# Macroeconomic Factors and the Life Insurance Sector in Greece: An Analytical Perspective

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**Abstract**

This study examines the determinants of life insurance demand in Greece using multiple and quantile regression techniques applied to quarterly data from 2007 to 2021. Autoregressive terms address residual autocorrelation, and variable selection is guided by the Akaike Information Criterion (AIC). The analysis incorporates "hard" macroeconomic variables, such as income and inflation, and broader economic sentiment indicators, including the Economic Sentiment Indicator and the World Uncertainty Index.

Recognizing the critical role of life insurance in the financial system, the study also examines the Granger causality between economic development and life insurance penetration in both bivariate and multivariate frameworks, as well as in the frequency domain.

Results indicate that life insurance demand tends to increase during periods of economic downturn, marked by declining GDP per capita, stable interest rates, and a slight consumer preference for spending over saving. A strong bidirectional Granger causal relationship is identified between GDP per capita and life insurance penetration, with an estimated lag of approximately 4.5 quarters. These findings underscore the macroeconomic significance of the life insurance sector and suggest that its dynamics should be factored into broader economic policy.

**Keywords:** Linear and quantile regression; Variable selection; Life insurance; Granger causality; Macroeconomic Factors

# 1 Introduction

Life insurance allows policyholders to build capital for their chosen beneficiaries, acting as both a savings method and a tool for wealth transfer. Related tax advantages further heighten the appeal. These policies reduce risks associated with mortality and long-term savings, ensuring financial protection for a specified term or throughout an individual's life. Payouts can be designed as a lump sum, annuity, or a mix of both, with returns either fixed or tied to investment performance. Insurers determine premium rates to cover risk costs, manage administrative fees, and earn profits.

Research indicates that each insurance market is influenced by the national economy it operates within, resulting in unique trends. The primary factors affecting demand can be generally divided into four categories: (1) sociodemographic factors, like life expectancy and education; (2) macroeconomic elements, such as income levels and inflation; (3) institutional aspects, including political checks and balances as well as compliance with civil rights; and (4) cultural elements, involving gender egalitarianism and uncertainty avoidance, as examined in the works of Chui and Kwok (2008) and Hofstede (1995).

Literature has examined various factors that affect life insurance demand, primarily employing panel data analyzed through linear models, which aggregate and analyze information from multiple countries. These studies have pinpointed essential demand drivers, clarified their influence's direction through parameter signs, and evaluated their elasticity. Significant contributions to this area, listed chronologically, are by Hammond et al. (1967), Mantis and Farmer (1968), Cummins (1973), Fortune (1973), Anderson and Nevin (1975), Cargill and Troxel (1979), Beenstock et al. (1986), Browne and Kim (1993), Outreville (1996), Ward and Zurbruegg (2002), Beck and Webb (2003), Li et al. (2007), and Elango and Jones (2011).

Furthermore, life insurance is shaped by several supply-side factors, such as the presence of skilled industry professionals, access to risk data, and a financial system that supports stable investments. Protecting property rights, ensuring robust regulatory oversight, and maintaining contractual obligations are vital for effectively operating private insurance markets.

This study investigates the relationship between macroeconomic factors and Greece's life insurance sector. Given the distinct characteristics of the national economy, a thorough country-specific analysis is essential.

This study extends prior research by integrating multiple regression, variable selection, and quantile regression methodologies. The multiple regression model serves as the baseline framework, capturing average marginal effects of explanatory variables on life insurance demand. Initial diagnostic testing revealed significant autocorrelation in the residuals, which could compromise the validity of statistical inference. To address this, autoregressive terms of the dependent variable were incorporated as instruments within the regression model. Subsequent analysis of the squared residuals indicated no significant autocorrelation, supporting the assumption of homoscedasticity.

To strengthen the analytical rigor of our study, we employed variable selection techniques to eliminate predictors with limited explanatory value, thereby focusing on the most significant determinants of life insurance demand. Autocorrelation diagnostics of the residuals were performed on the complete model and each intermediate model generated during the variable selection process to ensure statistical validity. We applied quantile regression to explore further the heterogeneity in relationships across the distribution of the dependent variable. This method enables the estimation of factor elasticities at various points in the distribution, for example, within the upper 30%, offering a more detailed understanding. A key advantage of quantile regression is its ability to capture distribution-specific variations in elasticity that may be masked in conventional mean-based models. This approach builds on Enz (2000), who documented significant variations in the income elasticity across different insurance penetration levels.

This research begins by examining how the macroeconomic environment impacts life insurance in a one-sided manner. However, it's essential to grasp the complex interactions that lead to a long-term, reciprocal influence (see, for example, Arena (2008); Ward and Zurbruegg (2000); Lee et al. (2013)). This highlights that private insurance is not merely a consumer choice but a vital part of the financial system. An effective insurance market bolsters the financial system's stability, fosters synergies with the banking sector, and facilitates more favorable lending conditions through non-life insurance.

Furthermore, private insurance is a vital institutional investor, directing life insurance reserves to offer financing. This role boosts the liquidity and stability of the financial system, encourages competition, and spurs innovation, ultimately benefiting the national economy. Thus, we need to examine the interrelation of the two figures, economic development and life insurance consumption. The primary methodological approach is the Granger causality analysis, both in the time and frequency domains.

The study examines demand-influencing factors, including the "hard" elements of income and inflation alongside broader economic indicators like the Economic Sentiment Indicator and the World Uncertainty Index. Although the "hard" factors are well-documented in existing literature, we contend that incorporating Economic Climate Indicators (ECI) will strengthen the statistical models' explanatory capacity.

This study contributes to the existing literature by analyzing the determinants of life insurance demand in Greece, with particular attention to the variation in elasticities across the distribution of the dependent variable. The impact of each factor is assessed individually through quantile regression models, allowing for a nuanced understanding of demand behavior. In addition to traditional macroeconomic variables, the analysis incorporates Economic Climate Indicators (ECIs), including the Economic Sentiment Indicator, the Consumer Confidence Index, the World Uncertainty Index, and the Pandemic Uncertainty Index, offering a novel perspective on the determinants of life insurance uptake. To support this analysis, we compiled a quarterly dataset, enabling detailed investigation of how life insurance premiums respond to shifts in the macroeconomic environment. Few prior studies, namely those of Fortune (1973), Headen and Lee (1974), and Guo et al. (2009), have employed quarterly data in this context. Furthermore, following the methodological framework pioneered by Geweke (1982), we apply a Granger causality test in the frequency domain, which has not been previously employed to examine the relationship between life insurance demand and macroeconomic indicators.

The structure of this research is as follows: After the introduction, a comprehensive literature review will be provided. Section 3 will detail the econometric methodologies employed in this study. In Section 4, we will analyze the data and present the results of our empirical investigation. Finally, the conclusion will summarize our findings and propose directions for future research.

# 2 Literature Review

A simplistic perspective may suggest that the production of insurance premiums directly correlates with a country's GDP. Nonetheless, pronounced variations in per capita insurance premiums among countries reveal that additional factors contribute to this phenomenon. For instance, in the first quarter of 2020, Norway recorded quarterly per capita life insurance premiums of €502, nearly 20 times larger than Latvia's €25. In contrast, Norway's quarterly GDP per capita amounted to €17.6k, not five times Latvia's €2.7k. This remarkable disparity underscores that income alone is insufficient to account for these variances. Beck and Webb (2002) reinforce this argument by demonstrating that, when considering other pertinent factors, the significance of income as a key determinant is greatly reduced.

