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DOI10.7251/ZJF2514514L

ULOGA RASTA PREMIJA ŽIVOTNOG I NEŽIVOTNOG OSIGURANJA U EKONOMSKOM RASTU ZEMALJA EVROSPKE UNIJE: PANEL ARDL ANALIZA

Apstrakt: Osiguranje igra ključnu ulogu u ekonomskom razvoju, pružajući finansijsku sigurnost, podstičući investicije i smanjujući rizike u privredi. Posebno, rast premija životnog i neživotnog osiguranja može doprinijeti stabilnosti i rastu bruto domaćeg proizvoda (BDP), kako kroz mobilizaciju kapitala, tako i kroz unapređenje efikasnosti tržišta. Cilj ove analize je da ispita da li i u kojoj mjeri stope rasta bruto premija životnog i neživotnog osiguranja doprinose rastu BDP-a u zemljama Evropske unije, kako u dugom, tako i u kratkom roku. Istraživanje se temelji na kvartalnim panel podacima za zemlje Evropske unije, obuhvatajući period od četvrtog kvartala 2017. do trećeg kvartala 2024. godine. Za analizu međuzavisnosti koristi se panel ARDL (Autoregressive Distributed Lag) model, koji omogućava konzistentnu i efikasnu procjenu dugoročnih i kratkoročnih efekata osiguranja na ekonomski rast. Ovaj model omogućava primjenu na varijable koje su istog ili različitog nivoa integracije, ali nižeg od I(2), čime osigurava preciznije rezultate. S obzirom na ograničenja softverskog okruženja, procjena parametara vrši se primjenom Pooled Mean Group (PMG) metoda, koji omogućava pouzdanu interpretaciju dugoročne veze između osiguranja i privrednog rasta, uz dozvoljenu heterogenost kratkoročnih efekata među jedinicama posmatranja.

Ključne riječi: osiguranje, ekonomski rast, premije životnog i neživotnog osiguranja, panel ARDL model

THE ROLE OF LIFE AND NON-LIFE INSURANCE PREMIUM GROWTH IN ECONOMIC GROWTH OF EUROPEAN UNION COUNTRIES: PANEL ARDL ANALYSIS

Abstract: Insurance plays a crucial role in economic development by providing financial security, encouraging investment, and reducing risks in the economy. In particular, the growth of life and non-life insurance premiums can contribute to economic stability and GDP growth by mobilizing capital and improving market efficiency. The aim of this analysis is to examine whether and to what extent the growth rates of gross life and non-life insurance premiums contribute to GDP growth in the European Union countries, both in the long and short run. The research is based on quarterly panel data for European Union countries, covering the period from the fourth quarter of 2017 to the fourth quarter of 2024. To analyze these interdependencies, the panel ARDL (Autoregressive Distributed Lag) model is employed, allowing for a consistent and efficient estimation of both long- and short-run effects of insurance on economic growth. This model accommodates variables of the same or different levels of integration, provided they are below I(2), ensuring more precise results. Given the limitations of the software environment, parameter estimation is conducted using the Pooled Mean Group (PMG) method, which allows for a reliable interpretation of the long-term relationship between insurance and economic growth while permitting heterogeneity in short-term effects across observational units.

Keywords: insurance, economic growth, life and non-life insurance premiums, panel ARDL model

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1. INTRODUCTION

In recent decades, the global insurance sector has undergone significant transformations driven by technological advancements, economic factors and changes in consumer preferences. Digitalization and the development of insurtech technologies have enabled faster and more efficient distribution of insurance products, while increased awareness of financial risks has contributed to the growing demand for insurance. This growth trend is particularly evident in developed economies, including European Union countries, where insurance plays a key role in maintaining economic stability and fostering investment.

Insurance, as a crucial segment of the financial sector, has a significant impact on economic development. Numerous studies confirm a positive correlation between the development of the insurance sector and economic growth, highlighting its role in stabilizing the financial system and stimulating investment (Piljan et al., 2015; Arena, 2008; Haiss & Sümegi, 2008; Ward & Zurbruegg, 2002). As part of national savings and capital accumulation, insurance helps reduce economic risks, encourages innovation and competitiveness and creates conditions for long-term investments. In addition to its primary function of protecting individuals and businesses from financial risks, insurance companies allocate collected premiums across various economic sectors, contributing to sustainable economic growth. Life insurance, in particular, promotes savings and capital growth, while non-life insurance provides security for businesses, mitigating the negative effects of unforeseen events such as natural disasters and traffic accidents.

