



Private Insurance Demand, Macroeconomic Conditions, and Economic Sentiment: An Econometric Analysis of Eight European Countries

By

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Ζήτηση ιδιωτικής ασφάλισης, μακροοικονομικές συνθήκες και
οικονομικό κλίμα:
Μία οικονομετρική ανάλυση σε οκτώ ευρωπαϊκές χώρες

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Vita

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ABSTRACT

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Private Insurance Demand, Macroeconomic Conditions, and Economic Sentiment: An Econometric Analysis of Eight European Countries

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This research employs multiple and quantile regression techniques to investigate the determinants of private insurance penetration, distinguishing between life and non-life insurance. Model specification is optimized through variable selection based on the AIC. To address serial correlation in the residuals, the models are augmented with ARMA components, while conditional heteroskedasticity is captured using GARCH specifications. The empirical analysis is based on a novel quarterly dataset covering eight European countries: Czechia, Denmark, Greece, Italy, Latvia, Norway, Slovenia, and Spain. It incorporates both “hard” macroeconomic indicators, such as income and inflation, and sentiment-based measures derived from Business Tendency Surveys (BTS), including the Business Confidence Index (BCI) and the World Uncertainty Index.

The results from the country-specific models reveal substantial heterogeneity in both the magnitude and direction of the estimated effects. The quantile regression analysis further demonstrates that the elasticity of the explanatory variables varies considerably across the distribution of insurance penetration, highlighting the presence of non-linear and state-dependent relationships. Across countries, autoregressive terms emerge as key determinants of insurance demand, while economic sentiment indicators support the models in several cases. Panel regression results indicate that life insurance penetration is primarily associated with banking sector development and long-term interest rates, whereas non-life insurance pen-

etration is linked to income, unemployment, financial sector conditions, external trade intensity, consumer spending behavior, and uncertainty.

Furthermore, the study examines the direction of causality between private insurance and economic development using both bivariate and multivariate Granger causality frameworks. To capture the temporal dimension of these relationships, the analysis is extended to the frequency domain. The empirical findings indicate a strong and consistent interaction between income and life insurance penetration, whereas the relationship between income and non-life insurance appears comparatively weaker and less systematic. More broadly, the results reveal heterogeneous and time-varying patterns of causal interaction across countries.

ΠΕΡΙΛΗΨΗ

Κωνσταντίνος Κ. Σταθόπουλος

Ζήτηση ιδιωτικής ασφάλισης, μακροοικονομικές συνθήκες και οικονομικό κλίμα:

Μία οικονομετρική ανάλυση σε οκτώ ευρωπαϊκές χώρες

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Η παρούσα έρευνα αξιοποιεί τεχνικές πολλαπλής παλινδρόμησης και ποσοστιαίας παλινδρόμησης για την διερεύνηση των προσδιοριστικών παραγόντων της διείσδυσης της ιδιωτικής ασφάλισης, διακρίνοντας μεταξύ ασφαλίσεων ζωής και κατά ζημιών. Η επιλογή των μεταβλητών πραγματοποιείται μέσω του κριτηρίου AIC. Για την αντιμετώπιση της αυτοσυσχέτισης στα κατάλοιπα, τα υποδείγματα εμπλουτίζονται με αυτοπαλίνδρομους όρους κινητού μέσου όρου (ARMA), ενώ η υπό συνθήκη ετεροσκεδαστικότητα αποτυπώνεται μέσω υποδειγμάτων υπό συνθήκη διακύμανσης (GARCH). Η εμπειρική ανάλυση βασίζεται σε ένα πρωτότυπο τριμηνιαίο σύνολο δεδομένων που καλύπτει οκτώ ευρωπαϊκές χώρες: Τσεχία, Δανία, Ελλάδα, Ιταλία, Λετονία, Νορβηγία, Σλοβενία και Ισπανία. Το σύνολο των επεξηγηματικών μεταβλητών περιλαμβάνει τόσο «σκληρούς» μακροοικονομικούς δείκτες, όπως το εισόδημα και ο πληθωρισμός, όσο και δείκτες οικονομικού κλίματος που προέρχονται από τις Έρευνες Οικονομικής Συγκυρίας, όπως ο Δείκτης Επιχειρηματικής Εμπιστοσύνης και ο Δείκτης Παγκόσμιας Αβεβαιότητας.

Τα αποτελέσματα των επιμέρους υποδειγμάτων ανά χώρα καταδεικνύουν σημαντική ετερογένεια τόσο ως προς το μέγεθος όσο και ως προς την κατεύθυνση των εκτιμώμενων επιδράσεων. Η ανάλυση ποσοστιαίας παλινδρόμησης αποκαλύπτει περαιτέρω ότι η ελαστικότητα των επεξηγηματικών μεταβλητών μεταβάλλεται ουσιαστικά κατά μήκος της κατανομής της ασφαλιστικής διείσδυσης, αναδεικνύοντας την ύπαρξη μη γραμμικών και εξαρτώμενων από την κατάσταση σχέσεων. Σε διακρατικό επίπεδο,

οι δείκτες οικονομικού κλίματος και οι αυτοπαλινδρομοί όροι αναδεικνύονται ως βασικοί προσδιοριστικοί παράγοντες της ασφαλιστικής ζήτησης. Τα αποτελέσματα των υποδειγμάτων panel παλινδρόμησης δείχνουν ότι η διείσδυση της ασφάλισης ζωής συνδέεται κυρίως με την ανάπτυξη του τραπεζικού τομέα και τα μακροπρόθεσμα επιτόκια, ενώ η διείσδυση των γενικών ασφαλίσεων σχετίζεται με το εισόδημα, την ανεργία, τις συνθήκες του χρηματοπιστωτικού τομέα, την ένταση του εξωτερικού εμπορίου, τη συμπεριφορά κατανάλωσης και την αβεβαιότητα.

Επιπλέον, η μελέτη εξετάζει τη φορά της αιτιότητας μεταξύ ιδιωτικής ασφάλισης και οικονομικής ανάπτυξης χρησιμοποιώντας τόσο διμερή όσο και πολυμεταβλητά πλαίσια αιτιότητας κατά Granger (Granger causality). Για την αποτύπωση της χρονικής διάστασης των σχέσεων αυτών, η ανάλυση επεκτείνεται στο πεδίο των συχνοτήτων (frequency domain). Τα εμπειρικά ευρήματα υποδεικνύουν μια ισχυρή και συνεπή αλληλεπίδραση μεταξύ εισοδήματος και διείσδυσης της ασφάλισης ζωής, ενώ η αντίστοιχη σχέση με τις γενικές ασφαλίσεις εμφανίζεται συγκριτικά ασθενέστερη και λιγότερο συστηματική. Σε γενικότερο επίπεδο, τα αποτελέσματα αναδεικνύουν ετερογενή και χρονικά μεταβαλλόμενα πρότυπα αιτιώδους αλληλεπίδρασης μεταξύ των χωρών.

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Chapter 1

Introduction

1.1 Motivation

Life insurance is a financial arrangement under which an individual pays premiums to an insurance company in exchange for a monetary benefit payable to designated beneficiaries upon the death of the insured, or, in certain cases, upon survival to a specified date. Its primary purpose is to provide financial protection and income support to dependents or other beneficiaries following the death of the insured. Throughout this thesis, the term insurance is used with consideration of, among other perspectives, the discussion provided by Glenn (2003). Life insurance also performs a dual function as both a savings instrument and a mechanism for inter-generational wealth transfer, providing protection against mortality and longevity risks.¹ Its attractiveness is often reinforced by favorable tax treatment and flexible benefit structures, which may include lump-sum payments, annuities, or hybrid

¹The term risk is employed in accordance with the conceptual framework outlined by Crowe and Horn (1967).

arrangements. Such products are typically designed to provide either term-limited or lifelong coverage, with returns that may be guaranteed or linked to investment performance. These characteristics make life insurance a central component of household financial planning and an important subject of empirical investigation in the economics of insurance.

Non-life insurance, also referred to as general insurance, comprises all insurance products that do not fall within the scope of life insurance. It provides financial protection against a broad range of risks, including property damage, liability, accidents, illness, and other unforeseen events. Common forms of non-life insurance include motor, property, and third-party liability (TPL) insurance, as well as various assistance services. These policies are typically short-term in nature, often renewed annually or at shorter intervals, and are designed to indemnify policyholders for specific losses associated with insured assets (e.g., vehicles or buildings) or liabilities (e.g., environmental liability or directors' and officers' liability). By facilitating the transfer of risk and supporting the continuity of both business operations and household activities, non-life insurance contributes significantly to economic stability and resilience. In both life and non-life insurance markets, premiums are determined through actuarial calculations that incorporate expected risk coverage, administrative costs, and profit margins.

Understanding the insurance market within a macroeconomic framework is crucial, as it is significantly influenced by it. The forces affecting the insurance market, including demographic (Burnett and Palmer, 1984), social, macroeconomic, institutional, e.g., (Bah and Abila, 2024), and cultural factors, significantly determine insurance demand (Hussels, Ward, and Zurbruegg, 2005). Demographic and social factors, including age dependency ratios, the share of the population with tertiary

education, and urbanization, play a vital role. The type of law (e.g., Common and Civil) and the importance of social security (i.e., the ratio of benefits to GDP) are examples of institutional characteristics. Cultural influences, such as religion and the organization of the economy, also shape the market. This aspect is examined in the context of life insurance by Chui and Kwok (2008), Chui and Kwok (2009), and Hofstede (1995), and in the context of non-life insurance by Park and Lemaire (2012). The relevant literature confirms that specific characteristics of the national economy have a significant relationship with the development of private insurance, though the conclusions are far from uniform. For example, the role of social security has been identified as both a positive (Browne and Kim, 1993) and a negative (Cutler and Gruber, 1996) determinant.²

Extensive empirical research has explored the relationship between these factors and life insurance demand, often employing linear panel regression models to assess the sign and magnitude of their influence. Seminal contributions in this field include studies by Hammond, Houston, and Melander (1967), Fortune (1973), Beenstock, Dickinson, and Khajuria (1986), Browne and Kim (1993), Beck and Webb (2003), and Elango and Jones (2011). The field of non-life insurance was studied and analyzed by: Trinh, Nguyen, and Sgro (2016), Treerattanapun (2011), Njegomir and Stojić (2012), Petkovski and Jordan (2014), Sherden (1984), and Browne, Chung, and Frees (2000), among others. While these provided valuable insights, they rely on annual data aggregated across countries, limiting the capacity to capture short-term dynamics or country-specific effects.³

²In recent years, a distinct research branch, microinsurance, has emerged. While related to the themes addressed in this thesis, it constitutes a separate area of inquiry. Interested readers are referred to Eling, Pradhan, and Schmit (2013) and Cole (2015) for further insights.

³An earlier draft of this research, which focused solely on an earlier period of Greece's life insurance market, was presented in the 11th Hellenic Observatory Centre for Research on Contemporary

The following figures depict three cases of the research's sample, those of Czechia, Greece, and Norway, that compare quarterly life and non-life insurance gross written premiums with nominal GDP. Also, in the tables below, the correlation coefficients are reported between life and non-life insurance premiums, their lagged values, and the nominal GDP. The positive correlation and the carryover effects between the quantities are more than evident.

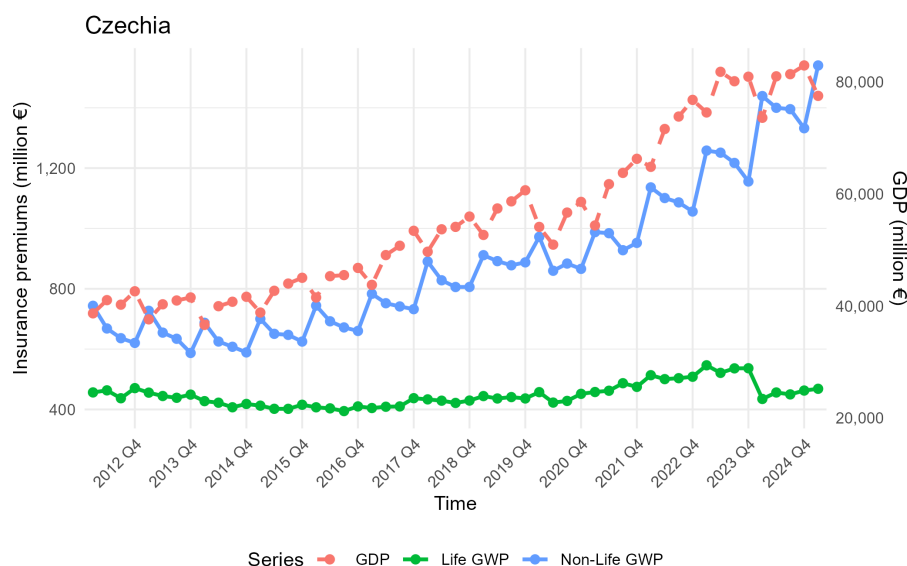


Figure 1.1. Life premiums, non-life premiums, and GDP in Czechia

The correlation matrix presented in Table 1.1 illustrates the pairwise linear relationships between life insurance premiums, non-life insurance premiums, and GDP in Czechia. The results indicate a strong positive correlation between life insurance premiums and their lagged values ($r = 0.84$), as well as between non-life insurance premiums and their respective lagged values ($r = 0.94$), suggesting a high degree

Greece & Cyprus PhD Symposium, where it benefited by the participants' comments (Stathopoulos and Vrontos, 2025).