Researchers have explored the factors affecting the demand for life insurance for many years, starting with Yaari's early contribution in 1965. This field of study has seen extensive investigation, with reviews of the significant findings aggregated by Zietz (2003) and Outreville (2013). Much of the research employs a consistent methodology, analyzing the link between life insurance premiums and various influencing factors, as mentioned in the Introduction, and ultimately assessing the effects of these factors.

Price plays a crucial role in purchase decisions. Nevertheless, limited information about life insurance products has obstructed research in this field. Consequently, insights into insurance pricing generally stem from their costs, which are affected by several factors. These factors encompass urbanization levels, economic stability, quality of public administration, compliance with the rule of law, corruption levels, and the banking sector's development.

This research created and employed a quarterly database that records insurance premiums and demand determinants.

## 2.1 Income

Life insurance premiums generally increase as income rises, reflecting higher demand for mortality coverage and greater savings ability. Higher income is often associated with boosted consumer spending and rising property values, heightening the need to protect future earnings and safeguard dependents from the threats posed by job loss or the death of a household's primary earners.

It is important to recognize that managing insurance policies offering substantial benefits necessitates correspondingly high premiums. Nevertheless, this increase does not significantly elevate insurance companies' operating costs. Consequently, the ratio of operating costs to revenues diminishes, enhancing the attractiveness of insurance services to consumers.

Income's importance as an explanatory variable is substantial, consistently appearing in all studies in this research area. Early mentions include Hammond et al. (1967) and Fortune (1973), which were followed by Campbell (1980), Outreville (1996), Li et al. (2007), Sliwinski et al. (2013), and many others.

Life insurance is considered a luxury good, with demand significantly influenced by income changes. This indicates that the demand for life insurance premiums increases as people's incomes rise. However, the demand elasticity for life insurance isn't consistent and can differ widely across various countries. This connection is illustrated as an "S-Curve Relation Between Per-Capita Income and Insurance Penetration" (Enz (2000), supported by additional evidence from Lee et al. (2013), Figure 2, p. 415.

In a study commissioned by the World Bank, Beck and Webb (2002) discovered that income becomes less significant as an explanatory variable when examined alongside factors like the youth dependency ratio to the working population, length of education, life expectancy, inflation, growth of the banking sector, and income inequality (refer to Model 5, p. 39).

Elango and Jones (2011) presented similar results. Their study indicated that models relying on a selection of independent variables from the complete model (Models 1 to 3, p. 11) displayed only slight decreases in explanatory power ($R^2$), despite the exclusion of conventional factors such as income and inflation.

Trinh et al. (2023) showed that income elasticity results can differ based on the modeling approach (OLS or GMM), the countries studied (advanced or developing), and the explanatory variables involved. While income has long been seen as a key factor influencing insurance demand, typically with a positive impact, recent literature reveals that this relationship is becoming more ambiguous and uncertain.

Recent research complicates the connection between income and insurance premiums by introducing another variable: foreign direct investment (FDI). Rising FDI boosts income levels and insurance premiums for life insurance (Carson et al. (2021)) and non-life insurance (Sawadogo et al. (2018)).

## 2.2 Inflation

An accommodative monetary policy frequently results in significant inflation, potentially diminishing consumers' confidence in the enduring value of money and complicating their financial strategies. Consequently, consumers might shy away from fixed-interest financial products, often linked to the life insurance industry, and instead choose investments such as stocks, which usually gain value during inflationary periods. This change can lead to a smaller customer base for insurance firms.

In response to the negative impacts of high inflation, insurance companies have developed products to provide inflation protection. Despite these initiatives, they often fall short (Babbel (1981)). Research conducted by Greene (1954), Browne and Kim (1993), Outreville (1996), Çelik and Kayali (2009), and Ertl (2017) shows that high inflation periods adversely affect life insurance policies.

Although inflation is known to be a major macroeconomic factor affecting the demand for life insurance, its importance might lessen when evaluated alongside other elements. For example, Feyen et al. (2011) demonstrated this in a study commissioned by the World Bank, which incorporated the credit-to-GDP ratio in a statistical model.

While most studies have mainly examined inflation, the life insurance sector may suffer in a scenario of persistently low inflation, potentially leading to deflation, an economic challenge that demands significant action from authorities. Deflation impacts consumers' capacity to afford life insurance premiums. However, this topic falls outside this research's scope and is more relevant to investigations into life insurance lapses and surrenders. Contributions in this area include the study conducted by Poufinas and Michaelide (2018) and Fier and Liebenberg (2013).

## 2.3 Unemployment

Unemployment—the proportion of the labor force actively seeking employment—is a key indicator of macroeconomic performance. Despite its significance, relatively few studies have examined its influence on life insurance demand. This oversight may be attributed, in part, to the fact that much of the existing literature focuses on economies characterized by low and stable unemployment rates. Additionally, prior research has often emphasized income as a primary explanatory variable, potentially subsuming the informational content of unemployment. This emphasis may also reflect an implicit assumption that individuals facing job insecurity are less likely to prioritize long-term financial instruments such as life insurance.

Notable exceptions to this trend include the work of Sliwinski et al. (2013), who analyzed the Polish life insurance market, and Ertl (2017), who examined markets in Central and Eastern Europe. The latter study offers an interesting temporal distinction: statistical models covering the pre-crisis period (1994–2008) suggest that lower unemployment rates supported higher life insurance consumption, whereas higher unemployment rates appeared to have a positive effect in the post-crisis period (2010–2014). However, it is essential to note that in both periods, the unemployment variable was statistically insignificant in most model specifications, suggesting a complex or indirect relationship between labor market conditions and insurance demand.

## 2.4 Banking Sector

When the banking sector functions without constraints, consumers typically develop a more positive perception of the financial industry, which includes private insurance. This scenario creates substantial opportunities for collaboration between these sectors in areas like cross-selling and investment management. In countries where the financial industry operates without restrictions, such as those affecting interest rates or price setting, business development opportunities emerge, allowing consumers to benefit from improved services (Levine et al. (2000)). Additionally, a strong financial system boosts the capacity to attract and distribute foreign direct investment (FDI), further fostering the expansion of the life insurance sector (Dragotă et al. (2023)).

In literature linking private insurance to macroeconomic factors, terms such as "banks," "financial sector," and "financial depth" are commonly referenced (see Sliwinski et al. (2013); Li et al. (2007); and Ertl (2017)). All represent a shared concept: the financial sector's degree of development and the economy's ability to mobilize and enhance circulating currency. It is proposed that a larger banking sector is positively associated with the delivery of high-quality financial services. While this connection aligns with the objectives of this research, it's crucial to acknowledge that financial development is not always advantageous for economic growth. Beyond a particular threshold, it may adversely affect the economy by exhausting resources without efficient use (Law and Singh (2014)).

## 2.5 Interest Rate

Interest rates are crucial to insurance companies' investment income. Life insurance reserves build significant capital, generating substantial investment income vital to life insurers' overall revenue. Insurers can reduce policy prices when investment returns are strong, encouraging demand.

