Academic Journal of Digital Economics and Stability
Volume 36, Dec-2023

ISSN 2697-2212 Available Online: https://economics.academicjournal.io

Enhancement of Insurance Underwriting Services Through Model Analysis (ARDL)

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Abstract

This article provides information on the improvement and development of underwriting services (ARDS) provided in the insurance market of Uzbekistan based on an analysis of the model. Proposals were also made to expand the underwriting service based on the analysis of econometric and statistical methods through the indicators of EISK Uzbekinvest JSC.

Keywords*: insurance activity, underwriting service, artificial intelligence, estimation coefficients, independent variable, insurance coverage, insurance premiums, risk assessment, ARDL model.*

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Introduction

In the country, the cessation of insurance services by legal and natural persons due to various natural, elemental, and entrepreneurial risks partially or entirely contributes to the hindrance of economic development, adding its share to this situation. Resolving the uncertainty issue in insurance and making strategic decisions based on risk assessment are key tasks for insurance agents. The development of insurance activities represents a crucial stage in risk analysis in the insurance sector. Observing information that in developed countries, the activities of individuals and legal entities do not take place without insurance services, it can be concluded that many countries have a high level of insurance. If we analyze the stages of the development of insurance activities, it becomes clear that underwriting services play an important role.

Underwriting is a process in which various investment funds come together in response to an individual or legal entity taking on financial risks. This risk is usually associated with credits, insurance, or investments. The term "underwriter" is ready to take on the responsibility for the total amount of trust that he is willing to accept in the form of compensation for the total amount of trust he is willing to accept. In Uzbekistan, there is a need to establish underwriting services in line with the requirements of the time by taking responsibility for risks, thoroughly analyzing the risks considered by the insurer.

In recent years, there has been an introduction of artificial intelligence into underwriting services in insurance. The rapid integration of artificial intelligence into our businesses, homes, and transportation, as well as in our personal lives, is already being felt. The COVID-19 pandemic and the data on the digital transformation in the world of insurance emphasized the need to accelerate digitization for global insurers. During the pandemic, most organizations, while not making significant investments in artificial intelligence, recognized that the growing attention to digital technologies and readiness for change create favorable conditions for the implementation of artificial intelligence in their operations.

Analysis of Literature on the Topic

The insurance industry is a vital component of the modern economy, playing a key role in providing various financial benefits, protecting the health and property of individuals and business entities from natural and financial risks. Effective underwriting services are of great importance in ensuring the financial stability of insurance companies. Underwriting is the process of assessing risks associated with insuring a specific individual and determining the corresponding rewards and insurance coverages. Continuous improvement of underwriting services not only strengthens the financial stability of companies but also provides customers with higher-quality services.

In the insurance system, the development of underwriting services is an integral part of ensuring the financial stability of insurance companies. The enhancement of underwriting services in insurance companies is characterized by the integration of data analysis, advanced technologies, customer-oriented strategies, systematic training, and integration into regulatory documents. The development of underwriting services aims to reduce the impact of risks on advantages, increase profitability, meet customer needs, and enhance competitiveness in the market. Ultimately, the development of insurance companies, their adaptation to changing risk conditions, and ensuring long-term financial stability play a crucial role in the underwriting process.

The development of underwriting services is essential not only for improving the financial stability of companies but also for directly influencing customers by providing them with more

ISSN 2697-2212 Available Online: https://economics.academicjournal.io

accurate assessments and more favorable conditions. Modern research in the field of insurance conducted by foreign economists emphasizes the importance of underwriting in risk management, risk modeling, and underwriting practices. They also highlight the significance of underwriting in reducing financial risks, ensuring capital stability, and increasing long-term financial efficiency.

Studies by foreign scholars, such as David Cummins, Michel Denuit, and many others, have made a significant contribution to understanding the importance of underwriting in the insurance industry. Their works cover a wide range of topics, including risk modeling, insurance analysis, underwriting risks, statistical methods, and strategies of insurance companies. The research of these scholars underscores the need for the use of modern methods and tools for assessing and managing risks in the face of constant changes in the economic and insurance environment.