In the European Union, the insurance sector holds a significant position within the overall financial system, with varying levels of market development across member states. According to data from *Sigma 3/2019*[1], in 2018, the EU accounted for 28.80% of the global insurance premium, with the United Kingdom, France and Germany among the leading countries in the sector. However, a high premium volume does not necessarily indicate a well-developed market, as it also depends on the size of the economy. For example, the highest premium per capita was recorded in Switzerland, Denmark and Ireland, confirming the link between the insurance sector and a country's economic prosperity.

EU regulations ensure high standards of consumer protection and financial sector stability, while economic policies aim to align the role of insurance with broader goals of sustainable growth and investment. Insurance companies allocate substantial resources to infrastructure projects, capital markets and other sectors, contributing to financial resilience and economic security. Additionally, digitalization enhances the distribution of insurance products, increasing accessibility and service efficiency.

It is particularly important to analyze the relationship between the growth of life and non-life insurance premiums and the economic development of EU countries. Understanding this relationship can help formulate strategies for further developing the insurance sector and adapting it to the needs of the modern economy. The objective of this study is to examine how insurance premium growth impacts

1 Swiss Re, Sigma, 3/2019, https://www.swissre.com/institute/research/sigma-research/sigma-2019-03.html

economic growth in the EU. In this context, existing studies, the methodological framework, and empirical research findings will be analyzed, followed by conclusions and recommendations for the further development of the insurance sector in support of economic prosperity.

2. LITERATURE REVIEW

The relationship between the insurance sector and economic growth is a significant topic in the literature, as insurance plays a crucial role in shaping economic conditions and stability. The insurance sector helps mitigate risks and provides financial security, but it also plays a vital role in capital mobilization, increasing investments and ensuring efficient resource allocation, all of which directly influence economic growth. Research by Levine (1997) and Arena (2008) suggests that the development of the insurance sector contributes to increased investment and technological innovation, which accelerate economic development. Similar conclusions were drawn by Outreville (1996) and Haiss & Sümegi (2008), who emphasized that reducing uncertainty through insurance fosters entrepreneurial initiatives and innovation, thereby increasing productivity and overall economic activity.

Insurance also plays a key role in maintaining financial stability. According to Skipper (2001), by assuming and redistributing risks, the insurance sector contributes to the stability of the broader economic system. Research by Ward and Zurbruegg (2000) indicates that a well-developed insurance sector reduces economic volatility and enhances long-term market predictability.

Further econometric studies confirm the link between the insurance sector and economic growth, particularly through analyses of life and non-life insurance premiums. Alhassan and Biekpea (2016) examined the relationship between insurance penetration and economic growth in African countries and found a long-term connection, suggesting that a larger insurance market positively impacts economic development. Apergis and Poufinas (2020) analyzed data from 27 OECD countries and concluded that the growth of the insurance sector contributes to GDP growth, reaffirming its importance for the economy.

Insurance also aids in the efficient allocation of capital, which is crucial for growth, especially in developed economies. Arena (2008) confirms that life insurance has a stronger impact on economic growth in high-income countries, while non-life insurance significantly contributes to growth in both developed and developing nations. This finding suggests that different types of insurance have specific effects depending on the level of market development and the economic characteristics of a country.

The role of the insurance sector in economic development is also reflected in its ability to reduce operational risks, facilitating easier access to financing, particularly for small and medium-sized enterprises. Studies such as those by Cristea, Marcu and Cârstina (2014) indicate that insurance helps small businesses survive economic turbulence and expand their operations. Through these various functions, the insurance sector contributes to long-term economic growth by enhancing market stability and fostering innovation.

Interestingly, econometric studies employ different methods, such as ARDL cointegration, GMM models, panel analyses and Granger causality tests, which confirm a bidirectional causal relationship between the insurance market and economic growth. The findings suggest that life insurance has a more pronounced impact on economic growth in high-income countries, whereas non-life insurance contributes to growth in both developed and developing nations. These studies further highlight the importance of institutional factors, such as per capita income levels and demographic characteristics, in shaping the insurance market and its impact on the economy.

In conclusion, the insurance sector plays a significant role in the stability and dynamics of economic systems. Beyond providing risk protection, it plays a key role in capital mobilization, reducing uncertainty and ensuring efficient resource allocation, all of which directly contribute to economic growth. Analyses of different types of insurance, both life and non-life, indicate that their impact varies depending on a country's level of development and the economic characteristics of its market.

This paper focuses on analyzing the impact of the growth of life and non-life insurance premiums on the gross domestic product in European Union countries, using advanced econometric methods such as the panel ARDL model. The aim of the research is to clarify how insurance contributes to economic growth in both the short and long term and to enhance the understanding of the interdependence between the insurance sector and economic activity in the EU.