	Life premiums lag 1	Non-life premiums	Non-life premiums lag 1	GDP
Life premiums	0.84	0.62	0.64	0.71
Life premiums lag 1		0.66	0.64	0.68
Non-life premiums			0.94	0.93
Non-life premiums lag 1				0.96

Table 1.1: Correlation between life premiums, non-life premiums, and GDP for Czechia

of persistence over time in both segments. In terms of economic activity, GDP is positively and strongly correlated with both life ($r = 0.71$) and non-life insurance premiums ($r = 0.93$), particularly with the latter. The observed correlations reflect a stable and interlinked relationship between insurance market development and overall economic performance.

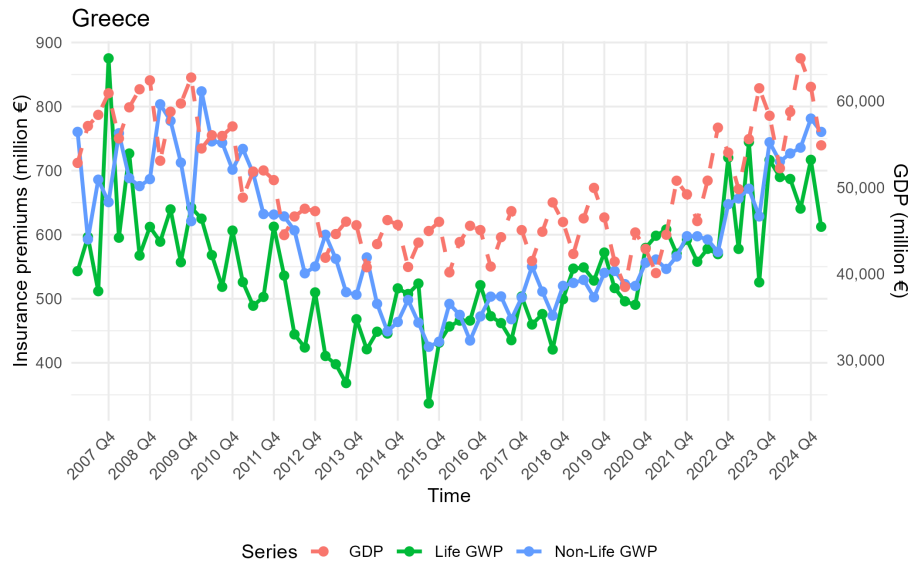


Figure 1.2. Life premiums, non-life premiums, and GDP in Greece

Table 1.2 presents the figures' correlations in the case of Greece. The results reveal

	Life premiums lag 1	Non-life premiums	Non-life premiums lag 1	GDP
Life premiums	0.53	0.64	0.56	0.65
Life premiums lag 1		0.71	0.62	0.57
Non-life premiums			0.86	0.73
Non-life premiums lag 1				0.78

Table 1.2: Correlation between life premiums, non-life premiums, and GDP for Greece

moderate to strong positive correlations between each insurance category and its own lagged value, with the highest being for non-life insurance premiums ($r = 0.86$), indicating significant persistence over time. The correlations with GDP are also noteworthy. Life insurance premiums show a moderate positive correlation with GDP ($r = 0.65$), while the corresponding coefficient is stronger for non-life insurance premiums ($r = 0.73$). These findings imply that economic activity in Greece is more closely associated with non-life insurance dynamics, though both sectors exhibit positive alignment with overall economic performance.

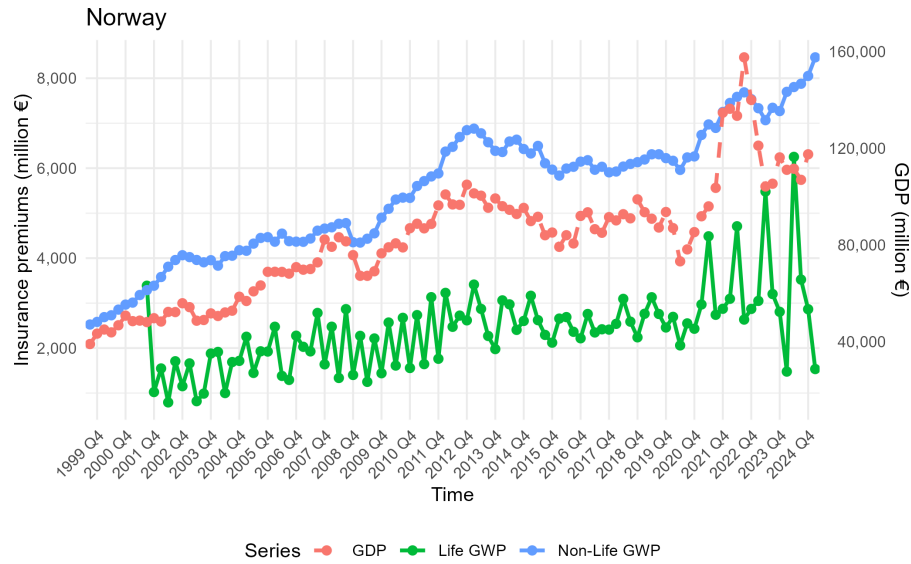


Figure 1.3. Life premiums, non-life premiums, and GDP in Norway

	Life premiums lag 1	Non-life premiums	Non-life premiums lag 1	GDP
Life premiums	0.30	0.70	0.70	0.62
Life premiums lag 1		0.66	0.66	0.62
Non-life premiums			0.99	0.92
Non-life premiums lag 1				0.91

Table 1.3: Correlation between life premiums, non-life premiums, and GDP for Norway

Table 1.3 presents the correlations in Norway's figures. The results reveal a relatively weak correlation between life insurance premiums and their lagged values ($r = 0.30$), suggesting low persistence over time in the life segment. In contrast, non-life insurance premiums display exceptionally strong persistence, with a near-perfect correlation between current and lagged values ($r = 0.99$).

Regarding economic activity, GDP shows a strong positive association with non-life insurance premiums ($r = 0.92$), while its correlation with life insurance premiums is lower ($r = 0.62$). These findings suggest that the non-life insurance sector in Norway is more closely aligned with overall economic trends than the life insurance segment.

1.2 Aim of the analysis - Research question

Therefore, it becomes evident that macroeconomic figures directly impact insurance premium generation, which demands an investigation to comprehend their influence. Moreover, considering the unique characteristics of each country's economy, a distinct study for each case is imperative. While this research commences by studying the one-way influence of the macroeconomic environment on Private Insurance, it is known there are complex relationships between the two that lead to their long-term mutual influence (see, for example, Arena (2008), Ward and Zurbruegg (2000), and Lee, Lee, and Chiu (2013)). Also, Outreville (2013) provided a review of the research area. This should not be alienating, as Private Insurance is not just a consumption option. On the contrary, a well-functioning insurance market stabilizes the financial system, creates synergies with the banking sector, and allows for more accommodating terms of lending through the operation of non-life insurance. It is also a large institutional investor, mainly by leveraging life insurance reserves. On that account, Private Insurance is a source of financing, alongside the banking sector and the stock market. Thus, it is a factor that promotes growth (Chang, Lee, and Chang, 2014) and intensifies competition, with obvious positive results for the country in which it is operating. As a result, we extend the research in the field of causality in order to investigate and provide evidence of the bidirectional impact

between the macroeconomic environment and Private Insurance.

1.3 Research overview

This research builds on the existing literature on private insurance demand and extends it through a more granular and flexible empirical framework. Multiple regression is adopted as the baseline approach, and it is subsequently enriched to address three recurring challenges in cross-country insurance-demand modeling: (i) heterogeneity in countries' economic structures and institutional settings, (ii) dynamic adjustment and delayed responses to macroeconomic and sentiment conditions, and (iii) the need to extract common patterns while preserving cross-country differences.

First, the empirical strategy begins with country-level regression models estimated separately for each country: Czechia, Denmark, Greece, Italy, Latvia, Norway, Slovenia, and Spain. To ensure that each specification remains relevant to its national context and to avoid imposing a uniform set of predictors across countries, both the complete model and the variable selection stage are implemented independently for each country. This design enables the identification of country-specific drivers of insurance demand, consistent with the premise that the determinants and their relative importance may differ across economies due to differences in, e.g., financial development, market maturity, regulatory environments, and broader macroeconomic conditions.

Second, the modeling framework explicitly incorporates dynamics by including lagged dependent variables. These terms capture persistence in insurance demand and allow the analysis to reflect gradual adjustment processes. More broadly,

the inclusion of lags supports inference on the timing of effects, recognizing that changes in macroeconomic fundamentals or economic sentiment may influence insurance activity with delays rather than contemporaneously.

Finally, the analysis is complemented by panel-regression models that pool information across countries. The panel setting is used to borrow strength from the cross-sectional dimension and to obtain evidence on systematic determinants of insurance demand across economies while still allowing for country-level heterogeneity through the panel structure. In these specifications, the models are further enriched by lagged dependent variables and selected interaction terms. The interaction terms are introduced to examine whether the influence of key determinants varies with the level of other macroeconomic conditions, thus providing a more detailed depiction of the mechanisms through which macroeconomic factors and sentiment jointly shape insurance demand.

Afterward, quantile regression was used to estimate the impact of explanatory variables across different levels of insurance demand. This approach provides conditional elasticity estimates and reveals how the determinants' (macroeconomic variables) effects vary in significance, sign, and magnitude, within the insurance penetration distribution. This approach allows for the identification of heterogeneous effects, thereby moving beyond the limitations of models focused solely on average responses. For example, factors influencing demand within the upper 25% of the distribution may differ substantially from those in the lower deciles. This perspective is grounded in Enz (2000), who found that income's elasticity to insurance premiums varies across income levels, underscoring the importance of distribution-sensitive modeling.

Model adequacy was evaluated using standard diagnostic checks based on the autocorrelation and partial autocorrelation functions of both the residuals and the squared residuals. The initial multiple-regression estimates exhibited statistically significant residual dependence, indicating serial correlation and, consequently, jeopardizing the reliability of conventional inference. To address this issue, the specification was extended to a time-series framework by incorporating Autoregressive and Moving Average components (ARMA), together with lagged dependent variables where appropriate.

After accounting for serial dependence, subsequent diagnostics provided evidence of conditional heteroskedasticity in several cases, motivating additional volatility modeling. Accordingly, further refinements were considered, including Generalized Autoregressive Conditional Heteroskedasticity (GARCH) specifications. Finally, the distributional properties of the innovations were examined, with particular attention to whether a Gaussian assumption was adequate or whether heavier-tailed alternatives, such as the Student's t distribution, were more appropriate.

In the panel stage of the empirical analysis, we constructed a balanced dataset by pooling quarterly observations from 8 European economies and estimated panel regression models to exploit both the time-series and the cross-sectional variation in insurance demand. The dependent variable $y_{i,t}$ (life and non-life insurance penetration) was modeled as a function of contemporaneous macroeconomic fundamentals and economic-sentiment indicators. To capture persistence and delayed adjustment, the specifications were enriched with lagged dependent variables $y_{i,t-\ell}$, $\ell = 1, \dots, 4$ and lag structures for the macroeconomic covariates, consistent with the idea that changes in economic conditions may affect insurance activity with non-negligible delays. Finally, to further probe heterogeneity in the transmission mechanisms, se-

lected interaction terms were introduced (e.g., between macroeconomic capacity and financial development, or between financial variables and sentiment), allowing the marginal impact of key determinants to vary with the prevailing economic environment.

While the initial focus of this research was on the unidirectional influence of macroeconomic variables on life insurance demand, it also acknowledges the long-term interplay between insurance development and economic growth. To further investigate this dynamic relationship, this research employs Granger causality tests performed in bivariate and multivariate settings in univariate and panel model specifications. Then, the research expands in the frequency domain; the latter following the methodology proposed by Geweke (1982). To the best of our knowledge, this represents the first application of frequency-domain analysis to the study of insurance and macroeconomic interactions.

The data include both traditional macroeconomic variables, such as income and inflation, and indicators contained in Business Tendency Surveys (BTS), including the Business Confidence Index (BCI) and the World Uncertainty Index (WUI).