High interest rates typically indicate a tight monetary policy, which can restrict growth opportunities. In this context, investors might consider life insurance a promising investment alternative. On the other hand, higher interest rates may lead consumers to channel their savings into different investments instead of buying insurance products. Since high interest rates can affect premiums in multiple ways, it's not surprising that relatively few studies examine the relationship between life insurance demand and interest rates. Research in this field includes contributions by Cummins (1973), Dragoş et al. (2019), Elango and Jones (2011), and Sliwinski et al. (2013). Moreover, several studies have explored the impact of interest rates after adjusting for inflation, including the works of C. P. Chang and Berdiev (2013), Beck and Webb (2003), Beenstock et al. (1986), Ertl (2017), Li et al. (2007), and Sen (2008).

## 2.6 Economic Climate Indicators

This research employs Economic Climate Indicators (ECIs) to follow public perceptions of the national economy and evaluate consumer intentions. Depending on the specific indicator, data may be gathered through personal interviews to assess public sentiment or through expert analyses of economic conditions. Since official macroeconomic indicators might not fully capture developments in certain sectors, ECIs offer insights for tracking economic trends. Their widespread application in national economic reports underscores their importance; for instance, the Economic Sentiment Indicator (ESI) is included in Greece's economic monitoring reports (Bank of Greece (2022)).

The exact influence of ECIs on the life insurance industry is still unclear. Typically, a rise in these indicators foreshadows a boost in macroeconomic activity, potentially facilitating growth in life insurance. In contrast, a drop in an ECI suggests public negativity, pushing individuals to pursue more conservative financial strategies. This increased caution often results in higher savings and a growing interest in life insurance products.

ECIs are seldom utilized in studies in this research area, with Fortune (1973) as a notable exception. Although they are extensively employed in macroeconomic evaluations, their scarce application in academic research could be due to the lack of data across different countries and timeframes. Consequently, scholars often turn to other data sources.

For instance, Beck and Webb (2003) assessed consumer confidence in the national economy and purchasing power by considering anticipated inflation and permanent income. Similarly, Browne and Kim (1993) focused on anticipated inflation rather than actual inflation, contending that past trends influence consumer expectations, using the average inflation rate from the last eight years as a proxy for anticipated inflation. Additionally, Cargill and Troxel (1979) examined consumer confidence through anticipated inflation obtained from the Livingston survey, which tracks expected changes in the Consumer Price Index over six- and twelve-month periods.

## 2.7 Population

Grouping the population into smaller geographic areas enables insurance companies and intermediaries to engage with consumers more efficiently. This results in reduced costs for advertising, contract distribution, premium collection, and claims management.

Furthermore, population growth increases the consumer pool for private insurance, which enhances risk assessment using the law of large numbers. A broader customer base reduces operating costs per person, making private insurance services more affordable and accessible.

The impact of population on life insurance has been examined from multiple perspectives. Urbanization has been explored by Luciano et al. (2016), Sen (2008), Beck and Webb (2002), and Beck and Webb (2003), while population growth has been analyzed by Elango and Jones (2011) and Outreville (1996). Additionally, Feyen et al. (2011) investigated population density, measuring a country's population relative to its area. Notably, this last study incorporated total population and population density into its analysis. Across all studies, the findings indicate a positive correlation between population growth, population density, and the expansion of the life insurance sector.

# 3 Research Methodology

Building on existing literature, this study empirically investigates the influence of Greece's macroeconomic indicators on life insurance demand. It is acknowledged, however, that aggregate economic figures do not uniformly affect individual consumers. Instead, individuals interpret and respond to these indicators differently, optimizing their financial decisions based on personal preferences and circumstances. In particular, consumers assess interest rates and the relative cost of life insurance products when deciding how to allocate resources between long-term savings via insurance and alternative forms of consumption.

After building the dataset, whose summary statistics are in Table 1 of the appendix, we tested the time series for stationarity, a property frequently lacking in insurance premiums data (Lee et al. (2013); Lenten and Rulli (2006)) using the Augmented Dickey-Fuller (ADF) test. After confirming the necessity for transformation, we implemented several adjustments: the natural logarithm function was applied to Penetration Life, Population, GDP, Unemployment, Banking Sector, ESI, and CCI. Next, the first difference was computed for all series, eliminating one observation from each dataset. The transformed data were re-assessed for stationarity using the ADF test, with results in Table 2 of the appendix.

## 3.1 Regression and Variable Selection

All explanatory variables were incorporated into the following multiple regression model:

Equation 1: The multiple regression model

$$Y_t = a + \sum_{\kappa} \beta_\kappa x_{\kappa,t} + \epsilon_t \tag{1}$$

where Y is the insurance penetration, t is time, $\alpha$ and $\beta$ are the regression parameters, $x_\kappa$ are the explanatory variables including the autoregressive terms of the dependent variable, and $\epsilon$ are the errors. The regression model assesses how changes in the independent variables (the regressors) affect the dependent variable. The errors in this model are assumed to be independent, identically distributed (i.i.d.), with a mean of zero and a constant variance ($\sigma^2$).

Figure 1: Data study methodology

| 1. Foundation | 2. Preliminary data processing | 3. Multiple regression | 4. Variable selection | 5. Examine the factors' impact | 6. Explore causality |
|---|---|---|---|---|---|
| • Literature review.<br>• Extensive review of online sources and correspondence to collect data. | • Test for stationarity and make necessary transformations to the variables. | • Elimination of variables due to multicollinearity (VIF).<br>• Residuals' correlations - treatment with lagged dependent variables as regression instruments.<br>• Testing squared residuals correlations to assess homoscedasticity.<br>• Test for the normality of residuals' distribution. | • Remove factors of low statistical significance.<br>• Ensure that residuals comply at each step (see multiple regression box). | • Quantile regression for multiple performance levels of life insurance penetration. | • Granger causality application between GDP pc and life insurance penetration in a) bivariate and multivariate settings, and b) the frequency domain. |

To strengthen the model and avoid complications such as multicollinearity, where predictors show high correlation with one another, we employed the Variance Inflation Factor (VIF). If a variable's VIF score exceeded 10, it would be deemed problematic and excluded from the analysis. Otherwise, the estimated relationships among predictors would be severely altered. By taking these steps, we enhanced both the stability and accuracy of the model, while also improving its interpretability, allowing for a clearer understanding of each independent variable's impact. As a result, the model became less vulnerable to errors, yielding more dependable and valid conclusions.

Afterward, the residuals —the differences between predicted and observed values —were analyzed for correlation using the Ljung-Box test, complemented by autocorrelation and partial autocorrelation plot assessments. The findings highlighted the need to include lagged dependent variables as regressors in the model, a regularly practiced methodology, e.g., C. P. Chang and Berdiev (2013) and Trinh et al. (2023). The Akaike Information Criterion (AIC) was utilized to identify the ideal number of lags to incorporate. This criterion guided the selection by balancing model complexity against goodness of fit, ensuring that the resulting model offered the data's most accurate and concise representation.

The analysis thoroughly evaluated the squared residuals for autocorrelation and partial correlation, utilizing the same methods as in the correlation assessment. As the squared residuals for Greece's models complied with the above criteria, no further steps were taken in this direction.

We evaluated model residuals to confirm their conformity to a normal distribution, utilizing the Jarque-Bera test alongside visual examination of distribution charts and Q-Q plots. Meeting these assumptions is essential; any deviation would compromise the validity of hypothesis testing results.

