneous impact across all jurisdictions is inappropriate. Secondly, insurer performance is influenced by both country-level factors and firm-level characteristics. The univariate analysis presented here does not account for the interaction of these factors with insurer performance. To address these limitations, a more robust empirical analysis using a hierarchical linear model is conducted in the next subsection.

4.4 HIERARCHICAL LINEAR MODEL

In this subsection, the hierarchical linear model is employed to provide a more robust analysis of the impact of the pandemic on insurers' performance and to investigate the effects of sophisticated ERM frameworks on insurers' resilience. The entire sample is fitted into the hierarchical linear model, which is described by Equations (2) and (3) in the study. This model allows for the examination of the firm-level characteristics, country-level factors, and their combined effects on insurers' performance after controlling for the potential nesting effects, i.e., insurers within the same country may exhibit more similarities than those from different countries. The results of the hierarchical linear model are presented in tables 5 and 6.

Table 5

HIERARCHICAL LINEAR MODEL WITH ROE AS PERFORMANCE MEASURE

Variable	Dependent variable: ROE (%)		
	(1) Whole sample	(2) Low-ERM-score subsample	(3) High-ERM-score subsample
Log (COVID-19 cases)	-0.176*** (-4.13)	-0.219*** (-3.37)	-0.149*** (-2.76)
Sophisticated ERM framework	2.028** (2.10)		
Country-level control variables			
Anticipated inflation	0.149 (0.82)	0.144 (0.56)	0.272 (1.22)
GDP	0.013 (0.10)	0.011 (0.06)	0.010 (0.08)
Firm-level control variables			
Leverage	8.125*** (2.95)	9.220*** (2.75)	3.754 (1.04)
Insurer size	2.089*** (10.21)	2.241*** (8.29)	1.255*** (4.87)
Liquidity	4.527 (1.08)	8.707* (1.80)	-9.422 (-1.53)
Market share	-0.886*** (-2.95)	-1.825** (-2.53)	-0.257 (-0.78)
Diversification	1.046 (0.72)	2.888 (1.40)	-1.180 (-0.54)
Insurer type	-0.717 (-0.41)	-4.781** (-2.04)	1.506 (0.74)

This table presents the regression results of the hierarchical linear model. The t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2017 to 2022, which covers the 3 years before the pandemic and 3 years after the start of the pandemic. Data on firm characteristics, macroeconomic factors, COVID-19, and ERM score are obtained from Thomson Reuters Datastream (Datastream), the World Bank, Our World in Data, and insurers' annual statements, respectively. The performance measure is calculated using firm-level data from Datastream. The variables are defined in appendix A.

Table 6

HIERARCHICAL LINEAR MODEL WITH ROA AS PERFORMANCE MEASURE

Variable	Dependent variable: ROA (%)		
	(1) Whole sample	(2) Low-ERM-score subsample	(3) High-ERM-score subsample
Log (COVID-19 cases)	-0.033*** (-2.72)	-0.044** (-2.22)	-0.028* (-1.88)
Sophisticated ERM framework	0.410 (1.23)		
Country-level control variables			
Anticipated inflation	0.059 (1.14)	0.141** (2.05)	0.056 (0.89)
GDP	0.009 (0.22)	-0.018 (-0.36)	0.023 (0.52)
Firm-level control variables			
Leverage	8.830*** (9.00)	9.204*** (8.34)	8.508*** (6.10)
Insurer size	0.586*** (10.01)	0.669*** (7.76)	0.362*** (4.92)
Liquidity	0.992 (0.54)	3.807 (1.58)	-3.097 (-1.20)
Market share	-0.281*** (-3.06)	-0.286 (-1.27)	-0.148 (-1.49)
Diversification	-0.350 (-1.36)	0.565 (1.21)	-0.546 (-1.05)
Insurer type	-0.983* (-1.86)	-1.833*** (-2.79)	-0.246 (-0.42)

This table presents the regression results of the hierarchical linear model. The t-statistics are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period is from 2017 to 2022, which covers the 3 years before the pandemic and 3 years after the start of the pandemic. Data on firm characteristics, macroeconomic factors, COVID-19, and ERM score are obtained from Thomson Reuters Datastream (Datastream), the World Bank, Our World in Data, and insurers' annual statements, respectively. The performance measure is calculated using firm-level data from Datastream. The variables are defined in appendix A.

The results in column (1) of tables 5 and 6 indicate that the estimated coefficients for *Log (COVID-19 cases)* are consistently negative and highly statistically significant, regardless of whether insurer performance is measured by ROE or ROA. This suggests that the severity of the pandemic in a jurisdiction has a significant and detrimental impact on insurers' performance.

Suppose an insurer operates in a jurisdiction with an average impact of the pandemic, where *Log (COVID-19 cases)* equals the sample mean of 9.591. In this case, the analysis suggests that the insurer's ROE and ROA would be expected to decrease by 1.688% (9.591 x 0.176) and 0.317% (9.591 x 0.033), respectively. These magnitudes align with the findings from the earlier univariate analysis presented in table 3.

When comparing insurers operating in jurisdictions with different levels of pandemic impact, specifically those with a mild impact (*Log (COVID-19 cases)* at the 25th percentile of 8.575) and those with a severe impact (*Log (COVID-19 cases)* at the 75th percentile of 11.517), the analysis shows that insurers in jurisdictions with a severe impact generally experience 0.518% ((11.517 – 8.575) x 0.176) lower ROE and 0.097% ((11.517 – 8.575) x 0.033) lower ROA. This suggests that the severity of the pandemic's impact is associated with greater declines in insurers' performance.

In summary, while the impact of the pandemic on the insurance industry may not be significant enough to render the business unprofitable, the adverse effects on insurers are not trivial. The empirical evidence strongly supports Hypothesis 1 and the notion that the pandemic has had a negative impact on insurers' performance.