1.4 Contribution of the research - Originality

This research makes several important contributions to the literature on insurance demand, spanning the domains of literature synthesis, data construction, and empirical methodology.

First, it provides a comprehensive and up-to-date review of the existing body of work on both life and non-life insurance demand. By systematically organizing

prior studies according to their methodological approaches and sets of explanatory variables, the thesis offers a clearer understanding of the evolution of the literature and identifies key gaps, particularly with respect to data frequency, modeling choices, and the treatment of heterogeneity.

Second, in terms of data, the study expands the set of explanatory variables by incorporating indicators derived from Business Tendency Surveys (BTS). These indicators capture economic sentiment and expectations, thereby introducing a behavioral dimension that has been largely overlooked in the insurance demand literature. In addition, the thesis constructs a novel quarterly dataset for eight European countries: Czechia, Denmark, Greece, Italy, Latvia, Norway, Slovenia, and Spain. The use of higher-frequency data allows for a more detailed examination of short-term dynamics and cyclical fluctuations in insurance markets, addressing a notable limitation of the existing literature, which relies predominantly on annual observations. To date, the use of quarterly data has been limited to a small number of studies, such as Fortune (1973), Headen and Lee (1974), and Guo, Fung, and Huang (2009), while Cavalcante, Sobreiro, and Kimura (2018) employs quarterly data in a more restricted setting focused on Granger causality.

Third, from a methodological perspective, the thesis departs from the conventional reliance on pooled panel models by estimating separate regression models for each country. This approach allows for country-specific dynamics to be captured and avoids the restrictive assumption of homogeneous slope coefficients across countries. Variable selection procedures are employed to identify the most relevant determinants in each case, thereby enhancing model parsimony and interpretability.

Fourth, particular attention is given to econometric rigor. The analysis systematically diagnoses and addresses issues related to residual behavior, including heteroscedasticity and autocorrelation, as well as patterns in squared residuals, ensuring that the estimated models are well-specified and statistically reliable. This careful treatment enhances the robustness and credibility of the empirical findings.

Finally, the selected models are further examined using quantile regression techniques, which allow for the investigation of heterogeneous effects across different points of the distribution of insurance penetration. This represents a significant extension beyond the mean-based approaches that dominate the literature. The analysis is complemented by the application of Granger causality tests in the frequency domain, which provide additional insights into the temporal structure of causal relationships, distinguishing between short-, medium-, and long-run dynamics.

Overall, the thesis contributes to the literature by combining richer data, more flexible modeling strategies, and advanced econometric techniques, thereby offering a deeper understanding of the determinants of insurance demand.

This thesis is structured as follows. Following the introduction, the literature review is presented, offering a critical synthesis of previous research. The subsequent chapter details the methodology employed in the empirical analysis. The data and results of the study are then discussed, highlighting the key findings. The thesis concludes with a summary of the main conclusions, policy implications, and avenues for future research. Extensive appendices are provided at the end of the document to supplement the main text. These materials are included separately to preserve the coherence and flow of the core argument while offering additional technical detail

for interested readers.

Chapter 2

Literature Review

As already stated, private insurance operations are divided into two distinct business branches: life insurance and non-life insurance. Life insurance covers risks related to mortality and provides savings for a specific period or a lifetime, offering returns on savings that can be predetermined or linked to investment performance.

Non-life insurance provides coverage against risks associated with tangible assets, such as buildings and vehicles. It also includes civil liability insurance, which protects against damages resulting from negligent acts or omissions. Compensation under non-life insurance policies may be provided either in monetary form or in kind, as is primarily the case with the Assistance sub-branch. A comprehensive classification of life and non-life insurance sub-branches is outlined in the European Solvency Directive (Directive 2009/138/EC, OJ L 335, 17.12.2009), particularly in Annexes I and II.

Figures found on the daily and financial press pages systematically influence the

production of insurance premiums. However, when we observe significant differences in per capita insurance premiums from country to country, ranging from €34,361 in Norway to €551 in Latvia in 2020, it sparks curiosity about the underlying causes of this variability. The literature reveals a complex interplay of various factors that shape the demand for Private Insurance, some of which are not directly quantifiable, such as education, the banking system, and inflation. Although GDP is often assumed to be the most essential factor in determining the total volume of premiums, studies, e.g., Beck and Webb (2002), find that income's statistical significance as a factor is marginalized when suitable determinants are considered.

One of the most characteristic indicators measuring the importance of private insurance is insurance penetration, defined as the ratio of insurance premiums to the country's GDP. Another important indicator is insurance density, defined as the per capita production of insurance premiums, i.e., the average amount of monetary units each resident of a country spends on insurance. Although the high values of the indices mentioned above suggest a well-developed insurance market, readers should bear in mind that these values may result from factors such as poor competition or a costly supervisory framework for insurance enterprises.

While it is reasonable to assume that the indicators are highly correlated, it is interesting to note that insurance density is more elastic concerning income than insurance penetration. In this context, elasticity refers to the degree of responsiveness of one variable to changes in another. For example, life policyholders in rich countries tend to insure dependents for larger funds, as the indemnities for death insurance in these countries are greater.

Undoubtedly, product price constitutes an important determinant of purchase decisions. Consequently, the absence of direct pricing data constrains the ability of this study to interpret the phenomenon under investigation with complete precision. Nevertheless, this limitation is not unique to the present research but is shared by all comparable studies to date. Moreover, Lee (2007) argue that information on insurance pricing may, in fact, be of limited relevance. Within the existing literature, price effects are typically proxied through cost-related indicators, which indirectly reflect a range of underlying determinants such as the degree of urbanization, monetary stability, the quality of public administration, adherence to the principles of the Rule of Law, the level of corruption, and the development of the banking sector.

The Private Insurance industry is not solely dependent on the demand side. Its supply is influenced by important factors, such as the specialized human resources who staff the sector, the availability of information on risk statistics, and a financial system that facilitates smooth investments. Moreover, the proper functioning of the industry also depends on the protection of property rights, the competence of regulatory authorities, and the observance of contracts. This highlights the industry's crucial role in promoting societal well-being and underscores the importance of these factors in maintaining its integrity.

The following two sub-sections outline the determinants of demand for each insurance branch, along with the typical direction of their effects. The term usual direction is deliberately employed instead of a more assertive phrase, such as expected direction, to reflect the inherent uncertainty surrounding these relationships. The impact of each determinant on insurance premiums can vary depending on contextual factors such as the country, time period, and the specific configuration of variables within each sample. This heterogeneity in findings across the literature

highlights the need for further empirical investigation.

2.1 Determinants of demand for life insurance

The study of the determinants of demand for life insurance has attracted research interest for a long time. A multitude of papers have addressed the research area, with excellent reviews of their conclusions provided by Zietz (2003). The research methodology involves relating life premiums to other variables (e.g., macroeconomic and institutional) and concluding on the latter's significance. The oldest piece of literature is considered to be Yaari (1965). On the same subject, that of a theoretical life cycle model, Pissarides (1980) also contributed.

Several studies have examined the factors mentioned above at the individual level. Such analyses fall within the domain of microeconomics and, as such, lie beyond the scope of this research. Notable examples include Cummins and Outreville (1984), Desrochers and Outreville (2013), Ferber and Lee (1980), Fitzgerald (1987), and Luciano, Outreville, and Rossi (2016).

2.1.1 Income

The production of life insurance premiums increases with rising income, as the need for mortality coverage and the opportunity to save also rise. Additionally, we can assume that increased income is positively correlated with overall consumer spending and property ownership. In this case, the need to secure both the future income and the consumption of dependent members against the risks of incapacity for work and the death of those who produce (the income) increases. Finally, it should not escape attention that the cost of operating larger insurance policies, and

therefore the increased production of insurance premiums, does not increase the operating costs of insurance companies; thus, the ratio of the latter to revenues decreases, rendering the services more accessible to private insurance consumers.

The use of income as an explanatory variable in research is well-established and has never been questioned. This historical use is evident in literary pieces as old as Hammond, Houston, and Melander (1967) and Fortune (1973), and in the following decades, those of Campbell (1980), Outreville (1996), Li (2007), and Sliwinski, Michalski, and Roszkiewicz (2013).

As a superior good, life insurance is expected to increase premiums as income increases, as indicated by its elasticity to income. However, this elasticity is not a fixed quantity (Chang and Lee, 2012) and can vary from country to country. For instance, Truett and Truett (1990) estimated the elasticity in Mexico to be three times that of the USA. This variability underscores the complexity of the relationship and has been further detailed as an “S-curve relation between per-capita income and insurance penetration” (Enz, 2000), and has been examined in greater analytical detail by Lee and Chiu (2012).

An exciting finding of Beck and Webb (2002) research paper, commissioned by the World Bank, is that income (GDP per capita) loses its status as a statistically significant explanatory variable when it is included in statistical models alongside a combination of explanatory variables such as the youth dependency ratio on the working population, duration of schooling, life expectancy, inflation, banking sector growth, and income inequality (see, for details, Beck and Webb, 2002). Another study that contains similar findings is that of Elango and Jones (2011), in which the models employing subsets of the independent variables of the complete model

suffer little loss in explanatory value (R^2), despite the removal of “traditional” explanatory variables such as income and inflation.

Recent studies have yielded additional significant findings regarding income and insurance premiums. They point out that an increase in foreign direct investment (FDI) not only boosts income but also leads to higher premiums in the life insurance (Carson, Chen, and Outreville (2021)) business. These findings have important implications for the insurance industry and the broader economy.

2.1.2 Inflation

High inflation is most probably a result of loose monetary policy. During periods of high inflation, consumers’ confidence in the long-term value of money is eroded, which hinders their financial planning. So, they avoid fixed-interest-rate financial products, which is the usual case for life insurance products, and direct their investment choices towards equity investments, whose values generally rise with prices, thereby depriving insurance companies of customers. Such is the adverse effect of high inflation that insurance companies supplied products with protection against it, an effort that ultimately proved unsuccessful, e.g., see Babbel (1981). Among the literature pieces that concluded that spells of high inflation rates hurt life insurance, there are some as old as Greene (1954) and Hofflander and Duvall (1967)¹, while in the most recent years, among many others, there are those of Browne and Kim (1993), Outreville (1996), Çelik and Kayali (2009), and Ertl (2017). It should be noted that there is limited evidence that inflation appeared as a supporting factor to life insurance consumption (Zerriaa and Noubbigh, 2016).

¹The latter prompted a scholarly exchange between Neumann (1968) and Hofflander and Duvall (1968), which provided readers with valuable insights into the subject.

Although the usual way to incorporate the figure into calculations is through the Consumer Price Index (CPI), some surveys use other versions of it, such as anticipated inflation or the average CPI of recent years, as a trend that has been ingrained in economic actors.

It is worth noting that when inflation is examined in conjunction with other determinants, it may not be considered statistically significant. An example is cited in a Feyen, Lester, and Rocha (2011), commissioned by the World Bank, where the fact above occurred when the ratio of credit to GDP was introduced into the statistical model. So, it is understood that other explanatory variables have already captured the information provided by inflation.

To date, the relevant literature has primarily focused on the study of inflation. Nevertheless, we should also be aware of deflation, a macroeconomic risk against which the authorities' actions are particularly vigorous. When it occurs, it hinders consumers' ability to pay life insurance installments, an issue beyond the scope of this paper, as it falls within the literature concerning life insurance lapses/surrenders. Relevant readings include Poufinas and Michaelide (2018) and Fier and Liebenberg (2013), etc.

Finally, it should be emphasized that, according to the findings of Beck and Webb (2003), inflation volatility is not a statistically significant explanatory variable. This suggests that it is the persistence of high inflation, rather than its variability, that erodes economic agents' confidence in the financial system.

2.1.3 Unemployment

Although the share of the labor force seeking a job is an important indicator that summarizes the state of an economy, it is surprising that very few pieces of literature have considered it. A possible reason is that they did not deal with countries suffering from high and persistent unemployment. Moreover, the GDP per capita, already used in this type of study, yields a significant share of the information provided by the unemployment rate. Additionally, another reason for the absence of the index is that consumers concerned about the stability of their employment are less likely to allocate their income to insurance. On the other hand, it should not escape our attention that in an environment of high inflation and unemployment, GDP growth is not sufficiently diffused among economic actors and consequently does not significantly affect the production of insurance premiums.

Notable exceptions to this trend include Sliwinski, Michalski, and Roszkiewicz (2013), who analyzed the Polish life insurance market, and Ertl (2017), who investigated life insurance dynamics in Central and Eastern European (CEE) countries. The latter study provides an instructive temporal analysis: during the pre-crisis period (1994 - 2008), lower unemployment rates were associated with higher levels of life insurance consumption, whereas in the post-crisis period (2010 – 2014), the relationship appeared to reverse, with higher unemployment rates exhibiting a positive, albeit seemingly counterintuitive, association with insurance demand. However, it is essential to highlight that in both temporal contexts, the unemployment variable was statistically insignificant across the majority of model specifications. This finding suggests a complex, possibly indirect, linkage between labor market conditions and life insurance uptake.