Analysis and Results

The Autoregressive Distributed Lag (ARDL) model was utilized for the analysis of time-series data, taking into account various explanatory variables, to develop econometric equations. Data from the "Uzbekinvest" Joint-Stock Company for Export-Import Insurance (https://uzbekinvest.uz) for the years 2017 to 2023, containing a total of 23 observations, were used in the study.

Additionally, the research employed the ARDL model to create visual matrix plots of time series data as a foundational basis. Various checks, including correlation matrix assessments between lagged and independent variables, stationarity tests through unit root tests, cointegration analysis through bound tests, and regression equations using the ARDL model, were conducted. Furthermore, the ARDL model was validated according to the Gauss-Markov assumptions and diagnostic tests using the Cusum method. Additionally, the ARDL model accounted for the impact of lagged changes in independent variables on the dependent variable in subsequent years.

The ARDL (Autoregressive Distributed Lag) model, or any statistical model, is typically evaluated based on its compatibility with the research question and the dataset it analyzes. The ARDL model is a valuable tool for analyzing time-series data, especially in exploring long-term relationships between variables. The effectiveness of the ARDL model is compared with alternative models or methodologies and is contingent on the nature of the results it produces. The ARDL model is a valuable tool for analyzing time-series data, especially in exploring long-term relationships between variables. The ARDL model and its relative advantages are highlighted when compared to other models or methodologies.

The evaluation of the ARDL model is essential in understanding its ability to identify primary relationships between variables, its statistical accuracy, and its practical significance in addressing the research question. The ARDL model must be able to determine the direct and extended dynamics and relationships between variables. Additionally, the ARDL model proposes a direction for the impact of changes in one variable on others, capturing not only direct effects but also persistent effects.

One of the main advantages of the ARDL model is its ability to capture short-term and long-term dynamics and relationships between variables. This is particularly crucial in analyzing how changes in one variable affect others over various time intervals. The ARDL model is a dynamic model that accounts for both short-term and long-term relationships. It provides a clearer representation of time-series data, accounting for possible time lags in the impact of changes.

ISSN 2697-2212 Available Online: https://economics.academicjournal.io

The ARDL model is a versatile model that allows for various combinations of stationary and non-stationary variables. This flexibility, especially concerning the stationarity characteristics of variables, is important.

Moreover, the ARDL model can be used for forecasting time-series data, making it particularly useful for predicting future values based on historical information, specifically relying on lagged and independent variables' past values. The ARDL model's application is also valuable for its potential use with historical data, especially predicting future values of dependent variables based on the lagged values of related and independent variables. The ARDL model has been used for forecasting time-series data, making it particularly useful for predicting future values based on historical information, especially relying on lagged and independent variables' past values.

The ARDL model's primary advantages include its ability to analyze direct and extended dynamics and relationships between variables, its flexibility in handling various combinations of stationary and non-stationary variables, and its applicability for forecasting time-series data based on historical information. The ARDL model, when applied appropriately, serves as a powerful tool in econometric modeling, offering insights into complex relationships and dynamics within time-series data.

$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \ldots + \beta_q X_{t-q} + \gamma_1 Zt_{-1} + \gamma_2 Z_{t-2} + \ldots + \gamma_r Z_{t-r} + \varepsilon_t$ (1)

In this context, Yt represents the dependent variable at time t. Yt-1, Yt-2, ..., Yt-p represent the lagged values of the dependent variable. Xt-k, Xt-k-1, ..., Xt-k-q represent the lagged values of the independent variable, and Zt-1, Zt-2, ..., Zt-r represent the lagged values of other variables influencing the dependent variable. α0, α1, ..., αp, β1, β2, ..., βq, γ1, γ2, ..., γr denote the coefficients to be estimated, and εt represents the error term at time t.

The research focuses on the following variables:

- y (dependent variable): the number of underwriters in the insurance company,

- x1 (independent variable): the number of insurance contracts,

- x2 (independent variable): the insurance premium, and

- x3 (independent variable): the insurance portfolio.

In formulating the econometric model for the analysis, the following hypotheses were established:

Null Hypothesis (H0): There is no statistically significant relationship between the number of underwriters, the number of insurance contracts, the insurance premium, the insurance portfolio, and other variables within the insurance company.