The complete model was refined using backward linear variable selection guided by the AIC, a method designed to identify a parsimonious model that balances explanatory power and model complexity. The procedure begins with the complete model, which includes all candidate explanatory variables. At each iteration, the variable whose removal leads to the greatest improvement in the AIC score is eliminated. The AIC is $AIC = 2k - 2ln(L)$, where $k$ represents the number of estimated parameters, and $L$ denotes the model's likelihood. This iterative process continues until no further reduction in the AIC can be achieved. By penalizing over-parameterization, this approach mitigates the risk of overfitting and retains only those variables that contribute meaningfully to model performance. The final model is considered optimal with respect to the AIC criterion, although outcomes may differ depending on the selection criterion employed by the researchers.

Furthermore, after each iteration, diagnostics on residuals were performed to verify the robustness of the refined models, as already outlined above. The iterative variable elimination process would proceed if the improved model met all required statistical criteria. If the resulting model did not satisfy the necessary criteria, it was discarded, prompting an exploration of alternative methods for variable elimination. This iterative process persisted until no additional variables could be removed without jeopardizing the model's effectiveness.

The Ljung–Box test results, which check for correlations in the residuals and squared residuals, are in Table 3 of the appendix. Moreover, the Jarque–Bera test value is 0.636, which passes the test for the normality of the residuals' distribution.

## 3.2 Quantile Regression

For the $\tau$th quantile, the model is expressed as shown in the following equation. Aside from $\tau$, representing the quantile being analyzed, all other variables are defined as specified in Equation 1. For simplicity, lagged dependent variables are incorporated as part of the $x_\kappa$'s. This model differs from the previous one by assuming that the errors $\epsilon_t$ are independent and follow a

Equation 2: The quantile regression model

$$Y_t = \alpha^{(\tau)} + \sum_{\kappa} \beta_{\kappa}^{(\tau)} x_{\kappa,t} + \epsilon_t \tag{2}$$

distribution $g_t(\epsilon)$, with the quantile level $\tau$ set to 0.

Koenker and Bassett (1978) presented quantile regression as an extension of linear regression. Additionally, outliers can markedly skew parameter estimates, reducing the reliability of this statistical method. In contrast, quantile regression is a more resilient alternative that estimates the conditional median or other quantiles, offering enhanced flexibility in managing data with non-normal error distributions and outliers.

Quantile regression provides a more reliable method for estimating parameters, enabling researchers to analyze specific dataset segments. This technique allows an evaluation of how each variable affects different parts of the distribution, making it particularly beneficial in fields like finance, where relationships can differ across varying outcomes. In private insurance, this method has shown its worth. For instance, Li et al. (2007) employed a one-at-a-time predictor strategy to assess the variability across quantiles of the factors impacting life insurance demand, identifying income, financial development, and inflation as key influences. Likewise, Sriram et al. (2016) applied quantile regression to assess cost efficiency among U.S. insurers in the non-life insurance sector.

This research employs quantile regression to assess the impact of the statistically significant determining factor on the demand for life insurance, focusing on various insurance penetration levels. Specifically, the analysis targets quantiles 0.1, 0.25, 0.5, 0.75, and 0.9, which have been chosen to capture a symmetrical representation of the distribution. This selection allows for a comprehensive understanding of how different factors influence life insurance demand across the entire performance spectrum, from lower to higher levels, providing valuable insights into the dynamics at various distribution points.

## 3.3 Granger causality

Granger causality (sometimes called causality) is a statistical concept that assesses if one time series can predict another. It does not establish a direct causal link; still, it evaluates whether the past values of one variable can contribute to predicting another variable more accurately than relying solely on its own past values. Developed by Granger (1969), this method utilizes (non-singular) vector autoregression (VAR) models, incorporating the regression equation's lagged values of both dependent and independent variables. If incorporating past values of the independent variable notably improves the dependent variable's predictive accuracy, it is inferred that the independent variable "Granger-causes" the dependent variable. This technique is essential for analyzing dynamic relationships between time-series data.

The null hypothesis suggests that past values of the independent variable do not predict the dependent variable, while its rejection indicates causality. Nonetheless, there are several limitations to implementing the technique: it is sensitive to selecting appropriate lags, does not consider unobserved confounders, and cannot identify causal mechanisms between variables. Despite these challenges, it remains a popular tool in time-series analysis for investigating relationships between time-dependent variables, including the interaction between macroeconomic indicators and private insurance.

Numerous studies have explored the dynamic interactions between economic growth and the insurance sector. For instance, T. Chang et al. (2014) performed a bivariate analysis to investigate the causal connections between GDP, serving as a proxy for economic development, and private insurance, indicated by insurance premiums.

Lee et al. (2013) furthered the field by introducing the "half-life" concept of deviations, quantifying the time needed for a shock to reduce by half. This metric shows how quickly time series data reverts to long-run equilibrium following a disturbance, deepening our comprehension of the dynamic relationship between macroeconomic factors and the insurance sector.

This study conducts bivariate Granger causality analysis by estimating Vector AutoRegression (VAR) models with one to four lagged terms. Model selection is guided by the Bayesian Information Criterion (BIC; Schwarz (1978)), which balances model fit and parsimony, helping to eliminate lags that could otherwise reduce the efficiency and robustness of the estimates. Once the optimal lag structure is identified, the Granger causality test is applied to assess whether a causal relationship exists in either direction. It is important to note that the underlying quarterly time series data have been transformed to ensure stationarity. The primary objective is to evaluate the dynamic interrelationship between life insurance consumption, proxied by penetration, and economic development, measured by GDP per capita, to determine whether each variable Granger-causes the other.

Equation 3: The Bivariate Granger causality model

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_y \\ \alpha_x \end{bmatrix} + \sum_{k=1}^{p} \begin{bmatrix} \beta_{11,k} & \beta_{12,k} \\ \beta_{21,k} & \beta_{22,k} \end{bmatrix} \begin{bmatrix} y_{t-k} \\ x_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{bmatrix}$$

where y is the causing variable, x is the effect variable, while $\alpha$ and $\beta$ are the regression coefficients. The regression error terms are uncorrelated.

Multivariate Granger causality enhances the standard bivariate method by integrating multiple variables into the analysis, which allows for a deeper investigation of causal relationships within complex systems. In this model, the causality of a variable is evaluated while also considering the effects of other related variables, which helps minimize the possibility of misleading results due to omitted variable bias. This approach is particularly important in financial models, where many interconnected factors affect outcomes. The analysis of macroeconomic elements impacting life insurance demand is a prime example. Researchers studying the connection between macroeconomics and private insurance include Pradhan et al. (2017).

Thus, this research shall also conduct a multivariate Granger causality analysis by incorporating control variables on the right-hand side of the equation 3. In this version of the Granger causality test, the t-test shall infer the individual factors' contribution. Afterwards, the roles of life insurance penetration and GDP per capita will be reversed, switching the response and causing variables, and the process shall be repeated to infer the reverse causality.

Granger causality studies have yielded varied results; the evidence for a one-way causation from the insurance market to economic growth depends on the sample and time period examined, while other research indicates the reverse causation or feedback loops between the two variables. Moreover, some investigations found no causality whatsoever. Pradhan et al. (2017) offered an extensive overview of this literature, emphasizing the intricate and context-sensitive relationships involved.