An alternative perspective involves using the number of employed individuals, either in general or within specific sectors such as the tertiary sector, as a determinant of insurance demand, rather than the unemployment rate. This approach has been proposed by Mantis and Farmer (1968), Beenstock, Dickinson, and Khajuria (1986), and Luciano, Outreville, and Rossi (2016). Such a multi-faceted framework is essential for developing a more comprehensive understanding of the relationship between labor market dynamics and insurance demand.

Finally, it should be noted that, for evident reasons, rising unemployment is associated with an increase in life insurance lapses and surrenders. This relationship is supported by the literature referenced earlier in the discussion on inflation. When policyholders experience unemployment, they may become eligible for a grace period during which premium payments are temporarily suspended, allowing the policy to remain in force.

2.1.4 Banking sector

When the banking sector is functioning properly, consumers tend to regard the financial sector favorably, which includes private insurance. Additionally, there is significant scope for cooperation between the two types of businesses, namely banks and insurance enterprises, in several activities, such as cross-selling and investment management. Of course, in countries where there are no restrictions on the operation of the financial sector, such as interest rate regulations, administratively determined prices, etc., plenty of room is available for economic growth, which in turn allows consumers a greater income on the one hand and to find better services on the other hand. The same factors that facilitate banking operations are also relevant for private insurance, including civil liberties, political stability,

regulatory quality, the rule of law, and a low level of corruption (Chang, Lee, and Chang, 2014).

There is little doubt that financial intermediation by banks is positively associated with economic growth. When economic agents have access to investment-related information, typically ensured through standardized accounting practices and corporate disclosure requirements, and when contractual obligations are reliably enforced, the foundational conditions for the effective functioning of both banking institutions and the broader economy are met. In the absence of these conditions, key financial activities such as identifying viable investment opportunities, gathering and processing relevant information, exercising corporate oversight, managing risk, mobilizing liquidity, and facilitating the transfer of funds become either severely hindered or altogether unfeasible.

In the literature linking private insurance with macroeconomic conditions, the size of the banking sector is described using various terms, including banks, financial sector, and financial depth; see for example, Sliwinski, Michalski, and Roszkiewicz (2013), Li (2007), and Ertl (2017)). In all cases, they refer to the same phenomenon, to the level of development, and the ability of the economy to mobilize and multiply the amount of circulating currency. Therefore, it is assumed that the size of the banking sector is positively and largely correlated with the provision of quality financial services. Although the scope of this research is served well by the assumption, it should not be taken for granted that financial development is always beneficial to economic growth. Beyond a certain level, it may be detrimental to the economy, as it siphons resources without making good use (Law and Singh, 2014).

Various approaches have been used to measure the abovementioned figure, depend-

ing on the researchers' judgment and the availability of information. For example, Levine, Loayza, and Beck (2000) used the ratio of loans to GDP, Outreville (1996) the ratio of M2 to M1, and Chui and Kwok (2008) the ratio of banks' assets to GDP. In addition, Feyen, Lester, and Rocha (2011) broadened their probe by examining the amount of bonds issued, reaching a similar conclusion that they positively affect life insurance. It is reminded that according to the European Central Bank (ECB), M1 is the sum of currency in circulation and overnight deposits, while M2 is the sum of M1 plus deposits with an agreed maturity of up to two years and deposits redeemable at notice of up to three months.

Additionally, some researchers, such as Chui and Kwok (2008), have extended the analysis of the relationship between private insurance and the financial sector by incorporating the ratio of stock market capitalization of listed companies to GDP. A similar approach was also employed by Cummins (1973). However, their findings were inconclusive. As Levine and Zervos (1998) noted, this ambiguity may arise from the fact that stock markets do not function as substitutes for traditional borrowing. Nonetheless, this does not detract from their important role in the economy more broadly, and in enhancing the functioning of the financial sector in particular.

2.1.5 Interest rate

Life insurers manage substantial reserves, which are invested in financial markets to generate returns. The latter constitutes an essential component of their overall income structure. The interest rates prevailing in these markets play a critical role in determining the magnitude of such investment income. When returns are favorable, insurers may reduce policy prices, thereby enhancing the attractiveness of their products and potentially stimulating demand.

High interest rates are typically indicative of a contractionary monetary policy, which may dampen overall economic growth prospects. In such contexts, life insurance products may be perceived as stable, long-term investment alternatives. Conversely, elevated interest rates can incentivize consumers to allocate their funds toward other investment vehicles offering more immediate or higher returns, potentially reducing the appeal of life insurance policies. Given the dual and sometimes opposing effects of interest rates on premium setting and consumer behavior, it is perhaps unsurprising that relatively limited empirical work has been devoted exclusively to this relationship. Notable contributions include Cummins (1973), Dragoş, Codruţa, and Dragoş (2019), Elango and Jones (2011), and Sliwinski, Michalski, and Roszkiewicz (2013).

Moreover, several studies have examined the effects of interest rates in conjunction with inflation, often analyzing the real interest rate to isolate its impact better. These include Chang and Berdiev (2013), Beck and Webb (2003), Beenstock, Dickinson, and Khajuria (1986), Ertl (2017), Li (2007), and Sen (2008).

2.1.6 Business Tendency Surveys (BTS)

BTS have been conducted since at least the 1920s. Business Tendency Surveys - A Handbook (OECD, 2003) informed that some of the earliest initiatives came from trade associations, including the Confederation of British Industries and Germany's ifo Institute for Economic Research. Since the 1950s, France's national statistical office, the Institut national de la statistique et des études économiques (INSEE), has also played a significant role in this field. There is evidence that the sentiment variables hold considerable predictive power for business cycles (Christiansen, Eriksen, and Møller, 2014) and short-term real GDP growth (Mourougane

and Roma, 2002).

This research employs BTS indicators to capture public perceptions of countries' economic conditions and to assess consumer intentions. Depending on the specific indicator, data may be sourced from consumer surveys, often conducted through personal interviews to gauge sentiment, or from expert evaluations grounded in broader macroeconomic analysis. Given that official macroeconomic indicators may overlook sector-specific dynamics or shifts in consumer confidence, BTS provide valuable supplementary insights into evolving economic trends. Their relevance is reflected in their integration into economic assessments; for example, the Economic Sentiment Indicator (ESI) is regularly included in Greece's economic monitoring reports (Bank of Greece, 2022), with empirical evidence supporting its capacity to forecast output fluctuations, e.g., Tkacova and Gavurova (2023). Furthermore, Ludvigson (2004) concluded that measures of consumer confidence enhance the forecasting accuracy for various types of consumption, including services.

The theoretical basis of BTS lies in the understanding that economic agents, households and firms, form expectations about future economic conditions that influence their current decision-making. They aggregate subjective assessments of economic prospects, providing timely signals that often precede actual shifts in economic activity. These indicators capture the anticipatory nature of economic behavior, reflecting how perceptions and confidence can impact spending, saving, and investment decisions even before objective economic data confirm a trend. This forward-looking perspective is particularly relevant for sectors such as life insurance, where consumer choices depend heavily on long-term expectations of economic stability and financial security.

The influence of BTS on the Private Insurance sector is not yet well established. Improvements in BTS indicators often precede periods of macroeconomic expansion, which may support growth in insurance uptake. Conversely, a decline in such indicators typically signals a rise in public pessimism, prompting more cautious financial behavior. This shift toward prudence can lead to increased household savings, including heightened demand for insurance products as a means of financial security.

Despite their value in macroeconomic analysis, BTS remain underutilized in empirical research on life insurance demand. One of the few exceptions is Fortune (1973). A key reason for this limited academic engagement may be the lack of comprehensive BTS data across countries and time periods, which constrains cross-national and longitudinal analyses. Consequently, researchers often turn to alternative proxies to assess consumer expectations and sentiment.

For example, Beck and Webb (2003) employed anticipated inflation and permanent income as indicators of consumer confidence in national economic performance. Similarly, Browne and Kim (1993) emphasized expected rather than actual inflation, arguing that consumer expectations, shaped by historical patterns, are more relevant for predicting life insurance behavior. They operationalized this by using the average inflation rate over the previous eight years. In a comparable approach, Cargill and Troxel (1979) relied on anticipated inflation from the Livingston survey, which estimates expected changes in the Consumer Price Index over six- and twelve-month periods.

The Business Tendency Survey (BTS) indicators employed in this research include the Business Confidence Index, the Consumer Confidence Index, the World Uncer-

tainty Index, and the World Pandemic Uncertainty Index. Detailed descriptions of these indicators are provided in the relevant section of Chapter 4.

2.1.7 Population

The concentration of the population in small geographical areas allows insurance enterprises and intermediaries to reach out to consumers more efficiently. Thus, the costs of advertising, contract distribution, premium collection, and claims management decrease. Additionally, as the population grows, it is implied that private insurance can appeal to a broader consumer base, which is beneficial for statistical calculations of the characteristics of insured risks. Finally, the large number of customers allows the distribution of operating costs over a broader base, proportionally reducing the cost of accessing private insurance services.

The concept of population has been studied in various forms. One of its versions is urbanization, which has been explored by researchers such as Luciano, Outreville, and Rossi (2016), Sen (2008), Beck and Webb (2002), and Beck and Webb (2003). Another example is population growth, as seen in studies by Elango and Jones (2011) and Outreville (1996). Finally, Feyen, Lester, and Rocha (2011) used the version of population density, which is the ratio of a country's population to its area. It is worth noting that the last-mentioned paper included both versions: population and population density. All concluded that population growth and density have a positive effect on life insurance.

2.2 Determinants of demand for non-life insurance

Although the two main branches of private insurance share several operational characteristics, it is reasonable to expect that the factors driving their development may differ. The following paragraphs outline the key determinants of non-life (property-casualty) insurance. To avoid redundancy, elements previously discussed in relation to life insurance that are also pertinent to non-life insurance are not repeated here. It should be reiterated that this research concentrates on the macroeconomic determinants of insurance demand, rather than on microeconomic factors, as examined by Falciglia (1980). Also, we do not take into account whether various types of insurance are mandatory.

2.2.1 Income

At first glance, the nature of non-life insurance classes might suggest that wealth, rather than income, would serve as a more appropriate determinant. However, comprehensive and high-frequency wealth data are not consistently available across countries, particularly at the quarterly level required for time series analysis. Even prominent studies, such as Browne, Chung, and Frees (2000), have relied on rough wealth approximations, which are unsuitable in the context of this research. In lieu of wealth, the latter employed education as a proxy for a country's intellectual capital, capturing collective knowledge, skills, and abilities, as an indirect measure of the population's capacity to engage with and benefit from insurance products.

Household Finance and Consumption Surveys conducted by European Central Bank (2021) provide periodic data on household wealth for relevant countries. While these datasets offer improvements over earlier approximations, they still fall short

of the frequency and consistency required for this study. Similar limitations apply to otherwise valuable resources such as the Global Wealth Report by UBS Global Wealth Management (2023) and UBS Global Wealth Management (2025).

Given these constraints, income is employed as the preferred variable. It is reasonable to assume that higher income levels are associated with a greater value of assets, thereby increasing the propensity to purchase insurance. This assumption is well supported by the literature, including studies by Sherden (1984), Outreville (1990), and Trinh, Nguyen, and Sgro (2016). Although most of the literature assumes a linear relationship between the two variables, Lee and Chiu (2012) extended the analysis to explore their potential non-linearity. It was also established that an increase in FDI leads to both higher income and non-life insurance premiums (Sawadogo, Guerineau, and Ouedraogo, 2018).

2.2.2 Inflation

Although inflation is a key macroeconomic indicator, its use in studies examining the relationship between macroeconomic variables and private insurance remains relatively limited. One possible reason is the short duration of non-life insurance contracts, which typically span a single year. Under conditions of low and stable inflation, significant price fluctuations within such short periods are not generally expected. However, this assumption does not always hold. For instance, unresolved claims, particularly those subject to lengthy legal proceedings, can experience substantial increases in value, even when inflation rates remain in the single digits.

Some researchers may downplay the role of inflation by focusing primarily on income, under the assumption that insurance premiums adjust proportionally with

general price levels. This perspective is evident in studies such as Feyen, Lester, and Rocha (2011), Ertl (2017), and Elango and Jones (2011). Both Feyen, Lester, and Rocha (2011) and Elango and Jones (2011) report a positive relationship between inflation and insurance premium volume, likely reflecting the pass-through of higher claim and operational costs to policyholders. In contrast, Ertl (2017) finds a negative impact of inflation on the insurance sector, suggesting that rising prices may deter demand.