3. EMPIRICAL ANALYSIS

The aim of this analysis was to examine the existence of a causal relationship between gross domestic product and gross premiums for life and non-life insurance in European Union member states from the fourth quarter of 2017 to the third quarter of 2024. Gross premiums for life and non-life insurance were used as indicators of the development of the insurance market, while gross domestic product served as an indicator of overall economic activity. Data on the gross premiums for life and non-life insurance were obtained from the official website of the European Insurance and Occupational Pensions Authority (EIOPA)[2], while data on gross domestic product were obtained from the website of the Statistical Office of the European Union (Eurostat)[3]. Since the data were expressed in millions of euros, they were first transformed by logarithmic conversion to ensure greater stability of the time series, after which their stationarity was tested before proceeding with further econometric analysis.

3.1. Panel Unit Root Test

The earliest tests, known in financial literature as the first generation of tests for the existence of a unit root in panel data series, were based on the assumption of cross-sectional independence. Despite the fact that this assumption is often unrealistic, the authors of the first generation of panel unit root tests generally focused their research on the analysis of autoregressive processes, with a set of appropriate restrictions on the observation units or variables in the panel.

2 Insurance statistics - EIOPA
3 Statistics | Eurostat

When comparing time series and panel unit root tests, we observe that the main difference lies in the heterogeneity of the model parameters. Given that time series analysis is conducted on the data of a single observation unit over a certain period of time, it is logical that the existence of homogeneity in the model parameters is not questioned. However, when dealing with panel data, which includes a larger number of observation units, the question arises: when testing for the existence of a unit root, can the same autoregressive model be used for all observation units, or is it necessary to form a separate autoregressive model for each unit of observation to accurately describe the dynamics of the dependent variable?

In line with this, the model restrictions for the first generation tests mainly concerned whether the autocorrelation coefficients were identical or different for each observation unit. The first group of tests, which assume homogeneity of autocorrelation coefficients, includes the Levin, Lin, and Chu (LLC) test, Breitung test, Harris-Tzavalis (HT) test, and Hadri test. The second group, based on the heterogeneity of autocorrelation coefficients, includes tests such as Im, Pesaran, and Shin (IPS), and the Maddala, Wu, and Choi test. One of the most commonly used tests is the LLC (Levin, Lin, and Chu) test, which assumes a homogeneous structure among cross-sections but also allows for heterogeneity in individual deterministic components (constant and trend). Testing the existence of a unit root is based on the common application of the Augmented Dickey-Fuller test, which assesses the model in the following form:

$$\Delta y_{it} = \alpha_i + \delta_i t + \rho^* y_{i,t-1} + \sum_{l=1}^{p_i} \theta_l \Delta y_{i,l-1} + \varepsilon_t \qquad (3.1)$$

where $\rho^* = \rho - 1$, assuming that $\rho = \rho_i$, by which the assumption of a homogeneous structure among cross-sections is fulfilled.

The null hypothesis of the LLC test implies the existence of a unit root for all units of observation, while the alternative hypothesis refers to their stationarity. Therefore, the null and alternative hypotheses can be expressed as follows:

$$H_0 : \rho^* = 0$$

$$H_1 : \rho^* < 0$$

In their paper, Levin, Lin, and Chu (2002) applied Monte Carlo simulation techniques and proved that the LLC test provides the best results on samples that include between 10 and 250 observation units, with each unit represented by a time series of length from 25 to 250 time periods.

Although the LLC test is often used in various studies, it is important to point out that its main disadvantage lies in the restrictive assumption that all observation units' time series either have or do not have a unit root, as well as the assumption of homogeneity of autocorrelation coefficients.

A similar, but simpler, test was proposed by Harris and Tzavalis (1999). Unlike the LLC test, their test was based on the assumption of variance homogeneity and was designed to provide efficient results for observation units that have a relatively small number of time series instances.

One of the tests in this group is the Hadri test, whose null hypothesis is defined in opposition to the aforementioned tests. In other words, the null hypothesis assumes that each individual time series is stationary, as opposed to the alternative hypothesis, which assumes that each time series has a unit root. The Hadri test is similar to the KPSS unit root test in time series analysis (Kwiatkowski, Phillips, Schmidt, and Shin, 1992) and is based on the LM test of the residuals of the regression model of the dependent variable on a constant, or on a constant and trend. The regression models used for the Hadri test are as follows:

Model of a random walk (including only a constant)

$y_{it} = \alpha_{it} + \varepsilon_{it}$, and

Model that includes a constant and a trend

$$y_{it} = \alpha_{it} + \beta_i t + \varepsilon_{it} \;, \quad i = 1, \ldots, n \;,\; t = 1, \ldots, T$$

where $\alpha_{it} = \alpha_{i,t-1} + u_{it}$ is random walk. $\varepsilon_{it} \sim IIN\left(0, \sigma_\varepsilon^2\right)$ and $u_{it} \sim IIN\left(0, \sigma_u^2\right)$ are mutually independent.