Geweke (1982) notably impacted the literature by suggesting that the bivariate Granger causality relationship could be analyzed using spectral analysis. He discovered long-term relationships aligned with existing macroeconomic literature by examining deflated income, money supply, and inflation. Building on this foundation, Farnè and Montanari (2022) sought to determine whether causality at a given frequency systematically deviates from zero. The main points of their methodology are as follows. Considering the bivariate stochastic process $Z_t = [X_t, Y_t]'$, we note that:

$$Z_t = A_1 Z_{t-1} + ... + A_p Z_{t-p} + \epsilon_t$$

, where $A_1, ..., A_p$ are $2 \times 2$ coefficient matrices. Applying a frequency-domain transformation, for each frequency $\omega$, the transfer function $P(\omega)$ of $Z_t$ is:

$$P(\omega) = \left( I_2 - \sum_{j=1}^{p} A_j e^{-ij\omega} \right)^{-1}, \quad -\pi \leq \omega \leq \pi,$$

Setting:

$$P(\omega) = \begin{bmatrix} P_{XX}(\omega) & P_{XY}(\omega) \\ P_{YX}(\omega) & P_{YY}(\omega) \end{bmatrix},$$

the model-based spectrum $h(\omega)$ is defined as:

$$h(\omega) = P(\omega)\Sigma_2 P(\omega)^*, \quad -\pi \leq \omega \leq \pi,$$

where $^*$ denotes the complex conjugate transpose. Setting :

$$\Sigma_2 = \begin{bmatrix} \sigma_2 & \upsilon_2 \\ \upsilon_2 & \gamma_2 \end{bmatrix},$$

and using the transform matrix:

$$S = \begin{bmatrix} 1 & 0 \\ -\frac{\upsilon_2}{\sigma_2} & 1 \end{bmatrix},$$

it is derived that the transformed transfer function matrix

$$\tilde{P}(\omega) = P(\omega) \times S^{-1}.$$

The process $Z_t = [X_t, Y_t]^\top$ is normalized accordingly as

$$\tilde{Z}_t = \tilde{P}(L)[X_t, Y_t]^\top,$$

and becomes

$$\tilde{Z}_t = [\tilde{X}_t, \tilde{Y}_t]^\top.$$

The unconditional Granger-causality spectrum of $X_t$ (effect-variable) with respect to $Y_t$ (cause-variable) is then defined as (Geweke (1982)):

$$h_{Y \to X}(\omega) = \ln \left( \frac{h_{XX}(\omega)}{\sigma_2 |\tilde{P}_{XX}(\omega)|^2} \right)$$

In the empirical analysis, the theoretical values for the coefficient and covariance matrices will be substituted with the respective SURE estimates (Zellner (1962)).

Regarding the issue of inference on Granger-causality spectra in the frequency domain, we continue on the path of Farnè and Montanari (2022), who assume that under the null the bivariate stochastic process [Xt , Yt ] is an independent process. Rather than defining a null hypothesis of zero causality, they employed the stationary bootstrap method (Politis and Romano (1994)) to resample the estimated causalities at each frequency and infer based on the distribution's median. This approach provided a more time-specific assessment of causal relationships while accounting for potential data dependencies.

In the frequency domain, regarding the functional $h_{Y \to X}(\omega)$, we shall conduct the study using a bootstrap procedure, following an algorithm. First, we shall simulate $N$=10 independent stationary bootstrap series $(X_t^*, Y_t^*)$ given the observed series $(X_t, Y_t)$ and for each simulated series $(X_t^*, Y_t^*)$, a VAR model (SURE) shall be estimated on $(X_t^*, Y_t^*)$, while the model selection will be based on the BIC. At Fourier frequencies $f_i = \frac{i}{T}$, $i = 1, \ldots, \lfloor \frac{T}{2} \rfloor$, the $\hat{h}_{Y^* \to X^*}(2\pi f_i)$ will be computed and then the med $\left\{\hat{h}_{Y^* \to X^*}(2\pi f_i),\ i = 1, \ldots, \lfloor \frac{T}{2} \rfloor\right\}$. Finally, for a given significance level $\alpha$, we compute $q_{\text{uncond},1-\alpha}$, the $100 \times (1-\alpha)$-th percentile of the bootstrap distribution across the $N$ bootstrap series, to make the inference on the results' significance.

# 4 Data and Results

The ratio of insurance premiums to GDP, known as insurance penetration, is frequently utilized in the literature as a comparative metric among various jurisdictions, irrespective of their size. Consequently, insurance penetration will be treated as the dependent variable in this study.

The explanatory variables are as follows:

a) Income is proxied by GDP per capita. GDP is calculated using chained volume prices, excluding inflation's impact, to reflect economic output. Data on GDP at market prices were also collected to determine the insurance penetration ratio.

b) Inflation: This is evaluated using the Harmonized Index of Consumer Prices (HICP), which monitors price changes for goods and services over time and is a crucial indicator of inflationary trends in the economy.

c) Unemployment: This variable represents the proportion of the labor force aged 20–64 that is actively looking for work, based on non-seasonally adjusted data.

d) Banking Sector: This is represented by the total private sector credit ratio to GDP, which gauges the importance and extent of financial intermediation within the economy. This ratio indicates the level of credit the private banking sector supplied in relation to the country's overall economic output. The methodology for this measurement is outlined in a report by the Bank for International Settlements (Dembiermont et al. (2013)).

e) Long-Term Interest Rate (LTI): This variable denotes the interest rate on newly issued government bonds with a maturity of 10 years and government-backed debt maturing in the same term. It is derived from a 3-month average of daily market prices and differs from the interest rate at issuance.

f) Population: This indicates the total number of individuals living in a country, gauging potential market size and demographic trends.

Furthermore, this research utilizes the following economic climate indicators:

g) Economic Sentiment Indicator (ESI): The ESI is a composite index released by the European Commission that gauges the economic sentiment within the European Union. It is based on surveys questioning businesses' present economic conditions and future outlooks. The index is normalized to a long-term average of 100, with a standard deviation 10. A reading above 100 represents above-average economic sentiment, whereas a reading below 100 suggests below-average sentiment. The data are also seasonally adjusted.

h) Consumer Confidence Index (CCI): It is a crucial economic metric that predicts future household spending and saving patterns. It derives from survey responses about individuals' expectations concerning their financial circumstances, views on the economy, job prospects, and savings capacity. A score exceeding 100 denotes greater consumer confidence, implying that individuals are more likely to make substantial purchases and less prone to save, indicating an optimistic outlook. In contrast, a score below 100 reflects a more negative perspective, prompting increased saving and diminished spending as consumers brace for possible economic difficulties.

i) World Uncertainty Index: Various studies have investigated the relationship between uncertainty and private insurance (Gupta et al. (2019); Balcilar et al. (2020); Canh et al. (2021)), underscoring its importance. This research employs the World Uncertainty Index, which measures uncertainty by evaluating Economist Intelligence Unit (EIU) reports for several countries.

The Index monitors how often terms like "uncertainty" are mentioned. As noted by Ahir et al. (2022), increasing uncertainty mainly impacts developing nations, leading to decreased GDP and heightened stock market volatility. This indicates that escalating uncertainty could significantly influence economic stability and, consequently, the life insurance sector.

j) World Pandemic Uncertainty Index: The COVID-19 pandemic has led to extensive social distancing and quarantine protocols, profoundly affecting social and economic operations. The private insurance industry, in particular, faced challenges as its distribution methods depend largely on direct interactions between brokers and potential clients. Moreover, administrative services became complicated due to limits on physical office attendance. Nonetheless, the rise of insurance aggregator platforms and digital services has lessened the need for face-to-face meetings, thereby enabling remote operations and online transactions. Given these developments, this research aims to broaden the exploration of the link between uncertainty and insurance by establishing the World Pandemic Uncertainty Index. This index quantifies the occurrences of the term "uncertainty" and its variations related to the term "pandemic" in EIU reports. This distinctive metric is designed to encapsulate the specific uncertainties brought on by the pandemic and their impact on the insurance sector.