These mixed findings underscore the importance of contextualizing the inflation–insurance nexus within each country’s specific economic environment. A nuanced understanding of this relationship requires careful consideration of each country’s characteristics, which impact non-life business.

2.2.3 Unemployment

Although unemployment is a crucial macroeconomic indicator, it is often overlooked in research literature. One possible reason is that researchers may find sufficient information in income figures alone. Additionally, consumers concerned about their employment stability might be less inclined to invest their income in insurance. Nevertheless, this research emphasizes the importance of unemployment as a significant macroeconomic measure, drawing on findings from Ertl (2017) related to Central and Eastern European countries, which suffered from high and persistent unemployment rates. The study concluded, as expected, that unemployment had a negative impact on the insurance industry, though it was statistically significant only before 2009 in their sample.

2.2.4 Banking sector

As discussed in the relevant section on life insurance, which also applies to non-life insurance, the banking sector is essential in promoting business cross-selling. Specifically, lenders safeguard the value of collateral through insurance. Moreover, insurance facilitates trade by covering various non-life classes such as “Goods in transit,” “Credit,” and “Suretyship.” Several researchers, including Ertl (2017), Trinh, Nguyen, and Sgro (2016), Petkovski and Jordan (2014), Outreville (1990), and Feyen, Lester, and Rocha (2011) included the banking sector in their analyses.

It is important to expand beyond these studies, as additional researchers have explored the issue from various perspectives. For example, Esho (2004) investigated the impact of legal frameworks, property rights protection, and the efficiency of the judicial system as elements essential for the effective operation of the credit business. Likewise, Elango and Jones (2011) identified the observance of property rights, the degree of business freedom, and financial management as key factors influencing the insurance sector. Ertl (2017) also indirectly addressed this topic by considering the number of mortgages as a significant variable.

We have chosen not to include the interest rate as a determining factor for the demand for non-life insurance. This decision stemmed from the sporadic appearance of interest rate discussions in the literature and their lack of statistical significance in previous studies. Our research data have corroborated this conclusion, revealing that the interest rate was not a meaningful factor in determining non-life insurance demand.

2.2.5 Business Tendency Surveys (BTS)

The role of Business Tendency Surveys is discussed in the corresponding subsection on life insurance and applies equally to the non-life insurance case.

2.2.6 External trade

The total volume of imports and exports serves as a key indicator of an economy's dynamism, reflecting both its competitiveness in international markets and its openness to diverse sources of goods and services. Active participation in foreign trade requires robust collaboration across sectors of the economy, including the private insurance industry. Insurers play a critical role in mitigating risks associated with international transportation, whether by land, sea, or air, as well as those linked to logistics infrastructure and the goods in transit.

Moreover, private insurance often provides coverage for civil liabilities and credit risks arising from international trade transactions. It thus serves as an essential instrument for managing the legal, financial, and operational complexities inherent in cross-border commerce, including the transport and storage of goods across jurisdictions.

In this context, external trade emerges as a significant driver of demand for private insurance. This view is supported by the findings of Petkovski and Jordan (2014), Feyen, Lester, and Rocha (2011), and Esho (2004). Similarly, Elango and Jones (2011) highlighted the importance of merchandise trade as a contributing factor to the development of the insurance market. The aforementioned studies primarily examined trade as a determinant of the non-life insurance industry. More specifically, Veer (2015) investigated this relationship and concluded that “the impact of private

export credit insurance on international trade is larger than the value of exports insured,” a finding from which several hypotheses can be drawn, all suggesting that export trade benefits the non-life insurance sector.

2.2.7 Population

The urbanization factor, an essential area of study in non-life insurance, has garnered its fair share of scholarly attention. For instance, Treerattanapun (2011), Browne, Chung, and Frees (2000), and Trinh, Nguyen, and Sgro (2016) have contributed to this field. Similarly, Petkovski and Jordan (2014) and Sherden (1984) have examined the role of population density. Finally, Elango and Jones (2011) investigated the implications of population growth.

Building on the role of population as a determining factor for life insurance, the influence of population growth on non-life insurance is significant due to the increased interaction of individuals and their assets, leading to friction. This is particularly evident in the case of automobile insurance, where demand for additional coverage is largely driven by increases in population density, as demonstrated by Sherden (1984). Furthermore, the rise in population suggests a shift away from the traditionally strong institution of the family, which reduces funding availability when its members face problems.

2.3 A note on stationarity in the field of Private Insurance consumption

Statistical theory emphasizes the importance of ensuring variable stationarity prior to conducting regression analysis. Regressions involving non-stationary variables risk producing spurious results, wherein statistically significant relationships may be observed between variables that, in reality, are unrelated, particularly when both follow independent random walks. This issue is further exacerbated by the inclusion of lagged dependent variables as regressors, which can distort the estimation results. For example, a coefficient that initially appears statistically significant may lose significance once appropriate adjustments are made. Therefore, apparent co-movements between time series should not be interpreted as evidence of a genuine relationship without the application of rigorous statistical techniques designed to assess the validity and robustness of such findings.

The property of stationarity, typically associated with mean reversion, is considered highly advantageous for a given time series, as it implies that the series tends to return to its long-term equilibrium following a temporary disturbance. This characteristic enables analysts to make informed assumptions based on historical behavior. In the context of insurance markets, if insurance premiums exhibit stationarity, it suggests that the effects of shocks may dissipate over time without the need for policy intervention. Consequently, in such settings, policymakers should exercise caution when responding to market disruptions, as the premiums are expected to revert to their underlying trend naturally.

This insight is particularly relevant for insurance firms operating under conditions of financial distress, such as during economic crises marked by significant declines

in asset values. In such contexts, a stable and predictable stream of premium income can serve as a critical buffer, enabling firms to maintain operations and meet obligations despite unfavorable market conditions. The consistent inflow of liquidity associated with stationary premium processes enhances the resilience of insurers, allowing them to absorb shocks and navigate extended periods of volatility with reduced reliance on external intervention.

In contrast, non-stationary processes are characterized by potentially unbounded volatility, which poses significant challenges for statistical analysis. The improper inclusion of a non-stationary series in a regression framework can lead to biased and misleading inferences. For instance, such misspecification may result in the erroneous conclusion that shocks to consumption have permanent effects, when in reality they may be transitory. This misinterpretation can undermine policymakers' ability to accurately evaluate both the magnitude and persistence of shocks stemming from key macroeconomic variables. In the present context, many macroeconomic time series exhibit non-stationarity, a concern first systematically addressed by Nelson and Plosser (1982), who demonstrated the non-stationary behavior of long-term historical data for the United States.

In a comprehensive review of the literature on the relationship between private insurance consumption and its determinants, Lee, Hsu, and Lee (2010) observed that only a limited number of studies examine the stationarity properties of the variables involved, a shortcoming that may lead to spurious regression bias. This remark suggests that much of the existing research may have implicitly assumed the stationarity of both insurance consumption and its explanatory variables. While this assumption may be valid in specific contexts, particularly within the mature insurance markets of Europe and North America, it does not universally apply. This pattern

was further confirmed in Lee, Chang, and Chen (2012) and Lee, Tsong (2013), who examined both life and non-life insurance consumption. Their findings indicated that insurance premium series tend to exhibit stationarity in high-income and European countries, reinforcing the importance of treating data to enforce stationarity when modeling insurance demand. Also, this gap underscores a potential source of bias in earlier empirical work and highlights the need for greater attention to the time-series properties of data in insurance-related research.

The preceding discussion underscores the necessity of transforming data to achieve stationarity. This raises a critical methodological question: how can stationarity be attained? As noted by Diebold and Kilian (2000), the choice between modeling a series as difference-stationary or trend-stationary can lead to markedly different forecasts and interpretations. For example, Pradhan (2017) reported in their empirical analysis that “all the time series variables were non-stationary in their levels... However, they were all stationary in first differences,” thereby concluding that the variables were integrated of order one. This distinction is essential, as the appropriate transformation depends on the underlying data-generating process and has direct implications for the validity and reliability of subsequent econometric modeling.

While this study adopts a univariate approach, i.e., by analyzing each country individually, a substantial portion of the literature employs a cross-country or regional perspective, frequently focusing on groups with shared characteristics, such as OECD membership, and utilizing panel data methodologies. This choice carries critical methodological implications, particularly concerning the selection of stationarity tests. Panel data techniques are generally associated with greater statistical power, allowing for more robust inferences regarding the presence or absence of unit roots across multiple time series (Pan, Chen, and Chang, 2016).

In concluding this discussion, it is important to highlight the contribution of Lee, Chang, and Chen (2012), who advanced the examination of stationarity in non-life insurance premiums using a panel data framework. Their findings indicate that the panel dataset exhibits stationarity once structural breaks are incorporated into the model and cross-sectional dependence across countries is properly accounted for. This result suggests that failing to model such features may lead to misleading conclusions regarding the time-series properties of insurance premiums. These structural breaks were associated with significant, atypical events, broadly classified under themes such as domestic and international financial market liberalization, integration, regulatory reforms, and globalization. Notably, their study identified at least one structural break for each individual country in the sample, underscoring the importance of accounting for such discontinuities in future research on insurance market dynamics.

2.4 Methodological approaches in the literature

2.4.1 Life insurance

The empirical literature on life insurance demand can be classified into four main methodological strands, reflecting a clear evolution in econometric approaches over time.

Early contributions, such as Mantis and Farmer (1968), Cummins (1973), Fortune (1973), and Cargill and Troxel (1979), rely primarily on simple regression frameworks, often applied to time-series or cross-sectional data. These studies focus on basic economic relationships, occasionally incorporating corrections for autocorrelation or dynamic effects through lagged variables. Similarly, Truett and

Truett (1990) employs standard regression techniques augmented with diagnostic testing. While methodologically straightforward, these approaches establish the foundational determinants of life insurance demand.

A second strand of the literature extends the analysis to cross-country settings using pooled or cross-sectional regressions. Studies such as Beenstock, Dickinson, and Khajuria (1986), Browne and Kim (1993), and Outreville (1996) introduce international heterogeneity and expand the set of explanatory variables to include demographic and institutional factors. These contributions mark an important step toward comparative analysis, although they remain limited in their ability to control for unobserved heterogeneity.

From the early 2000s onwards, panel data models become the dominant methodological framework. Seminal contributions by Beck and Webb (2002) and Beck and Webb (2003) are followed by a wide range of studies, including Sen (2008), Elango and Jones (2011), Dragoş (2014), and Grabova and Sharku (2021), which employ fixed-effects and random-effects estimators, typically combined with Hausman specification tests. These approaches allow for the control of time-invariant heterogeneity across countries and represent a significant methodological improvement over earlier models.

More recent research adopts dynamic panel techniques, particularly Generalized Method of Moments (GMM) estimators, to address endogeneity and persistence in insurance consumption. Studies such as Li (2007), Feyen, Lester, and Rocha (2011), Chang and Berdiev (2013), Alhassan and Biekpe (2016), Ertl (2017), and Trinh (2023) employ system or difference GMM frameworks, incorporating lagged dependent variables and instrumental variable strategies. This strand reflects a

growing emphasis on econometric rigor and the treatment of dynamic relationships.

In parallel, several studies introduce alternative methodologies. For instance, Millo and Carmeci (2015) incorporates spatial econometric techniques, while Sliwinski, Michalski, and Roszkiewicz (2013) and Chui and Kwok (2008) and Chui and Kwok (2009) employ factor analysis and principal component analysis to address dimensionality and multicollinearity issues. These approaches, although less widespread, indicate a diversification of empirical strategies in the literature.

Overall, the methodological evolution follows a clear trajectory from simple regression models to increasingly sophisticated panel and dynamic frameworks. This progression is accompanied by a growing awareness of econometric issues, including heteroscedasticity, autocorrelation, endogeneity, and non-stationarity.

With respect to the determinants of life insurance demand, a core set of variables appears consistently across studies. These include income (typically proxied by GDP per capita or disposable income), demographic characteristics (such as dependency ratios, population structure, and life expectancy), and macroeconomic conditions (notably inflation and interest rates). These variables constitute the baseline specification in most empirical models.

Over time, the literature expands to incorporate additional factors reflecting financial, institutional, and social dimensions. Financial development, education, and social security systems are progressively included, followed by governance indicators such as the rule of law, corruption, and political stability. More recent studies further extend the analysis to include inequality measures, health expenditure, market structure variables, and cultural factors.

This expansion is also reflected in the increasing dimensionality of empirical models. While early studies typically include a limited number of explanatory variables, more recent contributions often incorporate a large set of covariates, sometimes exceeding fifteen variables. In response to potential multicollinearity and dimensionality concerns, techniques such as principal component analysis are occasionally employed.

Despite these advances, the majority of studies rely on mean-based econometric approaches, including OLS, fixed-effects, random-effects, and GMM estimators. As a result, the literature primarily captures average effects and provides limited insight into potential heterogeneity across the distribution of life insurance demand.