The Hadri test statistic is given by:

$$LM = \frac{1}{NT^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{S_{it}^2}{\hat{\sigma}_e^2}$$

where $S_{it} = \sum_{j=1}^{t} \hat{e}_{ij}$ and $\hat{\sigma}_e^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{e}_{it}^2$.

Based on LM statistics, we obtain z-statistics, which, under certain conditions, tend to follow a standardized normal distribution. According to some studies, the Hadri test provides good results when the panel series has a moderate number of observation units (N), with each unit having a relatively large amount of time series data.

The first attempt to overcome the drawbacks of the first generation of tests that assume homogeneity of autocorrelation coefficients and to increase the power of panel unit root tests, was made by Im, Pesaran and Shin (2003). They proposed and developed the IPS test, based on the average value of individual unit root statistics. The initial model of the IPS test assumes heterogeneous autocorrelation coefficients, meaning that the coefficients of the lagged dependent variable are not the same across cross-sections. The IPS statistic is obtained as the average value of the t-statistics from the Augmented Dickey-Fuller test, calculated individually for each unit of observation:

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i}$$

The null and alternative hypotheses of the IPS test are defined as follows:

$$H_0 : \rho_i < 1 \quad \text{or} \quad \rho_i^* = 0$$

$$H_1 : \rho_i < 1 \quad \Leftrightarrow \quad \rho_i^* < 0 \quad for \quad i = 1,2,\ldots,N_1;$$

$$\rho_i = 1 \quad \Leftrightarrow \quad \rho_i^* = 0 \quad for \quad i = N_1 + 1,\ldots,N.$$

The null hypothesis of the IPS test assumes the existence of a unit root in the time series of all observation units, whereas the alternative hypothesis assumes that at least one time series of the observation units does not contain a unit root, meaning it is stationary at the level of data for which the test is conducted.

Using Monte Carlo simulation techniques, the authors of the IPS test demonstrated that the test provides satisfactory results even with small samples, i.e., a small number of both observation units and time intervals. Although the IPS test provides better results compared to the LLC test, its use is restricted to balanced panel data. Additionally, the requirement to use the same number of lags in individual regressions when implementing the Augmented Dickey-Fuller test can, in certain situations, lead users to incorrect conclusions.

The tests that provided further improvements in testing for a unit root in panel data are Fisher-type tests, which are known in the literature as combined unit root tests. Two such tests were proposed by Maddala and Wu (1999) and Choi (2001), and their advantage lies primarily in the fact that they can be used even when the available data consists of unequal time-series lengths across cross-sections. They also allow for different values of stochastic and non-stochastic components for each individual test. These tests are based on the use of nonparametric tests to ensure the removal of autocorrelation without introducing additional lags into the model. The Maddala and Wu test requires a predetermined number of lags in the model, while the Choi test, in addition to specifying exogenous variables (constant or constant and trend), requires the specification of a method for evaluating spectral analysis (Gligoric, 2015).

With the proposed tests, Maddala and Wu (1999) and Choi (2001) aimed to overcome the limitations of existing tests that required each observation unit to contain the same number of time instances. This is achieved by defining the tests based on the combination of p-values from independent time series tests for each observation unit individually.

Madalla and Wu proposed the application of the inverse χ^2 test in the form: $P = -2\sum_{i=1}^{N} \ln\left(p_i\right)$, while Chio proved that the best properties are achieved with the inverse test of the normal distribution: $Z = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} \Phi^{-1}\left(p_i\right)$,

where Φ represents the standardized cumulative normal distribution function (Glavaški, 2016).

The null and alternative hypotheses of the two previously mentioned tests are defined in the same way as the hypotheses of the IPS test.

It should be noted that the analysis is based on quarterly data on gross premiums for life and non-life insurance, as well as data on gross domestic product for the period from the fourth quarter of 2017 to the third quarter of 2024. The data on gross premiums for life and non-life insurance were obtained from the website of the European Insurance and Occupational Pensions Authority (EIOPA), while the data on gross domestic product were obtained from the website of the Statistical Office of the European Union (Eurostat). Since the data is expressed in monetary units in millions of euros, these data were initially transformed by logarithmizing, and then the stationarity of the transformed data was tested. Considering that the power of tests can be compromised in the case of shorter time series, we decided to determine the existence of a unit root using multiple different tests. For the appropriate tests, we also used the results from models that include a constant or a constant and trend.