Alternative Hypothesis (Ha): There is a statistically significant relationship between the number of underwriters, the number of insurance contracts, the insurance premium, the insurance portfolio, and other variables within the insurance company. Moreover, these relationships are economically significant within the context of the insurance sector.

The graphical representation of the time-series analysis of dependent and independent variables is depicted in the following figure (refer to Figure 1).

Figure 1. Time-series plot of dependent and independent variables.

As depicted in Figure 1, the time-series data exhibit a pronounced seasonal trend, highlighting temporary fluctuations. Under such conditions, forecasting potential influential factors over time becomes more accurate. Similarly, the graphical representation illustrates a sharp surge in the insurance portfolio between 2021 and 2023.

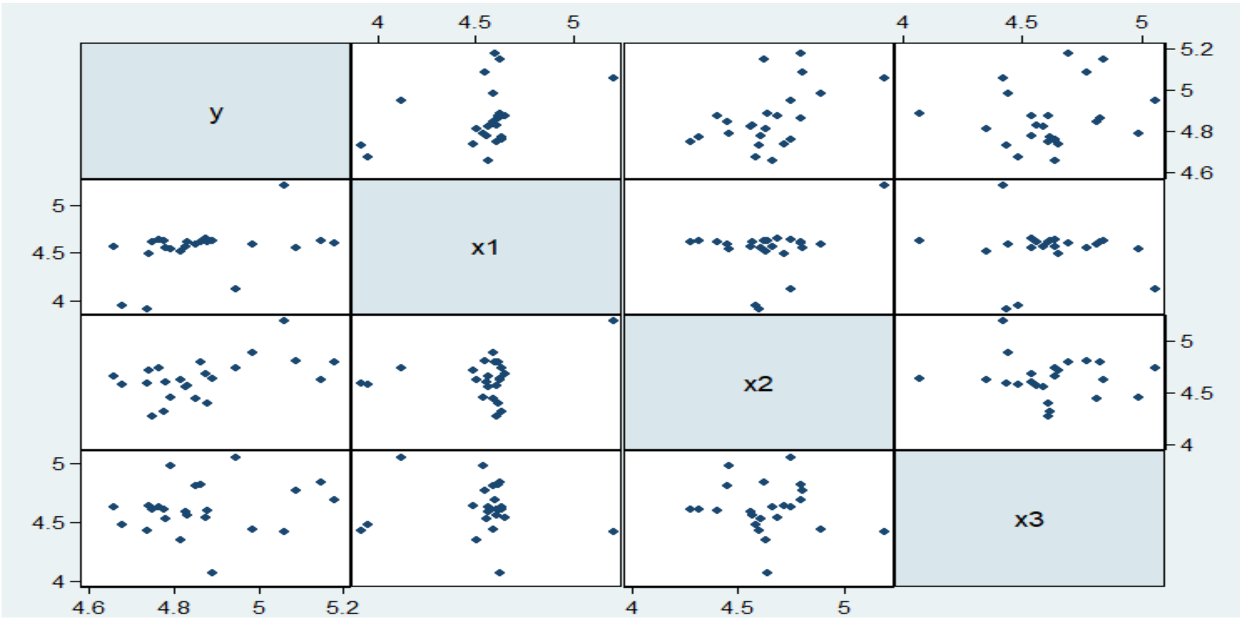


Figure 2. Matrix plot of dependent and independent variables.