This observation highlights an important gap in the literature. While significant progress has been made in addressing econometric challenges and expanding the set of explanatory variables, relatively little attention has been given to distributional aspects of insurance demand. This thesis contributes to the literature by addressing this limitation through the use of quantile regression techniques, allowing for the investigation of heterogeneous effects across different levels of insurance penetration.

A further important characteristic of the literature relates to the nature of the data and the underlying modeling assumptions. First, the vast majority of studies rely on annual data, largely due to data availability constraints. While suitable for capturing long-run relationships, this choice limits the ability to identify short-term dynamics and cyclical effects in life insurance demand, which may be better captured using higher-frequency data. Second, although panel data models have become the dominant empirical framework, they typically impose homogeneous slope coefficients

across countries. As a result, they may fail to fully capture cross-country heterogeneity in the effects of key determinants, particularly in the presence of structural, institutional, and cultural differences. This limitation further motivates the need for approaches that allow for heterogeneous effects across observations.

2.4.2 Non-life insurance

The empirical literature on non-life insurance demand exhibits a similar, albeit slightly more heterogeneous, methodological evolution compared to the life insurance literature. It can be broadly classified into four main strands.

Early contributions, such as Sherden (1984), Beenstock, Dickinson, and Khajuria (1988), and Outreville (1990), rely on simple regression frameworks applied to cross-sectional or pooled data. These studies focus on a relatively limited set of economic determinants, including income, price, and demographic characteristics. They are methodologically straightforward and establish the core relationships underlying non-life insurance demand.

Subsequently, the literature expands to incorporate cross-country and panel data approaches. Studies such as Browne, Chung, and Frees (2000) and Elango and Jones (2011) employ pooled OLS as well as fixed-effects and random-effects models, allowing for the control of unobserved heterogeneity across countries. These contributions significantly improve empirical specification and introduce a broader set of explanatory variables, including institutional and market structure indicators.

A third strand is characterized by the adoption of dynamic panel methodologies, particularly Generalized Method of Moments (GMM) estimators. Contributions such as Esho (2004), Chang and Berdiev (2013), Feyen, Lester, and Rocha (2011),

and Ertl (2017) explicitly address endogeneity and persistence in insurance demand by incorporating lagged dependent variables and instrumental variable techniques. This reflects a clear shift toward greater econometric rigor and more robust inference.

In parallel, several studies employ alternative or complementary methodologies. For instance, Lee, Hsu, and Lee (2010) focuses on time-series techniques and stationarity analysis, while Petkovski and Jordan (2014) adopts cointegration methods to explore long-run relationships. Additionally, Treerattanapun (2011) employs principal component analysis and non-parametric bootstrapping to address multicollinearity and distributional issues. These approaches indicate an increasing diversification of empirical strategies in the literature.

With respect to the determinants of non-life insurance demand, a core set of variables is consistently identified across studies. These include income-related measures (GDP or GNI per capita), price variables, and demographic indicators such as population density. Over time, the literature expands to incorporate financial development, education, and institutional variables, including legal systems, political risk, and property rights. More recent contributions also consider market structure variables, such as concentration and foreign participation, as well as sector-specific indicators, including vehicle ownership and exposure to natural disasters.

The number of explanatory variables increases substantially over time, reflecting both improved data availability and a broader conceptualization of insurance demand. While early studies typically rely on a small number of covariates, more recent analyses incorporate a large set of economic, institutional, and cultural factors. In some cases, dimensionality issues are addressed through techniques such

as principal component analysis.

In terms of data and modeling choices, the non-life insurance literature exhibits some distinct features. While annual data remain the dominant frequency, this is particularly consequential in the non-life context, where insurance demand is more closely linked to short-term economic activity, business cycles, and sector-specific shocks (e.g., vehicle purchases or natural disasters). As a result, the reliance on low-frequency data may obscure important cyclical and high-frequency dynamics that are more relevant for non-life insurance markets.

Furthermore, although panel data models are widely employed, their limitations are more pronounced in the non-life setting due to the greater heterogeneity of insurance lines and market structures across countries. The assumption of homogeneous slope coefficients may therefore be especially restrictive, as the impact of key determinants—such as income, risk exposure, or institutional quality—can vary substantially depending on the composition and maturity of non-life insurance markets.

Overall, while the methodological evolution in the non-life insurance literature parallels that of life insurance, it is also characterized by a greater diversity of empirical approaches, including time-series analysis, cointegration techniques, and sector-specific modeling. Nevertheless, the predominant reliance on mean-based estimators persists, limiting the ability of existing studies to capture heterogeneous responses across different segments of the non-life insurance market. This reinforces the need for empirical frameworks capable of uncovering such heterogeneity.

Table 2.1: Life insurance literature – detailed overview of determinants and methodologies

Study	Examined Factors	Methodology
Mantis and Farmer (1968)	Relative CPI (CPI–life insurance); Marriages; Births; Income; Population; Civilian employment	Regression
Cummins (1973)	Dividend–price ratios; Mortgages; GNP; Investments; Interest rates; Insurance companies investments	Regression; Use of lagged variables
Fortune (1973)	Time; Seasonal dummies; Real per capita wealth; Real per capita income; Real interest rate; Consumer sentiment	Regression
Cargill and Troxel (1979)	life insurance reserves; Policy loans; Pension reserves; Life insurance reserves; Household net worth; Disposable income; Anticipated CPI; Interest rates	OLS with Almon constraints; Cochrane–Orcutt correction for autocorrelated disturbances

Study	Examined Factors	Methodology
Beenstock, Dickinson, and Khajuria (1986)	Disposable income; Country; Life expectancy; Price level; Dependency; Interest rate; Social security; Inequality; Lagged variables; Working population in services	Pooled cross-section and time-series regression
Truett and Truett (1990)	Age; Education; Real per capita income	Regression; Durbin–Watson test
Browne and Kim (1993)	Income; Dependency ratio; Religion; Social security; Expected inflation; Education; Life expectancy; Price; Islamic	OLS (log-linear); Diagnostic tests
Outreville (1996)	GDP; Interest rate; Anticipated inflation; Life expectancy; Financial development; Monopoly; Foreign companies; Education; Demographics; Health; Religion; Social security; HDI	Regression; Park test

Study	Examined Factors	Methodology
Ward and Zurbuegg (2002)	GDP per capita; Inflation; Financial development; Social welfare; Dependency ratio; Risk aversion; Insurance price; Political and institutional indicators; Political cohesion; Civil rights; Rule of law; Muslim country	Pooled OLS; Panel GMM (dynamic specification)
Beck and Webb (2002) and Beck and Webb (2003)	Urbanization; Inflation; Institutional quality; Financial development; Dependency ratios; Education; Religion; Life expectancy; GDP; Social security; Income distribution; Region; Time; Interest rate; Expected inflation rate; Permanent income; Human development index	Panel regression (FE/RE); Hausman test
Hwang and Gao (2003)	GDP; Inflation; Education; Urbanization	Multiple regression; Durbin–Watson test; Glejser test for heteroscedasticity

Study	Examined Factors	Methodology
Hwang and Greenford (2005)	GDP; Social structure; Education; Social security; Price; Children; Economic development	Multiple regression; Fixed effects; Pooled cross-sectional model; F-test for equality of constants
Li (2007)	GDP per capita; Life expectancy; Dependency ratio; Education; Social security; Financial development; Foreign market share; Inflation (anticipated); Interest rate	OLS; GMM; Box-Cox transformation; Heteroskedasticity tests
Sen (2008)	GDP per capita; Savings; Financial depth; Urbanisation; Dependency ratios; Literacy; Life expectancy; Inflation; Interest rate; Price	Panel data (FE/RE); Hausman test; ADF and KPSS stationarity tests
Chui and Kwok (2008) and Chui and Kwok (2009)	Cultural and psychological dimensions; GDP; Expected inflation; Financial development; Social security; Legal environment; Dependency ratio; Religion	Regression; PCA; Fama–MacBeth; Random effects
Çelik and Kayali (2009)	GDP per capita; Education; Population; Inflation	OLS regression; White test

Study		Examined Factors	Methodology
Elango and Jones (2011)		GDP; Inflation; Interest rate; Trade; Working force in services; Population; Dependencies; Education; Institutional quality	Pooled OLS; FE/RE; Hausman test
Feyen, and (2011)	Lester, Rocha	Real GDP per capita; Inflation; Gini coefficient; Population; Population density; Old age dependency ratio; Young age dependency ratio; Life expectancy; Years of schooling; Muslim; Private ownership of insurance enterprises; Social security contribution rate; Market concentration; Private credit; Bond market capitalisation; Creditor protection rights	Multivariate regression (pooled country-year data); OLS with year-fixed effects; Huber–White heteroskedasticity-consistent standard errors; Dynamic panel GMM (Arellano–Bover)
Chang and Berdiev (2013)		GDP; Inflation; Interest rate; Health expenditure; Dependency; Political risk; Natural disasters	System GMM; Hansen test; Arellano–Bond autocorrelation tests

Study	Examined Factors	Methodology
Millo and Carmeci (2015)	GDP; Bank deposits; Dependency ratios; Female participation in workforce; Social security; Bank counters; Insurance agencies; Education; Trust	Panel data with spatial specifications; Space and time dummies; Two-step maximum likelihood
Sliwinski, Michalski, and Roszkiewicz (2013)	GDP; Term deposit interest rate; Inflation; Financial development; Life expectancy (male/female); Market concentration; Foreign capital share; Population; Education; Health expenditures; Social benefits; Dependency ratio; Birth rate; Unemployment	Factor analysis; Bartlett test; KMO test; Varimax rotation; Anderson–Rubin method
Brokešová, Pastoráková, and Ondruška (2014)	GDP; Inflation; Exports; Vehicles; Population; Age dependency; Life expectancy; Education; Urbanisation; Social security; Crime; Regulatory quality; Market concentration	Panel data (fixed effects); Hausman test; Stationarity checks; Multicollinearity treatment (four partial models)

Study	Examined Factors	Methodology
Dragoş (2014)	Income; Education; Urbanisation; Inequality	Panel data (FE/RE); Heteroscedasticity and serial correlation tests
Alhassan and Biekpe (2016)	GDP; Inflation; Financial depth; Urbanisation; Education; Health; Dependency; Life Expectancy; Institutional quality	System GMM; Lagged variables
Ertl (2017)	GDP growth; GDP per capita; Inflation; Unemployment; Interest rate; Credit; Investment; Institutional indicators; Dependencies	Panel GMM; Wald test; Hansen test
Dragoş, Co-druţa, and Dragoş (2019)	Institutional indicators; Inequality; Dependency; Inflation; Interest rate; Education; Urbanisation; GDP	Dynamic panel models; Hansen test; Wald test
Grabova and Sharku (2021)	GDP; Inflation; Credit; Dependency; Urbanisation; Education; Governance indicators	FE/RE; FGLS; Stationarity tests

Study	Examined Factors	Methodology
Trinh (2023)	GDP; Economic freedom; Health spending; Culture; Financial development; Education; Urbanisation; Dependency; Social security; Legal origin; Religion	Panel GMM; Endogeneity and dependence tests

Table 2.2: Non-life insurance literature – detailed overview of determinants and methodologies

Study	Examined Factors	Methodology
Sherden (1984)	Price; Income; Population density	Regression analysis
Beenstock, Dickinson, and Khajuria (1988)	Income per capita; Country; Interest rate; Lagged dependent variable; Lagged detrended unemployment	Cross-section and pooled regression; Propensity to insure
Outreville (1990)	GDP; Financial development; Price; Monopoly; Education; Agriculture	Multiple regression
Browne, Chung, and Frees (2000)	GDP; Foreign market participation; Education; Urbanisation; Wealth; Legal system	Panel data (fixed effects); Pooled cross-section

Study	Examined Factors	Methodology
Esho (2004)	GDP; Risk aversion; Education; Price; Urbanisation; Property theft; Property rights; Law type; External trade	Dynamic system GMM
Lee, Hsu, and Lee (2010)	Time series	ADF test; Seemingly Unrelated Regressions; Monte Carlo simulations; Half-life estimation
Elango and Jones (2011)	GDP growth; GNI per capita; Inflation; Interest rate; Working population in the services sector; Trade; Population; Dependency; Education; Life expectancy; Institutional variables	Pooled OLS; Fixed and random effects; Hausman test; Heteroscedasticity test
Feyen, Lester, and Rocha (2011)	GDP per capita; Inflation; Population; Population density; Muslim; Private credit; Creditor protection rights; Cars; External trade	Pooled OLS; Fixed effects; Huber–White errors; Dynamic panel GMM (Arellano–Bover)