When determining the optimal number of lags in the autoregressive model at the panel level, as well as for first-difference data, we used the Schwarz criterion. Additionally, for the appropriate tests, we used the Bartlett spectral window and the Newey-West method for estimating long-term variance.

The results of the tests applied to the data at the level are shown in Table 3.1.

Table 3.1. Results of the unit root tests in panel series for data at the level of observed variables.

	Ln(GDP)		Ln(Non_life)		Ln(Life)	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
LLC -intercept	3.36970	0.9996	35.4500	1.0000	331.3095	1.0000
LLC – intercept and trend	-1.80026	0.0359**	76.8984	1.0000	64.5080	1.0000
LLC - none	8.56310	1.0000	9.20367	1.0000	4.80854	1.0000
Breitung t-stat – intercept and trend	-1.88166	0.0299**	3.37181	0.9996	1.39449	0.9184
IPS – intercept	6.51670	1.0000	5.86769	1.0000	-1.86008	0.0314**
IPS – intercept and trend	-2.69461	0.0035**	-3.48012	0.0003**	-4.95032	0.0000**
Fisher ADF –intercept (Maddala i Wu)	6.91349	1.0000	39.1457	0.9358	92.85744	0.0008**
Fisher ADF – intercept and trend (Maddala i Wu)	71.7877	0.0531	344.809	0.0000	111.971	0.0000**
Fisher ADF – none (Maddala i Wu)	2.53156	1.0000	6.63364	1.0000	14.4142	1.0000
Fisher PP – intercept (Choi)	21.2001	1.0000	537.698	0.0000**	748.767	0.0000
Fisher PP – intercept and trend (Choi)	218.479	0.0000**	1863.89	0.0000**	2456.90	0.0000
Fisher PP – none (Choi)	1.81064	1.0000	18.5131	1.0000	26.7837	0.9993
Hadri – intercept	15.9616	0.0000**	10.6058	0.0000**	6.85670	0.0000**
Hadri – intercept and trend	11.1364	0.0000**	9.17618	0.0000**	9.20087	0.0000**

Source: Author's calculations

** Denotes significance at the level of 5%

The results of the unit root tests in Table 3.1 show that for Ln(GDP), the null hypothesis of a unit root can be rejected in most tests when considering the trend (LLC – intercept and trend, Breitung t-stat, IPS – intercept and trend, Fisher ADF – intercept and trend, Fisher PP – intercept and trend), suggesting that the series is stationary at the level when the trend is taken into account. However, for Ln(Non_life) and Ln(Life), the results are not consistent, as most tests indicate that the null hypothesis of a unit root cannot be rejected, which suggests that these series are non-stationary at the level.

For this reason, it is necessary to further test the stationarity of the series for Ln(Non_life) and Ln(Life) at the first difference to determine if they become stationary after differencing.

Table 3.2. Results of unit root tests in panel series for first-order differenced data of the observed variables.

	d(lnGDP)		D(lnNonLife)		d(lnLife)	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
LLC -intercept	-9.61419	0.0000**	-59.7662	0.0000**	-87.4013	0.0000**
LLC – intercept and trend	-6.46117	0.0000**	-60.7060	0.0000**	-81.2118	0.0000**
LLC - none	-18.4181	0.0000**	-8.48376	0.0000	-12.6765	0.0000**
Breitung t-stat – intercept and trend	-12.4148	0.0000**	-0.60311	0.2732	-3.34276	0.0004**
IPS – intercept	-16.8644	0.0000**	-61.6856	0.0000**	-44.4277	0.0000**
IPS – intercept and trend	-17.8440	0.0000**	-65.4354	0.0000**	-44.3171	0.0000**
Fisher ADF –intercept (Maddala i Wu)	357.464	0.0000**	132.043	0.0000**	131.367	0.0000**
Fisher ADF – intercept and trend (Maddala i Wu)	445.561	0.0000**	1355.16	0.0000**	593.534	0.0000**
Fisher ADF – none (Maddala i Wu)	342.012	0.0000**	89.2049	0.0018**	182.898	0.0000**
Fisher PP – intercept (Choi)	697.530	0.0000**	783.390	0.0000**	699.365	0.0000**
Fisher PP – intercept and trend (Choi)	3984.57	0.0000**	5021.8	0.0000**	5834.47	0.0000**
Fisher PP – none (Choi)	1030.69	0.0000**	2285.25	0.0000**	3118.17	0.0000**
Hadri – intercept	3.19601	0.0007**	4.71154	0.0000**	5.51931	0.0000**
Hadri – intercept and trend	14.6267	0.0000**	20.5615	0.0000**	24.7315	0.0000**

Source: Author's calculations

** Denotes significance at the level of 5%

The results of the unit root tests for the first differences of Ln(NonLife) and Ln(Life) indicate that the null hypothesis of the existence of a unit root can be rejected at the 5% significance level in almost all tests. This means that both variables are integrated of order I(1), i.e., they become stationary after first differencing.