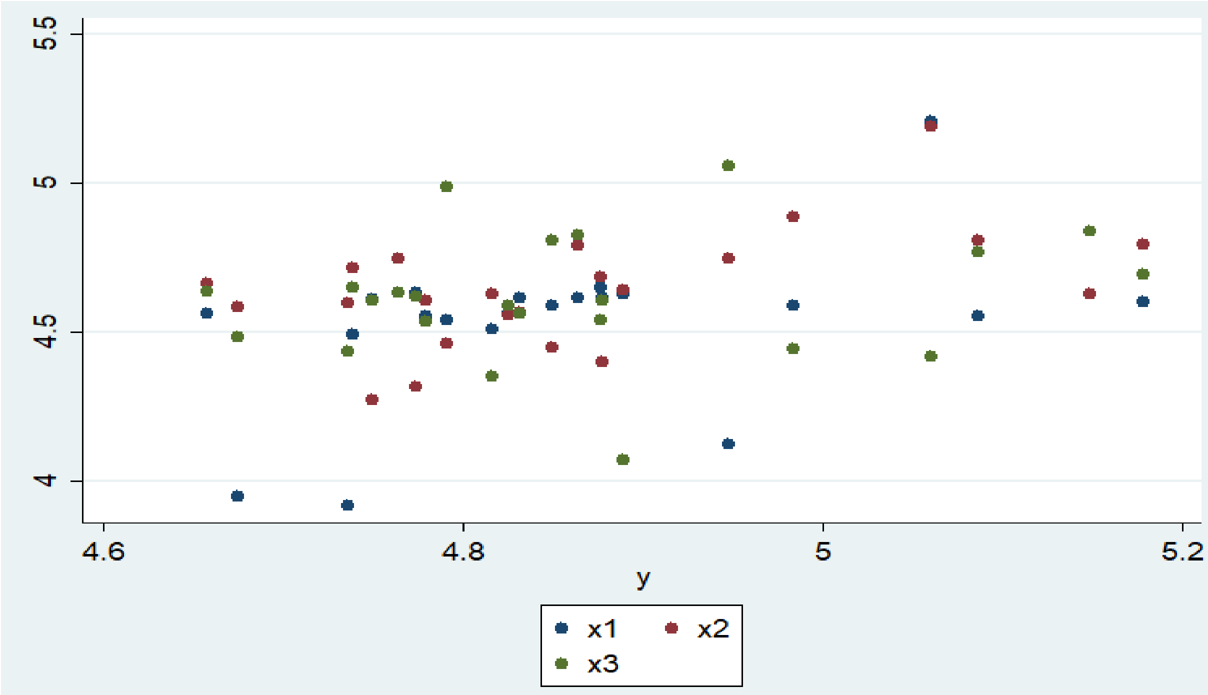


Figure 3. Scatter plot matrix of dependent and independent variables.

In Figures 2 and 3, as illustrated, the characteristic variables depicting the tendency of the dependent and independent variables show a robust correlation. Significant points of information concentration indicate clustering of data and reveal the positional distribution through arrows.

In the next stage of the study, the correlation matrix for the dependence and independence of variables has been presented using statistical software (refer to Table 1).

1-Table Correlation matrix of dependent and independent variables.

Variables	(1)	(2)	(3)	(4)
(1) y	1.000			
(2) x_1	0.6012	1.000		
(3) x_2	0.4763	0.1273	1.000	
(4) x_3	0.4135	0.0593	0.1670	1.000

According to Table 1, there is a strong, moderate, and significant correlation among the dependent and independent variables. Additionally, the correlation matrix indicates the absence of multicollinearity between the result and characteristic variables.

In the research, a Unit-root test was conducted to identify the stationarity of dependent and independent variables (refer to Table 2).

2-Table Indicators of the Unit-Root test for dependent and independent variables.

O'zgaruvchilar	*Test Statistic*	*1% Critical Value*	*5% Critical Value*	*10% Critical Value*	*p-value for Z(t)*
Bog'liq o'zgaruvchi (y)	-4.517	-3.750	-3.000	-2.630	0.0003
Mustaqil o'zgaruvchi (x_1)	-4.455	-3.750	-3.000	-2.630	0.0000
Mustaqil o'zgaruvchi (x_2)	-4.504	-3.750	-3.000	-2.630	0.0003
Mustaqil o'zgaruvchi (x_3)	-5.327	-3.750	-3.000	-2.630	0.0000

ISSN 2697-2212 Available Online: https://economics.academicjournal.io

According to Table 2, the unit-root test provides a statistic value of (-4.517) for the dependent variable and critical values of (-4.455, -4.504, and -5.327) for the explanatory variables, at significance levels of 1%, 5%, and 10%, respectively. The negative values beyond the critical values (-3.750, -3.000, -2.630) indicate a significant association.