Study	Examined Factors	Methodology
Treerattanapun (2011)	GDP per capita (PPP); Urbanisation; Market concentration; Education; Legal system; Political risk; Religion; Cultural variables (power distance, individualism, masculinity, uncertainty avoidance)	Linear regression; Non-parametric bootstrapping; PCA; Treatment of data to achieve homoscedasticity
Njegomir and Stojić (2012)	Market concentration; Barriers to entry; Human capital; Insurance demand; Foreign direct investment; Market profitability; Return on investment	Panel data (cross-section and time-series); F-test; Welch test; Fixed effects; Hausman test
Park and Lemaire (2012)	GDP; Urbanisation; Education; Market concentration; Legal system; Political risk; Religion; Cultural dimensions	Panel data (year fixed effects)
Chang and Berdiev (2013)	GDP per capita; CPI; Interest rate; Health expenditure; Dependency ratio; Political risk; Natural disasters	System GMM (Arellano–Bond); Hansen test; Autocorrelation tests

Study	Examined Factors	Methodology
Dragoş (2014)	Income; Education; Urbanisation; Gini	Panel data; Fixed and random effects; Heteroscedasticity and serial correlation tests
Petkovski and Jordan (2014)	GDP per capita; Passenger vehicles; External trade; Financial development; Inflation; Population density; Education; Rule of law	Panel data; Log-linear model; Cointegration tests; DOLS (Stock–Watson); Bartlett kernel
Trinh, Nguyen, and Sgro (2016)	Index of economic freedom; GDP per capita; Bank development; Education; Urbanisation; Cultural variables; Legal system	Pooled OLS; Pooled GLS; Random effects; FGLS; 2SLS (IV); Durbin–Wu–Hausman test; Heteroscedasticity tests
Ertl (2017)	GDP growth; GDP per capita; Inflation; Unemployment; Interest rate; Credit growth; Mortgages; Vehicle registrations; Investment; EBRD transition indicator; Business costs to start up	Panel GMM; Wald test; Hansen test; Serial correlation tests

Chapter 3

Research Methodology

Guided by the existing literature, this research empirically examines the influence of macroeconomic indicators as determinants of private insurance demand. The analysis is based on eight datasets corresponding to European countries and considers both life and non-life insurance markets. The empirical investigation is conducted at two levels. First, each country is examined individually in order to capture country-specific macroeconomic structures and the potentially heterogeneous relationships between macroeconomic conditions and insurance demand. Second, the countries are also analyzed collectively within a panel data framework, allowing for the identification of broader patterns and common dynamics across the sample.

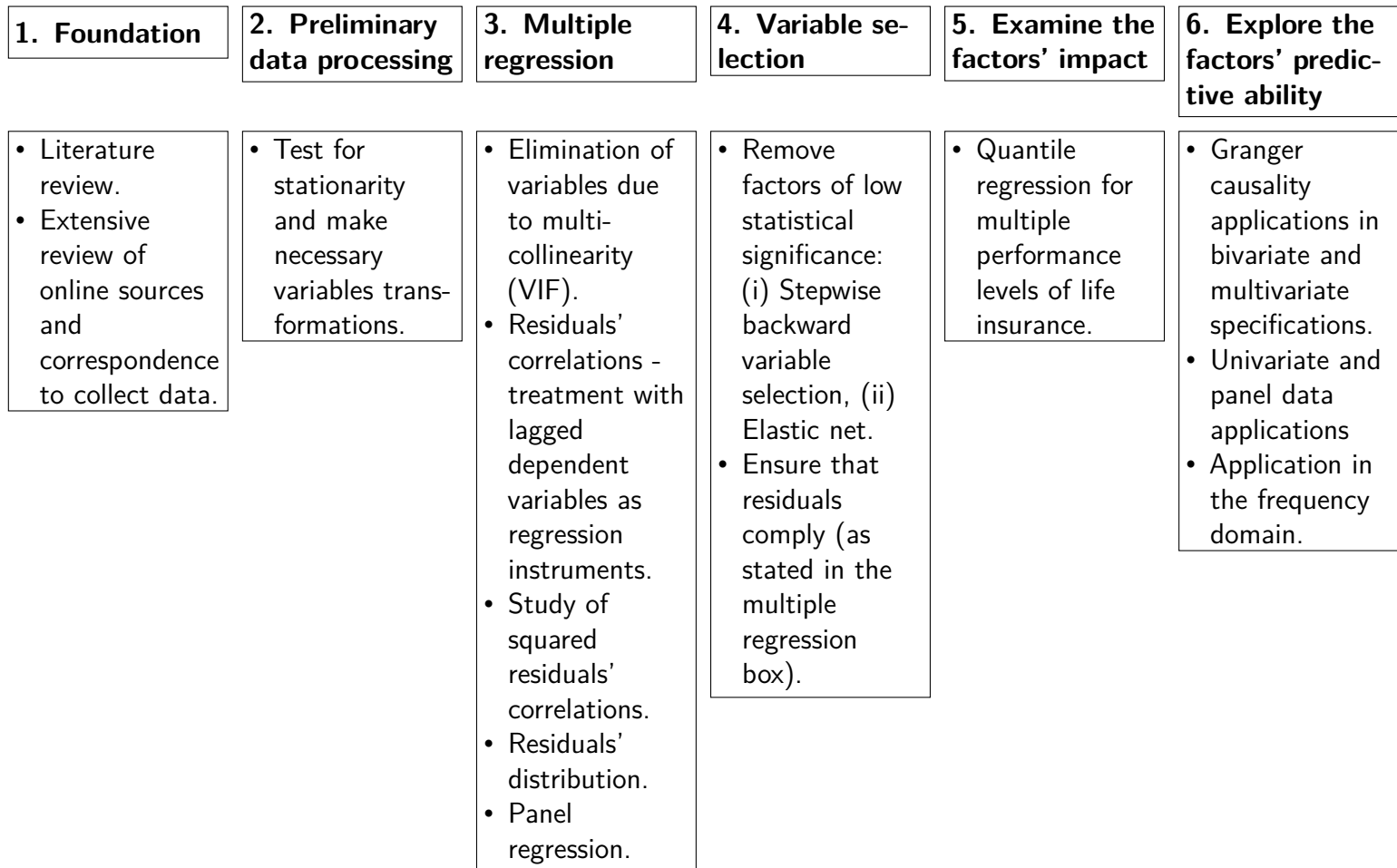
Figure 3.1 presents the overall research methodology followed in this study. The process is organized into six sequential stages. First, the foundation stage consists of an extensive literature review and the collection of the necessary datasets through the examination of online sources and relevant correspondence. Second, during the preliminary data processing stage, the time series properties of the variables are

examined, with particular emphasis on testing for stationarity and applying the necessary transformations.

The third stage involves the multiple regression framework, where several diagnostic procedures are implemented, including tests for multicollinearity using the Variance Inflation Factor (VIF), examination of residual autocorrelation and heteroskedasticity, and the treatment of residual correlations through the inclusion of lagged dependent variables as regression instruments. In addition, panel regression techniques are employed to capture common patterns across countries. The fourth stage focuses on variable selection, where factors with low statistical significance are removed using stepwise backward selection and Elastic Net methods, while ensuring that the regression diagnostics remain satisfactory.

The fifth stage examines the impact of the identified factors through quantile regression, allowing the analysis of how determinants influence different levels of life insurance performance. Finally, the sixth stage explores the predictive relationships among variables by applying Granger causality tests in both bivariate and multivariate settings, including an analysis in the frequency domain. Together, these steps provide a comprehensive empirical framework for investigating the determinants and dynamics of private insurance demand.

Figure 3.1. Research methodology



3.1 Stationarity

Prior to the empirical analysis, the data series, whose summary statistics are provided in Appendix A, were tested for stationarity, a property often absent in insurance premium data (Lee, Lee, and Chiu, 2013; Lenten and Rulli, 2006). It was conducted using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979; MacKinnon, 2010), whose p-values appear in Appendix B.

Upon confirming the need for transformation, the following adjustments were implemented. The natural logarithm was applied to the variables Penetration Life, Penetration Nonlife, Population, and GDP per capita. Then, for all series found to be non-stationary, successive differencing was applied as needed to achieve stationarity. As a result, each dataset was reduced by one observation for every differencing operation performed. The transformed series were subsequently re-evaluated, with the ADF test results reported also in Appendix B.

In cases where the examined time series exhibited, or were suspected to exhibit, structural breaks, the Bai–Perron multiple structural break test was employed to detect the presence of m breakpoints and to estimate their number (Bai and Perron, 1998; Bai and Perron, 2003). The identified breakpoints divided the series into $m+1$ regimes, allowing the data to be adjusted for these structural changes. The break-adjusted series were then subjected to the ADF test to confirm whether stationarity had been achieved.

3.2 Regression and Variable Selection

For each studied country, all explanatory variables were incorporated into the following multiple regression model:

Equation 3.2: The multiple regression model

$$Y_t = a + \sum_{\kappa} b_{\kappa} x_{\kappa,t} + \epsilon_t \quad (3.1)$$

where, the dependent variable Y represents life insurance penetration. Time is denoted by t , measured in quarterly intervals. The intercept of the model is represented by a , while b_{κ} denote the parameters associated with the explanatory variables. The variables x_{κ} represent the contemporaneous explanatory variables included in the model. Finally, ϵ is the error term.

In simpler terms, the regression model assesses how changes in the independent variables (the regressors) affect the average change in the dependent variable. It should be noted that outcomes that are desirable at the level of the aggregate economy do not necessarily coincide with those that are optimal for individual economic agents. This distinction between macroeconomic and microeconomic perspectives, illustrated by phenomena such as the paradox of thrift, implies that policies or conditions that support overall economic stability may not always align with the immediate interests of individual consumers. At the microeconomic level, consumer welfare is maximized when individuals evaluate interest rates and the prices of insurance-related products and make decisions according to their own preferences regarding the trade-off between saving through insurance and other forms of

consumption. The errors in this model are assumed to be uncorrelated, identically distributed (i.i.d.), with a mean of zero and a constant variance (σ^2).

In line with insights from the existing literature and findings from a preliminary data analysis, the long-term interest rate was found to be an insignificant determinant of non-life insurance, while the external trade variable did not exhibit a significant influence on life insurance. Consequently, each variable was excluded from the respective multiple regression model.

Multicollinearity, where explanatory variables are highly correlated, was addressed using the Variance Inflation Factor (VIF). Variables exhibiting VIF values above 10 were deemed problematic and excluded from the analysis. By mitigating the risks posed by multicollinearity, which can severely distort the estimated relationships among variables, the model yielded more reliable and valid conclusions.

Subsequently, the residuals, defined as the differences between the fitted and observed values, were examined using the Ljung and Box (1978) test, along with an analysis of autocorrelation and partial autocorrelation plots. Depending on the case, the results indicated the necessity of incorporating lagged dependent variables (autoregressive terms) and moving average terms as regressors in the model. The methodological approach of employing autoregressive terms was used in previous studies, e.g., Chang and Berdiev (2013) and Trinh (2023). The Akaike (1973)'s Information Criterion (AIC) was used to determine the optimal number of lags to include. This criterion guided the selection process by balancing the trade-off between model complexity and goodness of fit, ensuring that the final model provided the most accurate and parsimonious representation of the data. The AIC score is computed as equal to $2k - 2 \ln(L)$, where k is the number of estimated parameters

and L is the likelihood of the model.

The diagnostic analysis of the regression residuals also tested the second moment of the error process. Specifically, the ACF/PACF of the squared residuals indicated statistically meaningful dependence, consistent with volatility clustering and conditional heteroskedasticity. In such settings, treating the disturbance variance as constant may lead to inefficient inference and understated uncertainty. Therefore, the error variance was modeled explicitly using a Generalized Autoregressive Conditional Heteroskedasticity model, $GARCH(q, p)$, which generalizes the ARCH framework of Engle (1982) by allowing the conditional variance to depend on both past shocks and its own past values (Bollerslev, 1986; Bollerslev, Chou, and Kroner, 1992; Francq and Zakoian, 2010).

Let the regression disturbance be written as

$$\epsilon_t = \sqrt{h_t} z_t,$$

where $h_t = \text{Var}(\epsilon_t \mid \mathcal{F}_{t-1})$ is the conditional variance given the information set $\mathcal{F}_{t-1}$, and z_t is an i.i.d. innovation with $E(z_t) = 0$ and $\text{Var}(z_t) = 1$. In empirical macro-financial applications, z_t is often assumed to be conditionally Gaussian, although heavy-tailed alternatives (e.g., Student- t) are frequently employed to better capture excess kurtosis in standardized residuals.