Given that we are examining the existence of cointegration between GDP and gross premiums for life and non-life insurance, differing levels of integration among the variables would complicate the application of standard cointegration tests such as the Pedroni, Kao, and Fisher-Johansen tests. Therefore, cointegration testing among the variables will rely on the results of the relatively new panel ARDL (Autoregressive Distributed Lag) model, proposed by Pesaran (1997) and Pesaran and Shin (1999). This model allows for consistent and efficient estimation of both long-term and short-term effects in panel data that include a large number of observation units and time instances, provided that the analyzed variables have the same or different levels of integration, but do not exceed I(2).

3.2. ARDL model

Paseran and Shin (1990) define the form of the dynamic ARDL (p, q) model as follows:

$$y_{it} = \sum_{j=1}^{p} \lambda_j \, y_{i,t-j} + \sum_{j=0}^{q} \delta_j \, x_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (3.2)$$

where:

i represents the number of observation units $i = 1,2,\ldots,N$,

t represents the number of time instances $t = 1,2,\ldots,T$,

x_{it} is vector of independent variables of dimension $k \times 1$,

λ_{ij} is coefficient of lagged dependent variable,

μ_i is parameter that determines the specific effects of the group or observation unit.

The model in expression (3.2) can be extended by including a trend and other fixed regressors.

In the analysis, we first test whether a long-term co-integration relationship exists between the variables. If we find that there is no co-integration, we proceed with the analysis of short-term effects. However, if we find that co-integration does exist between the variables, we will need to form an error correction model to determine the speed at which the dependent variable adjusts to its long-term equilibrium. The error correction model is of the form:

$$\Delta y_{it} = \phi_i \left(y_{i,t-1} - \theta_i x_{it} \right) + \sum_{j=1}^{p-1} \lambda_j^* \, \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta_j^* \Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \qquad (3.3)$$

where $y_{i,t-1} - \theta_i x_{it}$ represents the error correction term, i.e., the error correction coefficient that measures the speed of adjustment to the long-term equilibrium.

The two most commonly used methods for parameter estimation of ADRL model are: Mean Group Estimator (MG) and Pooled Mean Group Estimator (PMG). These two parameter estimation methods were developed by Pesaran, Shin and Smith

(1999), and their adventage is reflected in the fact that they are robust to heterogeneity of regression coefficients in structural dimension as well as to the existence of autocorrelation in time dimension.

Pooled Mean Group Estimator is characterized by the fact that it implies heterogeneity of coefficients which determine the existence of a long-term co-integration relationship between variables, while the coefficients of the speed of adjustment to long-term equilibrium, as well as the coefficients of the specific effects vary across observation units. Application of this method is justified and especially useful in situations when there exist reasons to expect a similar long-term relation between the variables across all observation units, or at least among some of them. PMG Estimator will give consistent and efficient estimates, provided that certain conditions are met. The first condition, which is also necessary for making a decision on the existence of long-term relation between the variables, refers to the value of error correction coefficient. The value of this coefficient must be negative, but not less than -2, and also statistically significant. The second condition for the fulfillment of the consistency of the results of ARDL model refers to non-existence of serial correlation between residuals of error correction model.

The second estimation method is Mean Group (MG) estimator based on the estimates of regression model for each observation unit individually. In other words it means that there are no restrictions in terms of coefficient homogeneity, meaning that the coefficients that determine both long- and short-term relationship between the variables may differ across observation units. In order for this method to provide consistent estimates, the number of observation units should vary between 20 and 30, and each observation unit should have a sufficiently long time series of data.

In the following, an ARDL model will be formed to evaluate the existence of a cointegration relationship between gross domestic product and gross premiums for life and non-life insurance. Given the limitations of the student version of EViews 12, which does not allow the application of the MG method, the Pooled Mean Group (PMG) method will be used in this study to estimate the parameters of the ARDL model. This method is particularly suitable in situations where a similar long-term relationship is expected between variables, with allowed variation in short-term parameters across observation units, which in this case is based on the characteristics of panel data.