The data were sourced from the Hellenic Association of Insurance Companies, Eurostat, the European Central Bank, the OECD, and the World Uncertainty Index website (see Table 4 of the appendix).

## 4.1 Regression Results

Table 1 of the main article illustrates the multiple regression and optimal models after variable selection for Greece's life insurance penetration.

The multiple regression report shows that the demand for life insurance rises in Greece due to the increasing population, LTI, ESI, CCI, and overall uncertainty. In contrast, elements such as GDP per capita, inflation, unemployment, the banking sector, and uncertainties related to the pandemic negatively impact the growth of life insurance. Three lagged dependent variables were incorporated at lags of 1, 2, and 3 to address correlations in residuals.

Among these factors, GDP per capita is the only variable with statistical significance besides the lagged variables. This indicates that life insurance is particularly sought after during challenging economic times.

The variable selection model indicates that the life insurance sector expands in response to rising interest rates and increases in the CCI, while contracting as income levels rise. The dependent variable exhibits an inverse relationship with its past values at lags of one, two, and three periods.

Notably, the life insurance industry in Greece tends to thrive during economic downturns and when consumers prioritize spending over saving.

The GDP per capita-related parameter in the quantile regression report is negative across all quantiles, with statistical significance observed in the top two. Additionally, the magnitude of the parameter decreases as one moves from lower to higher quantiles, suggesting that life insurance is perceived as a viable investment option during economically challenging times. In contrast, the parameter values associated with LTI are positive in the three lowest quantiles but become negligible in the higher ones, exhibiting a declining trend in magnitude. This pattern indicates that increases in interest rates benefit life insurance penetration while coinciding with its lowest performance levels. On the other hand, stable interest rates have a negligible effect on the dependent variable while coinciding with its best performances.

Furthermore, as anticipated, the parameters related to the CCI show a decreasing trend in magnitude across quantiles. An increase in the index is associated with a negative outlook for the life insurance sector, probably reflecting a shift towards more optimistic consumer spending behaviors. Conversely, small magnitude values of the explanatory variable parameters correspond to better performance in the life insurance sector, reinforcing that life insurance performs better under more stable or less optimistic economic conditions.

The quantile regression report is visualized in Figure 2.

Table 1: Regression results for the complete and variable selection models

| | Complete model | | Variable selection model | |
|---|---|---|---|---|
| | Parameter estimate | S.E. | Parameter estimate | S.E. |
| Intercept | 0.016 | 0.020 | 0.005 | 0.013 |
| Population | 13.924 | 19.078 | – | – |
| GDPpc | -0.819 | 0.388 | -0.625 | 0.287 |
| Inflation | -0.043 | 0.034 | – | – |
| Unemployment | -0.333 | 0.372 | – | – |
| Banking sector | -0.122 | 0.886 | – | – |
| LTI | 0.013 | 0.009 | 0.011 | 0.007 |
| ESI | 0.193 | 0.401 | – | – |
| CCI | 1.634 | 2.168 | 3.055 | 1.506 |
| Uncertainty | 0.036 | 0.095 | – | – |
| Pandemic Uncertainty | $-10^{-4}$ | $10^{-4}$ | – | – |
| Penetration lag 1 | -0.674 | 0.111 | -0.625 | 0.094 |
| Penetration lag 2 | -0.537 | 0.157 | -0.505 | 0.136 |
| Penetration lag 3 | -0.495 | 0.113 | -0.504 | 0.106 |
| Adj. $R^2$ (%) | 55.4 | – | 59.7 | – |
| n | 59 | | | |

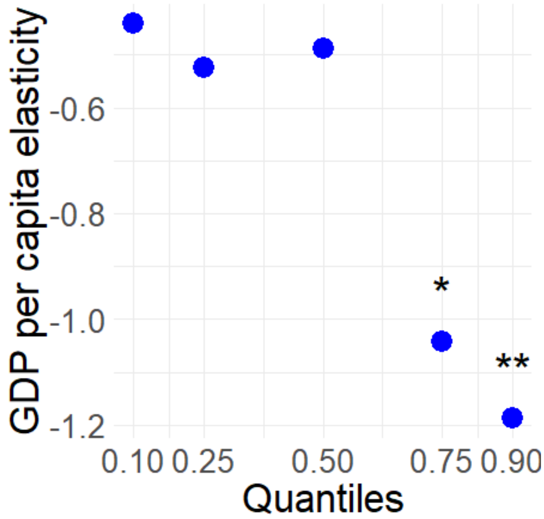
Table 2: Quantile regression - Parameter estimates and standard errors of the factors

| Variable / Quantile | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 |
|---|---|---|---|---|---|
| Intercept | -0.119 | -0.049 | 0.003 | 0.076 | 0.123 |
| S.E. | 0.022 | 0.020 | 0.020 | 0.021 | 0.019 |
| GDPpc | -0.441 | -0.524 | -0.487 | -1.042 | -1.188 |
| S.E. | 0.403 | 0.392 | 0.441 | 0.547 | 0.545 |
| LTI | 0.022 | 0.012 | 0.007 | $-10^{-4}$ | 0.001 |
| S.E. | 0.008 | 0.015 | 0.014 | 0.014 | 0.013 |
| CCI | 7.427 | 2.855 | 2.883 | -0.909 | 0.217 |
| S.E. | 2.473 | 3.045 | 2.468 | 2.924 | 2.679 |
| Penetration lag 1 | -0.551 | -0.604 | -0.622 | -0.477 | -0.549 |
| S.E. | 0.125 | 0.139 | 0.155 | 0.188 | 0.210 |
| Penetration lag 2 | -0.696 | -0.594 | -0.532 | -0.222 | -0.322 |
| S.E. | 0.198 | 0.234 | 0.254 | 0.214 | 0.203 |
| Penetration lag 3 | -0.555 | -0.599 | -0.461 | -0.355 | -0.355 |
| S.E. | 0.124 | 0.158 | 0.181 | 0.179 | 0.153 |

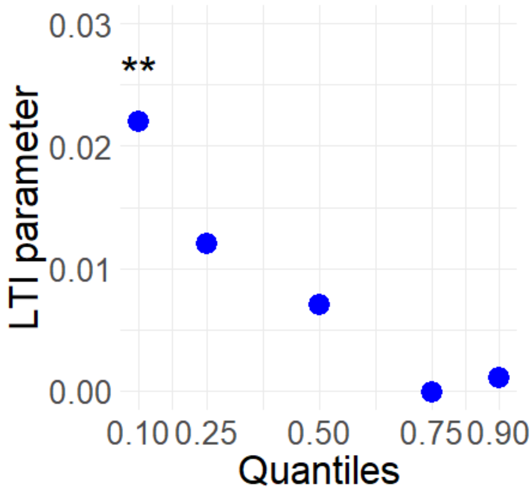
S.E.: Standard Error, LTI: Long-Term interest rate, ESI: Economic Sentiment Indicator, CCI: Consumer Confidence Index.