Based on the results of the unit-root test, the stationary behavior of the dependent and forecasting variables was observed for the qaram variable and the predictive factors, confirmed by their low MacKinnon values and Z(t) being equal to 0.0000. Furthermore, the unit-root test results after the initial integration of dependent and independent variables confirm their attainment of stationarity.

In the research, an econometric model was developed using the ARDL model. The following econometric model is constructed based on the ARDL model:

$$ \Delta y_{it} = c_0 + c_1 \sum_{p=1}^{n} \Delta y_{i,t-p} + c_2 \sum_{p=1}^{n} \Delta x_{1i,t-p} + c_3 \sum_{p=1}^{n} \Delta x_{2i,t-p} + c_4 \sum_{p=1}^{n} \Delta x_{3i,t-p} + \alpha_1 Y_{i,t-p} + $$

$$ \alpha_2 x_{1i,t-1} + \alpha_3 x_{2i,t-1} + \alpha_4 x_{3i,t-1} + \varepsilon_{i,t} $$

In this equation:

- Δy_{it} represents the change in the number of underwriters in the insurance company.

- y_{t-1} denotes the number of underwriters in the insurance company one year prior.

- x_1 represents the number of insurance policies.

- x_2 represents the insurance premium, and x_3 represents the insurance aggregate.

- c_0 is the constant term, and c_1, c_2, c_3, c_4 are short-term elasticity coefficients.

- $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are long-term dynamic multipliers.

- n is the lag order, and p is the lag length.

Equation (2) outlines the linear ARDL model, providing expressions for short and long-term forecasts.

Furthermore, the ARDL model estimation was conducted using the Stata software, generating the results shown in Table 3.

3-table ARDL(1,2,2,2) regression model indicators [1]

ARDL(1,2,2,2) regression

Number of obs = 21

R-squared = 0.9670

Adj R-squared = 0.9340

Log likelihood = 44.517891

[1] Stata dasturi asosida muallif tomonidan mustaqil ishlab chiqildi.

Root MSE = 0.0421	Coef.	Std.Err.	t	P>t	[95%Conf.	Interval]
D.y						
ADJ						
y						
L1.	-1.424	0.182	-7.820	0.000	-1.829	-1.018
LR						
x1	0.408	0.085	4.800	0.001	0.219	0.598 ***
x2	0.330	0.074	4.490	0.001	0.166	0.494 ***
x3	0.641	0.088	7.310	0.000	0.446	0.837 ***
SR						
x1						
D1.	-0.195	0.080	-2.440	0.035	-0.373	-0.017 ***
LD.	-0.323	0.071	-4.580	0.001	-0.480	-0.166 ***
x2						
D1.	-0.301	0.141	-2.140	0.058	-0.614	0.012 *
LD.	0.114	0.065	1.750	0.110	-0.031	0.260
x3						
D1.	-0.615	0.103	-5.950	0.000	-0.845	-0.385 ***
LD.	-0.296	0.065	-4.560	0.001	-0.440	-0.151 ***
_cons	-2.106	0.850	-2.480	0.033	-4.000	-0.212 ***

Based on the information presented in Table 3, the ARDL(1,2,2,2) model indicates a high goodness-of-fit, with an R-squared of 0.96, demonstrating a strong relationship among the variables. Additionally, the model's coefficient of determination is positive, indicating a favorable fit.

Furthermore, the results of the ARDL(1,2,2,2) test, including the F-statistic and t-statistic, show statistical significance at the 0.05 significance level, providing evidence of the model's validity. As a result, the null hypothesis (H0) was rejected in favor of the alternative hypothesis (H1).

In the research, the cointegration status of the ARDL(1,2,2,2) model was examined using the Bound Test, as illustrated in Table 4.