Next, the analysis divides the entire sample of insurers into two subsamples based on their ERM Scores. Insurers with an ERM Score higher than the median value of 2 are grouped into the high-ERM-score subsample, while the remaining insurers are grouped into the low-ERM-score subsample. The hierarchical linear model analysis is then repeated separately for each subsample, and the empirical results are presented in columns (2) and (3) of tables 5 and 6.

The results in columns (2) and (3) of table 5 and 6 show that insurers with a sophisticated ERM framework, as indicated by a high ERM Score, experience a significantly lower adverse impact of the pandemic on their ROE and ROA. Suppose an insurer operates in a jurisdiction with an average impact of the pandemic, where *log (COVID-19 cases)* equals to the sample mean of 9.591. In this scenario, the analysis suggests that insurers with a sophisticated ERM framework experience a decrease of 1.429% (9.591 x 0.149) and 0.269% (9.591 x 0.028) in ROE and ROA, respectively. On the other hand, insurers with less sophisticated ERM frameworks experience a decrease of 2.100% (9.591 x 0.219) and 0.422% (9.591 x 0.044) in ROE and ROA, respectively. These findings support Hypothesis 2, which suggests that insurers with more sophisticated ERM frameworks are less affected by the pandemic in terms of their performance.

Additionally, it is noted that a sophisticated ERM framework has a substantial positive effect on ROE. In column (1) of table 5, it is estimated that a sophisticated ERM framework improves ROE by 2.028%. This improvement is statistically significant, indicating that insurers with more sophisticated ERM frameworks tend to have higher ROE. Similarly, in column (1) of table 6, it is found that a sophisticated ERM framework improves ROA by 0.410%, although the estimated coefficient is not statistically significant. These findings are consistent with a previous study by Malik et al. (2020) that suggests implementing ERM leads to improved firm performance.

Section 5: Conclusion

This study examines the impact of the pandemic on insurers and investigates the role of a sophisticated ERM framework in enhancing insurers' resilience during this period. The analysis includes 2,425 firm-year observations from a total of 413 listed insurers across 62 jurisdictions. The data covers a span of six years, consisting of three years before the pandemic and three years during the pandemic. To measure the sophistication level of insurers' ERM frameworks, we construct an ERM Score, which is a comprehensive measure that considers various aspects of ERM. The hierarchical linear model is employed to address potential nesting effects and control for country-level and firm-level variables. The findings reveal that, on average, insurers experience a decline of 1.688% in ROE and 0.317% in ROA during the pandemic period. However, a sophisticated ERM framework significantly mitigates these adverse effects. Insurers with a sophisticated ERM framework experience a reduction of 31.963% in the impact on ROE and 36.363% in the impact on ROA compared to insurers with less sophisticated ERM frameworks.

The study is important for at least two reasons. Firstly, it aims to understand the financial impact of the pandemic on insurers. By gaining a comprehensive understanding of these impacts, insurers will be better equipped to accurately price pandemic risk into their insurance products in the future. Additionally, regulators will be able to assess the adequacy of pandemic reserves set aside by insurers. Secondly, the study addresses the value of implementing sophisticated ERM frameworks in the insurance industry. While previous studies have discussed the advantages of ERM, none have specifically examined how the level of sophistication of insurers' ERM frameworks has affected their resilience against the adverse effects of the pandemic. This study provides new insights into the importance of a sophisticated ERM framework, which could lead to wider implementation in the industry. This, in turn, may help reduce losses from future pandemics.

In conclusion, this study is crucial for insurers and regulators alike. It provides insights into the financial impact of the pandemic on insurers and highlights the importance of implementing sophisticated ERM frameworks. By understanding these aspects, insurers can improve their risk management practices, accurately price pandemic risk, and potentially reduce losses in the face of future pandemics.

Section 6: Acknowledgments

The author's deepest gratitude goes to those without whose efforts this project could not have come to fruition: the volunteers who generously shared their wisdom, insights, advice, guidance, and arm's-length review of this study prior to publication. Any opinions expressed may not reflect their opinions nor those of their employers. Any errors belong to the author alone.

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Appendix A: Variable Definitions

Variables	Definitions
[Thomson Reuters Datastream items in brackets]	
Performance measures	
ROE (%)	Net income [WC01551] in the current year divided by the average of common shareholders' equity [WC03501] in the current year and the previous year x 100
ROA (%)	Net income [WC01551] in the current year divided by the average of total assets [WC02999] in the current year and the previous year x 100
COVID-19 measures	
Log (COVID-19 cases)	Natural logarithm of number of annual confirmed COVID-19 cases per million people
Country level control variables	
Anticipated inflation	Average consumer price changes over 5 years
GDP	Natural logarithm of GDP in U.S. dollars
Firm level control variables	
Leverage	Common shareholders' equity [WC03501] divided by total assets [WC02999]
Insurer size	Natural logarithm of total assets [WC02999] in thousands of U.S. dollars
Liquidity	Cash - generic [WC02005] divided by total assets [WC02999]
Market share	Premium earned [WC01002] divided by to total premium written by the market
Diversification	(Total liabilities [WC03351] - insurance reserves [WC03030]) divided by total liabilities [WC03351]
Insurer type	Dummy variable that equals 1 for life insurers and 0 for nonlife insurers
ERM Sophistication	
ERM Score	A 6-point score that quantifies the sophistication of ERM framework. For detailed information on how the score is calculated, please refer to subsection 3.2.
Sophisticated ERM framework	Dummy variable that takes a value of 1 if the ERM Score is greater than 2, and a value of 0 if the ERM Score is equal to or less than 2.

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