Table 3.3. Estimated ARDL model using the PMG method to evaluate the existence of a cointegration relationship between gross domestic product and gross premiums for life and non-life insurance.

D(lngdp)		Pooled Mean Group (PMG)		
Variable	Coeff.	Std. Error	t-Statistic	Prob.*
Long Run Equation				
D(lnlife)	0.236784	0.033421	7.084920	0.0000
D(lnnonlife)	-0.142071	0.044655	-3.181522	0.0016
Short Run Equation				
Error correction Coeff.	-0.887530	0.082706	-10.73115	0.0000
D(lngdp(-1),2)	-252926	0.075560	-3.347338	0.0009
D(lngdp(-2),2)	-0.194377	0.049936	-3.892560	0.0001
D(lnlife,2)	-0.026714	0.042704	-0.625569	0.5320
D(lnlife(-1),2)	-0.182802	0.061816	-2.957186	0.0033
D(lnlife(-2),2)	-0.111817	0.060266	-1.855385	0.0643
D(lnlife(-3),2)	-0.031643	0.041509	-0.762314	0.4463
D(lnnonlife,2)	0.401256	0.161327	2.487218	0.0133
D(lnnonlife(-1),2)	0.593435	0.181039	3.277946	0.0011
D(lnnonlife(-2),2)	0.526104	0.175436	2.998839	0.0029
D(lnnonlife(-3),2)	0.414923	0.167751	2.473450	0.0138
C	0.014317	0.002083	6.871797	0.0000
Const.	0.0301148***	0.0097315		0.002
Root MSE	0.022173	Mean dependent var		-0.000273
S.D. dependent var	0.141670	S.E. of regression		0.029822
Akaike info criterion	-3.184545	Sum of squared resid		0.358415
Schwarz criterion	-1.131204	Log likelihood		1486.767
Hannan-Quinn criter.	-2.392301			

Source: Author's calculations

** Denotes significance at the level of 5%

It should be noted that the residuals of the estimated model satisfy the condition of normal distribution, as well as the condition of absence of serial correlation, ensuring the efficiency and consistency of the model. The normality test was conducted using the Jarque-Bera test, while panel unit root tests of the first generation were used to test for the absence of serial correlation among the residuals of the estimated model. The results of the unit root tests for the residuals of the ARDL model showed that the residual series are stationary at the level. The values of the unit root tests are presented in Table 3.4.

Table 3.4. Results of unit root tests for the residuals of the estimated ARDL model

	Reziduali ocijenjenon ARDL modela	
	Statistic	p-value
LLC -intercept	-8.199447	0.0000**
LLC – intercept and trend	-6.74106	0.0000**
LLC - none	-15.8702	0.0000**
Breitung t-stat – intercept and trend	-5.64589	0.0000**
IPS – intercept	-8.20160	0.0000**
IPS – intercept and trend	-5.81117	0.0000**
Fisher ADF –intercept (Maddala i Wu)	164.455	0.0000**
Fisher ADF – intercept and trend (Maddala i Wu)	122.842	0.0000**
Fisher ADF – none (Maddala i Wu)	303.980	0.0000**
Fisher PP – intercept (Choi)	333.173	0.0000**
Fisher PP – intercept and trend (Choi)	279.456	0.0000**
Fisher PP – none (Choi)	504.625	0.0000**
Hadri – intercept	0.15883	0.4369**
Hadri – intercept and trend	3.35442	0.0004**

Source: Author's calculations

** Denotes significance at the level of 5%

Once we have demonstrated that the models provide efficient and consistent estimates, we can conclude the existence of a cointegrating relationship between the observed variables based on the values of the coefficients and their statistical significance. In this context, the analysis of the long-term effects of insurance on economic growth reveals clear patterns of impact—life insurance has a positive effect, while non-life insurance shows a negative effect.

The positive and statistically significant coefficient for life insurance suggests that the growth of premiums in this sector contributes to an increase in GDP. This result aligns with expectations for European Union countries, as life insurance encourages long-term savings and investments, reduces financial uncertainty for households, and facilitates the redirecting of capital into productive sectors of the economy. Insurance companies often reinvest the collected funds into government bonds, the capital market, and infrastructure projects, further contributing to the stability and growth of the economy.

In contrast, non-life insurance shows a negative effect on economic growth in the long term, which is somewhat unexpected. Although it is theoretically anticipated that this segment of insurance would contribute to economic stability by reducing risk and enabling faster recovery from unforeseen losses, the negative effect can be explained by higher premium costs, regulatory restrictions, and administrative expenses that reduce its efficiency. Increased premiums may limit household disposable income and reduce aggregate consumption, while excessive regulation may hinder the functioning of insurance companies. Additionally, moral hazard may play a role, as greater insurance coverage can reduce the caution of individuals and firms in managing risks, leading to higher costs and a diminished positive effect on the economy.