4-jadval

					F = 15.623
	[I_0] [I_1] L_1 L_1	[I_0] [I_1] L_05 L_05	[I_0] [I_1] L_025 L_025	[I_0] [I_1] L_01 L_01	
K_4	2.45 3.52	2.86 4.10	3.25 4.49	3.74 5.06	

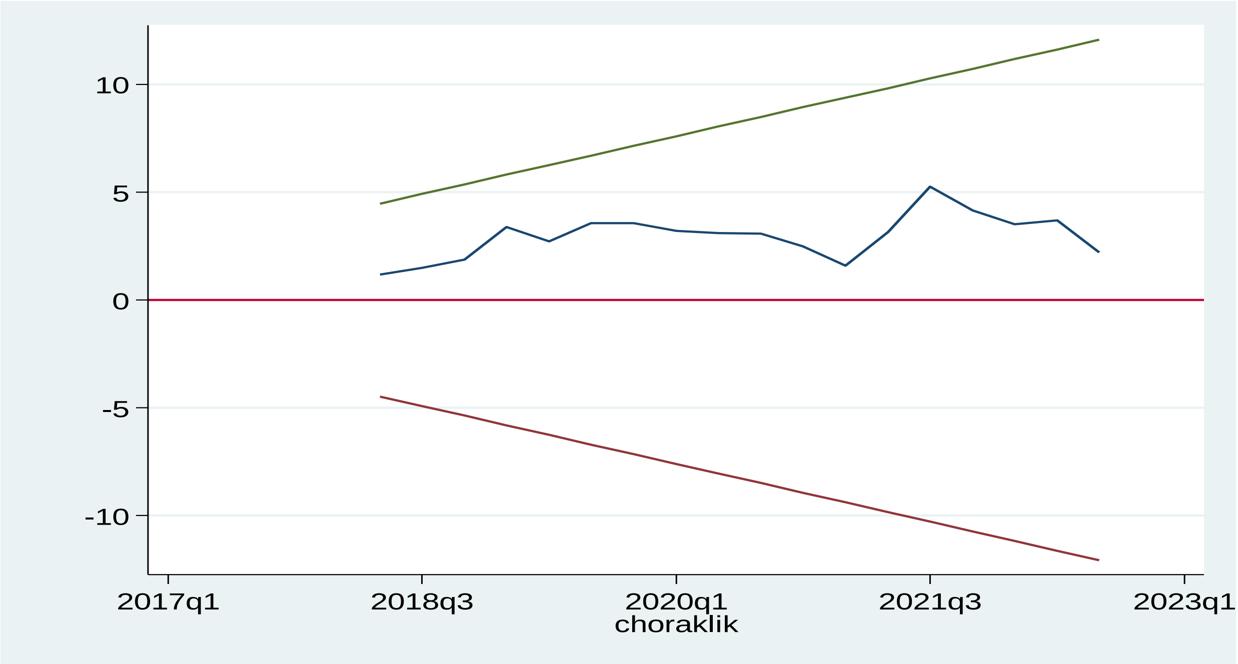
As shown in Table 4, the F-statistic value is greater than the critical value in all intervals, rejecting the null hypothesis regarding the absence of cointegration. The F-statistic value of 15.263 consistently exceeded the critical thresholds across all intervals, indicating a positive result for the Bound Test. Considering the significant level of the F-statistic, it supports the presence of cointegration in this model.

The ARDL(1,2,2,2) model produced the following results:

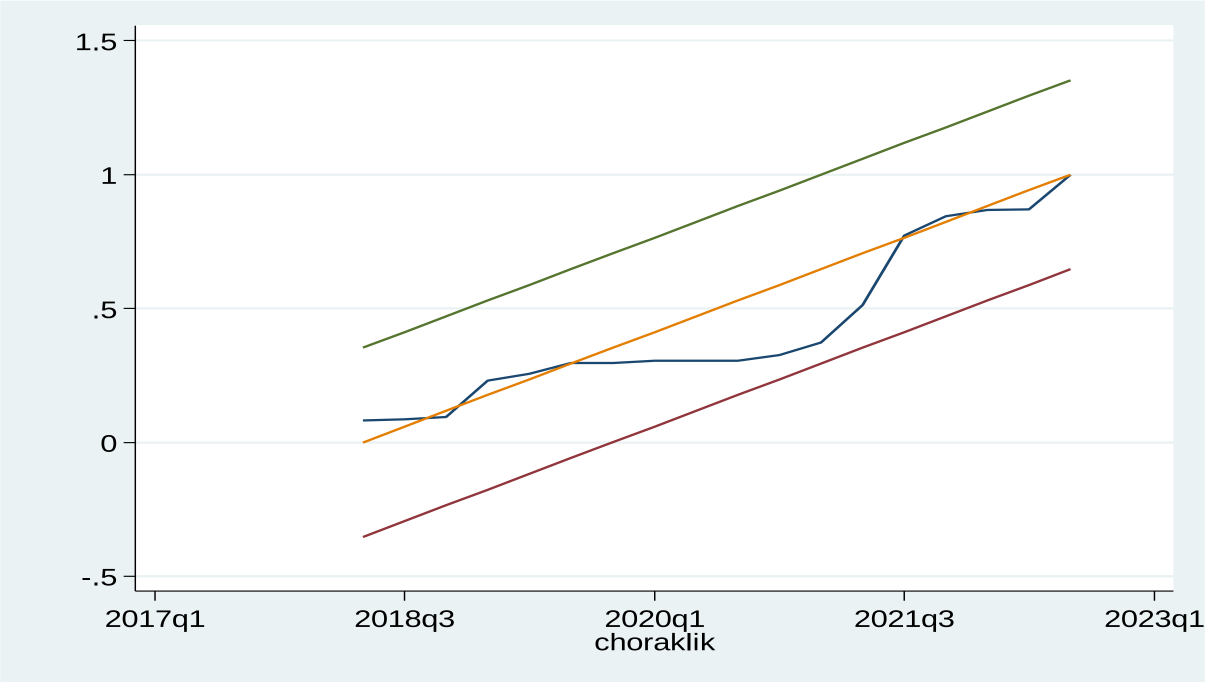
Result: A 1% increase in the number of insurance policies in the insurance company leads to a 0.40% increase in the number of underwriters in the insurance company. Similarly, a 1%

increase in insurance compensation results in a 0.33% increase in the number of underwriters in the insurance company. Additionally, a 1% increase in the insurance company's insurance premium leads to a 0.64% increase in the number of underwriters in the insurance company.

In the next step of the research, the CUSUM diagnostic test was conducted for the ARDL(1,2,2,2) model, as illustrated in Figures 4 and 5.



4- picture. CUSUM diagnostic test graph



5- picture. CUSUM diagnostic test graph

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The hypothesis statements for the CUSUM (Cumulative Sum) diagnostic test in the ARDL(1,2,2,2) model can be expressed as follows:

Null Hypothesis (H0): The parameters in the ARDL model are stable over time, and there are no systematic changes in the relationships between the variables. This implies that the model is genuine and reliable over the entire period.

Alternative Hypothesis (H1): The parameters in the ARDL model are not stable over time, and there are systematic changes in the relationships between the variables. This suggests that the model does not perform consistently over the entire period.

As indicated in the graphs presented in Figures 4 and 5 above, the CUSUM diagnostic test statistic remains within the critical bounds, and no significant deviations are observed. This implies that the CUSUM diagnostic test did not detect any structural breaks or significant changes in the relationships between the variables over time.

In the subsequent stages of the research, the ARDL model was assessed for compliance with the Gauss-Markov assumptions through various diagnostic tests. The results of the diagnostic tests are summarized as follows:

1. Durbin-Watson Test: The Durbin-Watson statistic was found to be 2.35.

2. Breusch-Pagan Test: The p-value for the Breusch-Pagan test was 0.10.

3. Shapiro-Wilk W Test: The Shapiro-Wilk W statistic yielded a result of 0.60.

4. Breusch-Godfrey LM Test: The p-value for the Breusch-Godfrey LM test was 0.10.

Furthermore, the joint hypothesis test (H0: $y = 0$) and (H1: $y \neq 0$) with $r > 0.05$ was conducted after the completion of the diagnostic tests. The statistical significance level was met, supporting the acceptance of the null hypothesis and confirming the compliance of the econometric model with the Gauss-Markov assumptions.

In conclusion, the econometric analysis using the ARDL(1,2,2,2) model provided evidence that the parameters in the model are stable over time, and the relationships between the variables remain consistent. The diagnostic tests affirmed the reliability of the model in capturing the dynamics of the analyzed variables.

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