n: observations' count after differencing

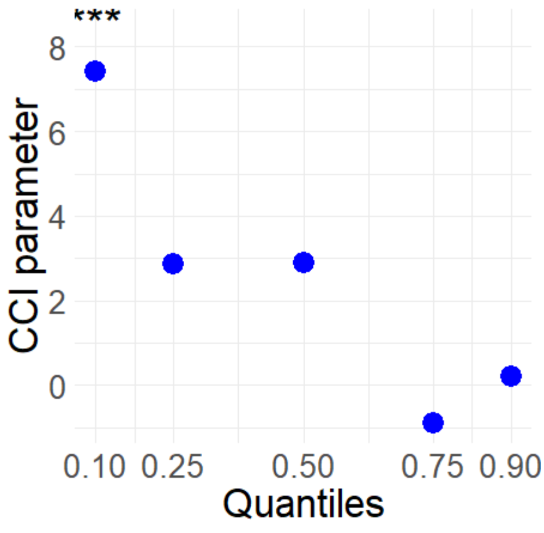
Figure 2: GDP per capita, LongTerm Interest rate, and Consumer Confidence Index parameters across quantiles




(a) GDPpc quantiles




(b) LTI quantiles




(c) CCI quantiles

## 4.2 Granger causality

Table 3A presents the results of the bivariate Granger causality tests between Greece's GDP per capita (GDPpc) and life insurance penetration. The findings indicate a statistically significant bidirectional causality between the two variables. Specifically, GDP per capita Granger-causes life insurance penetration at the 5% significance level (p = 0.031), suggesting that changes in economic development precede and may help predict movements in life insurance uptake. Conversely, life insurance penetration Granger-causes GDP per capita at the 1% significance level (p = 0.002), highlighting a strong reverse relationship in which developments in the life insurance sector provide predictive information about, and potentially influence, economic performance. These results underscore the dynamic and interdependent nature of the relationship between economic growth and life insurance demand in Greece.

Table 3A: Bivariate Granger test results

| **Cause** | **Effect** | **p-value** |
|---|---|---|
| GDP per capita | Life insurance penetration | 0.031 |
| Life insurance penetration | GDP per capita | 0.002 |

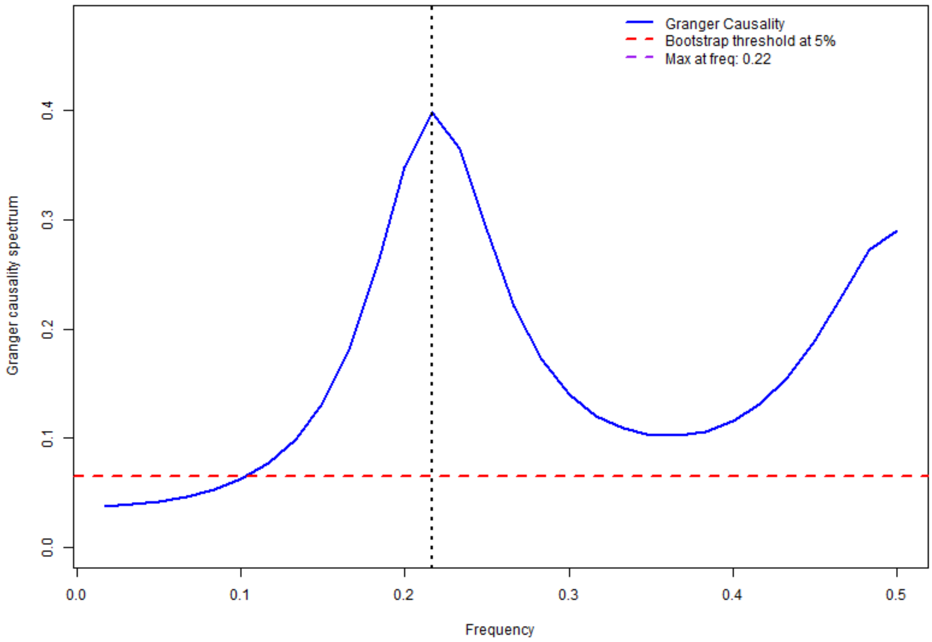
Table 3B: Multivariate Granger Causality Test Results

| **Cause** | **Effect** | **p-value** |
|---|---|---|
| Life insurance penetration | GDP per capita | 0.126 |
| GDP per capita | Life insurance penetration | $10^{-4}$ |

Table 3B reports the results of the multivariate Granger causality tests between life insurance penetration and GDP per capita, controlling for key macroeconomic variables, which are Population, Inflation, Unemployment, Banking Sector, LTI, the ESI, the CCI, the Uncertainty Index, and the Pandemic Uncertainty Index. The analysis reveals a unidirectional Granger causality from GDP per capita to life insurance penetration. Specifically, GDP per capita Granger-causes life insurance uptake with a highly significant p-value ($p < 0.001$), indicating that economic growth precedes and potentially drives changes in life insurance demand, even after accounting for broader economic conditions. In contrast, the reverse causality test provides no meaningful evidence of a predictive relationship from life insurance penetration to GDP per capita at conventional significance levels ($p = 0.126$). This finding diverges from the bivariate analysis and underscores the importance of accounting for confounding macroeconomic variables when assessing causal relationships in economic research.

The figure below presents the Granger causality spectrum from life insurance penetration to GDP per capita for Greece. The x-axis represents the frequency domain, while the y-axis shows the magnitude of the Granger causality spectrum. The blue solid line depicts the estimated Granger causality across different frequencies. The red dashed horizontal line represents each bootstrap sample's significance threshold at the 5% level, indicating the minimum causality level required for statistical significance. The spectrum shows a clear peak at the frequency of approximately 0.22, as indicated by the vertical black dotted line. This suggests that the impact of life insurance on GDP per capita is transmitted with a lag of ( 1 / 0.22 = ) 4.5 quarters, calculated as the reciprocal of the frequency. This implies that life insurance has the strongest predictive power over GDP per capita movements at this specific frequency. Furthermore, at lower and higher frequencies, the Granger causality remains relatively lower but still, at most points, exceeds the significance threshold, suggesting meaningful causality.

Figure 3: Granger causality of Life insurance to GDP pc

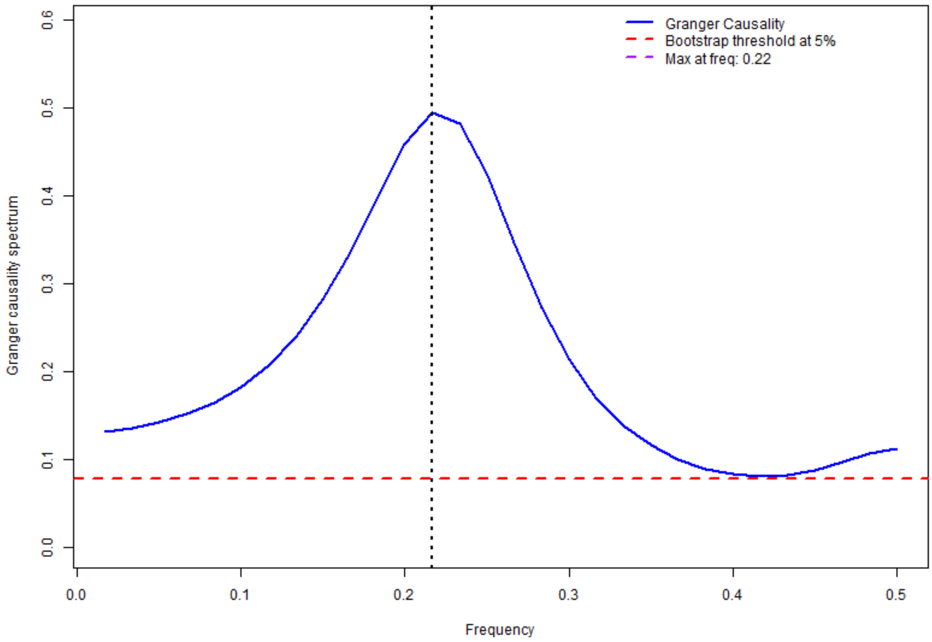



Significant causality at almost across the entire spectrum indicates that the impact of life insurance on economic performance is not uniform over time but instead concentrated at specific cyclical intervals.