This result may indicate specific challenges in the non-life insurance market in the analyzed EU countries, including high premium prices, insufficient competition, or inefficient regulation, which potentially limits its contribution to economic growth.

Although the long-term effects of insurance are clearly visible, the analysis in the short term shows a contrasting pattern. The results of the PMG estimation indicate that non-life insurance has a positive and statistically significant effect on economic growth, while life insurance shows a negative impact with a time lag. The effect of non-life insurance in the current period is significantly positive (coefficient 0.401256, p = 0.0133), and the lags of non-life insurance (D(lnnonlife(-1),2), D(lnnonlife(-2),2), D(lnnonlife(-3),2)) also show positive coefficients, suggesting a long-term positive impact.

On the other hand, the current effect of life insurance is not statistically significant (p = 0.5320), meaning that its impact is not immediately present, but negative effects emerge in later periods. The lags of life insurance (D(lnlife(-1),2) and D(lnlife(-2),2)) show negative and statistically significant coefficients (-0.182802, p = 0.0033 and -0.111817, p = 0.0643), indicating a delayed negative impact on GDP.

These results suggest that non-life insurance has a positive effect in the short term, likely due to the rapid settlement of claims and increased consumption, which directly stimulates economic growth. In contrast, life insurance, although important for long-term economic development, may have a negative effect in the short term, as it locks up capital, reduces households' disposable income, and directs money into savings that does not immediately flow back into the economy.

For EU countries, these results may be expected for several reasons. Non-life insurance in the EU often has a direct and rapid economic impact, as it allows for the swift restoration of economic activity in the event of accidents, natural disasters, or other unexpected events. Additionally, the non-life insurance market in the EU can reduce financial risks, which enables higher consumption and greater economic stability. In contrast, life insurance, while important for long-term economic stability, may have a negative impact on short-term financial flows because its effects on savings and investments are not immediately visible.

Furthermore, the coefficient for the error correction term (ECT), which is -0.887530, suggests a very fast market adjustment toward equilibrium after shocks. This coefficient indicates that approximately 88.8% of the equilibrium error is corrected in each period, meaning the market reacts very quickly to changes and shocks in the economy. The swift return to equilibrium is largely due to the efficiency of the insurance market, which allows for rapid mobilization of resources and stabilization of economic variables following negative or positive shocks. Such a result is particularly expected for the EU, where insurance markets possess high liquidity, developed regulations, and mechanisms for effectively managing crises. Thus, the insurance market enables EU economies to recover quickly after shocks, confirming that the economies in this region are well-prepared to manage crises and maintain stability over the long term.

4. CONCLUSION

Based on the conducted research, it can be concluded that there is a significant relationship between life and non-life insurance premiums and economic growth in the European Union, with the effects varying depending on the time frame.

Regarding life insurance, in the long term, it has a positive impact on economic growth. An increase in life insurance premiums contributes to higher savings and investments, thereby reducing the financial uncertainty of households and encouraging the redirecting of capital into economic sectors that support growth. Insurance companies often reinvest funds in the capital market and infrastructure projects, which helps stabilize and expand the economy.

On the other hand, non-life insurance shows negative effects on economic growth in the long run. This result can be attributed to higher premium costs, excessive regulatory demands, and administrative burdens that reduce the efficiency of the non-life insurance market. In particular, high premiums can reduce the disposable income of households, limiting consumption and negatively affecting overall economic activity. Furthermore, there is a possibility of moral hazard, where individuals or businesses become less careful in managing risks, further diminishing the positive effects of this segment of the insurance industry.

In the short term, the effects are opposite. Non-life insurance initially shows a positive impact on the economy, likely due to the rapid payout of claims that stimulates consumption, while life insurance, at first, may reduce disposable income due to higher premiums, which negatively affects current consumption. The effects of long-term savings and investments gradually become apparent.

The Error Correction Term (ECT) indicates that the insurance market in the EU reacts quickly to economic changes and shocks, with as much as 89% of imbalances being corrected within a relatively short period. This suggests that the insurance market plays a key role in maintaining financial stability and enabling the rapid recovery of European economies after periods of crisis.

In conclusion, while life insurance contributes to long-term economic growth by stimulating savings and investments, its short-term effect may be negative. In contrast, non-life insurance has a positive impact on the economy in the short run, but in the long term, it may cause negative effects, indicating the need for further regulatory adjustments and optimization of the insurance market.

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