The following figure presents the Granger causality spectrum from GDP per capita to life insurance. A prominent peak is observed around a frequency of 0.22, i.e., after 4.5 quarters, where the causality spectrum reaches its maximum value. This indicates that the influence of GDP per capita on life insurance is strongest at this particular frequency. This peak is highlighted with a dashed vertical line and annotated in the legend.

Overall, the results suggest that GDP per capita significantly Granger-causes life insurance, particularly at medium frequencies, reflecting a medium-term dynamic relationship between the two variables.

Figure 4: Granger causality of GDP pc to Life insurance




# 5 Conclusions and Suggestions for Further Research

This study explored the relationship between the macroeconomic environment and the life insurance industry in Greece. It found that declining incomes, rising interest rates, and optimistic consumer confidence are the main drivers of life insurance penetration. Moreover, the quantile regression identified that the best performances of the life insurance penetration coincide with large decreases in income, stable interest rates, and balanced consumer confidence between saving and spending. Insurers' solvency likely provides a safe refuge during difficult macroeconomic conditions, offering a secure option compared to riskier investments.

The findings reveal a dynamic relationship between economic growth and life insurance demand in Greece. While bivariate analysis suggests a bidirectional Granger causality, the multivariate results, accounting for key macroeconomic controls, indicate a unidirectional effect from GDP per capita to life insurance penetration. This highlights the predictive role of economic growth in shaping insurance demand and underscores the importance of controlling for confounding variables when assessing causal links in macroeconomic contexts.

It is also noteworthy that there is considerable feedback between income and the life insurance consumption in the medium term (after 4.5 quarters) between life insurance consumption and income. Thus, it becomes clear that policymakers should pay particular attention to promoting life insurance demand, considering its broader and multiplicative effects on accelerating economic growth.

However, the analysis did not cover all aspects. A more thorough evaluation could produce more robust results by including additional macroeconomic factors that affect life insurance demand. For instance, examining employment distribution among the primary, secondary, and tertiary sectors might reveal how varying occupational categories influence life insurance purchases. Furthermore, analyzing the structure of economic activity using the statistical classification of economic activities (NACE) could shed light on the connection between industry-specific performance and life insurance demand, provided that adequate historical data are accessible. Additionally, acknowledging the importance of income from tourism for Greece, specific metrics should be integrated, such as air transport volume and hotel stays, which would enhance our understanding of how international and domestic travel trends impact insurance demand.

Furthermore, as previously mentioned, factors beyond macroeconomics affect insurance markets. However, the limited availability of quarterly data restricted their incorporation into this study. With the growing accessibility of higher-frequency data, researchers will be better positioned to formulate and examine more advanced hypotheses. Country-specific impact analyses are crucial, as insurance consumption factors vary. Since insurance consumption relies on the availability of high-quality, competitively priced insurance products and recognizes the dynamic nature of these elements, it is essential to understand that no conclusive statements can be made. Therefore, findings should be regularly updated to promote deeper insight into the forces at play in the insurance market.

We aim for this research to motivate policymakers and researchers to delve deeper into the complex interconnections between macroeconomic factors and the demand for life insurance. Further exploration and a more substantial commitment to understanding these intricate dynamics are essential.

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# Appendix

Table 1: Statistical Summary - Greece

| | Mean | StDev | Median | Q1 | Q3 | Skewness | Kurtosis | Min | Max |
|---|---|---|---|---|---|---|---|---|---|
| Penetration Life | 0.011 | 0.002 | 0.011 | 0.010 | 0.012 | 0.404 | 3.106 | 0.007 | 0.015 |
| Population | 10,900.49 | 169.964 | 10,892.45 | 10,738.08 | 11,074.18 | -0.023 | 1.407 | 10,612.70 | 11,122.90 |
| GDPpc | 4,580.70 | 564.45 | 4,383.23 | 4,235.78 | 4,954.36 | 0.81 | 2.561 | 3,732.46 | 5,831.82 |
| Inflation | 1.098 | 1.940 | 0.783 | -0.400 | 2.933 | 0.301 | 2.017 | -1.900 | 4.967 |
| Unemployment | 18.107 | 6.480 | 18.050 | 12.875 | 23.700 | -0.192 | 1.801 | 7.200 | 27.700 |
| Banking sector | 122.692 | 10.582 | 124.569 | 115.726 | 132.099 | -0.782 | 2.964 | 94.097 | 135.764 |
| LTI | 7.447 | 5.702 | 5.875 | 4.255 | 9.629 | 1.485 | 5.163 | 0.697 | 25.400 |
| ESI | 96.208 | 9.323 | 95.533 | 88.492 | 103.275 | 0.088 | 1.837 | 80.900 | 112.667 |
| CCI | 97.858 | 2.322 | 97.794 | 96.015 | 99.550 | 0.263 | 2.270 | 93.917 | 103.636 |
| Uncertainty index | 0.210 | 0.197 | 0.190 | 0.000 | 0.355 | 0.630 | 2.541 | 0.000 | 0.714 |
| Pandemic index | 33.102 | 86.126 | 0.000 | 0.000 | 0.000 | 2.263 | 6.335 | 0.000 | 318.155 |

StDev: Standard Deviation, Q1: First Quartile, Q3: Third Quartile, Min: Minimum Value, Max: Maximum Value
LTI: LongTerm interest rate, ESI: Economic Sentiment Indicator, CCI: Consumer Confidence Index



Table 2: Stationarity reports – Augmented Dickey-Fuller Test score

| **Parameter** | **Greece** |
|---|---|
| Penetration Life | -10.131 |
| Population | -0.102 |
| GDP per capita | -8.447 |
| Inflation | -1.942 |
| Unemployment | -5.488 |
| Credit | -3.881 |
| LTI | -4.207 |
| ESI | -6.139 |
| CCI | -5.109 |
| Uncertainty Index | -9.294 |
| Pandemic Index | -7.448 |

Table 3: Ljung-Box Q-stat for residuals' lags

| **Lags** | **4** | **8** | **12** |
|---|---|---|---|
| Residuals | 0.576 | 5.373 | 11.573 |
| Squared residuals | 2.179 | 6.284 | 8.246 |

Table 4: Data sources

| **Description** | **Source** |
|---|---|
| Written premium, in thousand € | Hellenic Association of Insurance Companies |
| GDP at current prices, in million € | Eurostat |
| Population, in thousand persons | OECD |
| Premium to GDP (Insurance penetration) | Own calculations |
| GDP at chain linked volumes (2010), in million € | Eurostat |
| Inflation (HICP) | Eurostat |
| Unemployment | Eurostat |
| Private credit to GDP | ECB |
| Long-Term Interest rate | ECB |
| Economic Sentiment Indicator | Eurostat |
| Consumer Confidence Indicator | OECD |
| World Uncertainty Index | World Uncertainty Index |
| Pandemic Index | World Uncertainty Index |