In the $GARCH(q, p)$ specification, the conditional variance is modeled as

$$h_t = \omega + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j},$$

where $\omega > 0$ is a constant, $\alpha_i \geq 0$ ($i = 1, \dots, q$) measure the short-run impact of

past squared shocks (the “news” effect), and $\beta_j \geq 0$ ($j = 1, \dots, p$) capture volatility persistence through lagged conditional variances. Positivity constraints ($\omega > 0$, $\alpha_i, \beta_j \geq 0$) ensure $h_t > 0$ that the variance h_t is well defined at every time period t , i.e. $h_t > 0$. A common sufficient condition for covariance stationarity is

$$\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j < 1,$$

in which case the unconditional variance exists and equals

$$E(h_t) = \omega / \left(1 - \sum \alpha_i - \sum \beta_j\right).$$

In practice, high values of $\sum \alpha_i + \sum \beta_j$ imply strong persistence, meaning that volatility shocks decay slowly over time.

The GARCH models were estimated using (quasi-)maximum likelihood, i.e., by maximizing the conditional log-likelihood of the jointly specified mean and variance equations. Depending on the specification, the standardized innovations were assumed to follow either a Gaussian distribution (Gaussian QMLE) or a standardized Student- t distribution. Inference was based on heteroskedasticity-robust (sandwich) standard errors in the sense of White (1982).

Residuals were evaluated for conformity to the normal distribution using both the Jarque and Bera (1980) test and visual inspection of distribution histograms and Q-Q plots. Assessing this assumption is essential, as violations may compromise the validity of subsequent hypothesis testing. If the residuals were found to deviate from normality, the models were re-specified under the assumption that the errors follow a Student (1908)’s t -distribution.

The full models were refined using backward stepwise selection based on the AIC, a method designed to identify a parsimonious specification that balances explanatory power with model complexity; see for example, Heinze, Wallisch, and Dunkler (2018). The procedure begins with the saturated model, which includes all candidate explanatory variables. At each iteration, the variable whose exclusion yields the greatest improvement in the AIC score is removed. This iterative process continues until no further reduction in the AIC score is possible. By penalizing excessive model complexity, the approach reduces the risk of overfitting and retains only variables that contribute meaningfully to model performance.

If the refined model satisfied all necessary statistical diagnostics, namely, the absence of autocorrelation and partial autocorrelation in the residuals and squared residuals, as well as the fitting of the residuals in the normal or Student's distribution, the iterative variable elimination process was continued. If, however, the resulting model failed to meet these criteria, it was discarded, and an alternative way for variable elimination was pursued. This iterative refinement continued until no additional variables could be removed without compromising model adequacy. The final specification is considered optimal to the AIC, although results may vary depending on the specific model selection criterion employed by the researchers.

The complete regression models are presented in Chapter 4 under the subsection "Ordinary Least Squares – Complete models." The models obtained through the variable-selection procedure are presented in the same chapter under "Ordinary Least Squares – Variable selection models." For the final models, the results of the Ljung–Box test, which evaluates the presence of autocorrelation in both the residuals and their squares, are reported in Appendix E. Additionally, the Jarque–Bera test statistics, used to assess the normality of the residuals, are presented in

the same appendix. In the cases where the error terms were assumed to follow a Student's t-distribution, the estimated degrees of freedom are reported instead.

3.3 Univariate regression: Elastic Net screening

Beyond the baseline approach (removing high-VIF covariates followed by stepwise AIC), we adopt one more approach. For each macroeconomic factor, we consider four lagged values, whereas sentiment variables enter contemporaneously only. In addition, we include four autoregressive lags of the dependent variable, consistent with diagnostic evidence of substantial residual autocorrelation in related specifications. With many and highly correlated predictors, OLS estimates can be unstable and stepwise selection can be sample-dependent. The elastic net (EN) addresses this by combining the sparsity-inducing ℓ_1 penalty of the lasso (Tibshirani, 1996) with the shrinkage and grouping properties of the ridge ℓ_2 penalty (Hoerl and Kennard, 1970). In environments with strong multicollinearity and a non-negligible parameter-to-sample-size ratio, EN typically yields more stable selections and coefficient estimates than either penalty alone (Zou and Hastie, 2005; Hastie, Tibshirani, and Friedman, 2009). Formally, with $\mathbf{y} \in \mathbb{R}^T$ and $\mathbf{X} \in \mathbb{R}^{T \times p}$, EN solves

$$\hat{\boldsymbol{\beta}}(\lambda, \alpha) = \arg \min_{\boldsymbol{\beta} \in \mathbb{R}^p} \frac{1}{2T} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda \left(\frac{1-\alpha}{2} \|\boldsymbol{\beta}\|_2^2 + \alpha \|\boldsymbol{\beta}\|_1 \right), \quad \lambda \geq 0, \alpha \in [0, 1].$$

A two-stage pipeline is designed. At stage 1, elastic-net regularization is applied to screen covariates and obtain a sparse yet stable predictor set (Zou and Hastie, 2005). Stage 2 then refits the selected specification without penalization, while explicitly modeling serial dependence through ARMA disturbances (Box, 2016) and, where indicated by diagnostics, conditional heteroskedasticity via ARCH/GARCH

(Engle, 1982; Bollerslev, 1986). To further guard inference against outliers and fat-tailed residuals, we allow for standardized Student- t innovations (Tsay, 2010). Compared with purely stepwise procedures, this strategy is preferable when regressors are strongly correlated or when the number of parameters to be estimated is large relative to the available sample size, as it promotes greater model parsimony and improves out-of-sample stability.

3.3.1 Ridge, lasso, and elastic net

Ridge regression augments OLS with an ℓ_2 penalty that shrinks coefficients toward zero without setting them exactly to zero. With $\mathbf{y} \in \mathbb{R}^T$ and $\mathbf{X} \in \mathbb{R}^{T \times p}$, ridge solves

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \frac{1}{2T} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \frac{\lambda}{2} \|\boldsymbol{\beta}\|_2^2, \quad \lambda \geq 0,$$

yielding a unique and numerically stable estimator that is well behaved under multicollinearity and when p is not small relative to T (Hoerl and Kennard, 1970). Because shrinkage induces bias, ridge embodies a bias–variance trade-off; λ is typically chosen by (blocked) cross-validation. Predictors are standardized prior to fitting so that the penalty treats regressors on comparable scales.

The lasso adds an ℓ_1 penalty,

$$\min_{\boldsymbol{\beta} \in \mathbb{R}^p} \frac{1}{2T} \|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|_2^2 + \lambda \|\boldsymbol{\beta}\|_1,$$

which promotes sparsity by driving some coefficients exactly to zero (Tibshirani, 1996). Lasso is attractive when only a subset of predictors is expected to matter, but under strong collinearity it may select arbitrarily among correlated regressors, lead-

ing to selection instability. Because lasso estimates are shrunk, a common practice is a post-lasso OLS refit on the selected set for interpretation and inference.

The elastic net blends both penalties. Setting $\alpha = 1$ recovers lasso, $\alpha = 0$ recovers ridge, and $0 < \alpha < 1$ yields EN. The ℓ_2 component stabilizes coefficient paths under collinearity, while the ℓ_1 component delivers sparsity (Zou and Hastie, 2005). Efficient solutions are obtained by cyclic coordinate descent (Friedman, Hastie, and Tibshirani, 2010). In our lag-rich, collinear designs, EN typically provides more stable selection and improved predictive bias–variance trade-offs than either penalty alone.

Tuning employs blocked (contiguous) K -fold cross-validation to respect time ordering (Bergmeir, Hyndman, and Koo, 2018). To favor parsimony, we apply a δ +SE rule: we choose the largest λ whose cross-validated error lies within $CV_{\min} + \delta SE_{\min}$, where $CV_{\min}$ is the minimum CV error across the grid and $SE_{\min}$ is its associated standard error (we use $\delta \in [1, 1.5]$). Lags of the dependent variable treated as structural terms are left unpenalized via penalty factors (i.e., setting the corresponding entries of the penalty vector to zero) and are always retained to mitigate serial correlation observed in preliminary residual diagnostics. Let S denote the resulting selected set (the union of predictors with nonzero EN coefficients and any forced terms); S is then passed to Stage 2 for unpenalized refitting and disturbance modeling.¹

¹This specification rests on two observations: (i) under the baseline selection in § 3.2, lagged dependent variables were consistently statistically significant and reduced residual autocorrelation; and (ii) in separate (unreported) runs, these lags also survived LASSO selection even without being protected.

3.3.2 Post-selection estimation and error modeling.

Given the predictor set S from Stage 1, we refit the mean equation as

$$y_t = \beta_0 + \mathbf{X}_{t,S}^\top \boldsymbol{\beta} + u_t,$$

and then diagnose the disturbance process u_t . If Ljung–Box tests on u_t indicate residual serial correlation, we re-estimate the model with ARMA(p, q) disturbances,

$$\phi(B) u_t = \theta(B) \varepsilon_t, \quad \varepsilon_t \stackrel{\text{i.i.d.}}{\sim} \begin{cases} \mathcal{N}(0, \sigma^2), & \text{(Gaussian)} \\ t_\nu(0, \sigma^2), & \text{(Student-}t\text{)}, \end{cases}$$

where $\phi(B) = 1 - \phi_1 B - \dots - \phi_p B^p$ and $\theta(B) = 1 + \theta_1 B + \dots + \theta_q B^q$. We select $(p, q) \in \{0, \dots, 4\}^2$ by AIC. When volatility clustering persists (e.g., significant Ljung–Box tests on u_t^2), we model the conditional variance using a GARCH specification (e.g., sGARCH(1, 1)) under Gaussian or Student- t innovations. Residual adequacy is required at different lags for both residuals and squared residuals. Further backward elimination of mean covariates is permitted only when (i) AIC strictly improves and (ii) residual diagnostics remain satisfactory, as assessed by Ljung–Box tests on u_t and u_t^2 at different lags. We report mean-equation coefficients, AR/MA parameters, and, where applicable, the Student- t degrees of freedom ν .

The models resulting from the proposed method are presented in Chapter 4 under the subsection titled “Elastic net algorithm.”

3.3.3 Algorithm summary

1. Feature construction: Build the design with macroeconomic lags $x_{t-\ell}$ for $\ell = 1, \dots, 4$, contemporaneous sentiment indicators, and autoregressive terms $y_{t-\ell}$ for $\ell = 1, \dots, 4$.
2. Elastic-net screening: Select a sparse set S via EN with contiguous (blocked) K -fold cross-validation to respect time order. Choose λ by the δ +SE rule for parsimony; y -lags are treated as structural and left unpenalized via penalty factors. The selected set S is carried forward.
3. Post-selection mean fit and error checks: Refit by OLS:

$$y_t = \beta_0 + \mathbf{X}_{t,S}^\top \boldsymbol{\beta} + u_t.$$

If serial correlation remains (Ljung–Box on u_t and u_t^2 at different lags), re-estimate with ARMA(p, q) disturbances under Gaussian or Student- t innovations. If conditional heteroskedasticity is detected (e.g., ARCH LM or Ljung–Box on u_t^2), augment with a GARCH component (e.g., sGARCH(1, 1)).

4. Diagnostics-constrained pruning: Iteratively prune mean terms only when AIC improves and residual diagnostics continue to pass; re-check ARMA/GARCH orders after any change.
5. Reporting: Present coefficient estimates, standard errors (robust where appropriate), p -values, information criteria, residual diagnostics, and robustness notes (e.g., alternative EN α , ARMA(p, q) orders, and innovation distributions).

3.4 Panel-data study

3.4.1 Motivation for a panel-data approach

This thesis examines the macroeconomic determinants of private insurance demand across a set of European economies over time. A central methodological choice is whether to study demand using (i) purely time-series models estimated separately for each country, (ii) a single cross-sectional snapshot comparing countries at one point in time, or (iii) a panel that combines the cross-country and time dimensions. For the present research question, a panel-data framework is the natural choice because it exploits both the temporal evolution of insurance markets and the structural heterogeneity across countries within a coherent econometric setting (Baltagi, 2005; Wooldridge, 2010).

A country-by-country time-series approach is informative for describing national dynamics in isolation. However, estimating separate models for each country complicates cross-country inference: it is difficult to distinguish mechanisms that are broadly common across economies from patterns that are idiosyncratic to particular institutional settings or sample periods. Moreover, separate estimation reduces statistical power and makes results more sensitive to country-specific shocks, model specification choices, and limited time-series length. By contrast, panel methods pool information across countries while allowing for unobserved heterogeneity, enabling more efficient estimation and more credible identification of systematic macroeconomic relationships.

A purely cross-sectional design (e.g., comparing countries in a single year) has the opposite drawback: it can highlight differences across economies, but it discards the rich information contained in within-country changes over time. Because in-

insurance demand is shaped by slow-moving processes—such as income growth, demographic change, institutional evolution, financial deepening, and shifts in risk perceptions—cross-sectional snapshots risk confounding persistent structural differences with transitory macroeconomic conditions. They also cannot describe adjustment dynamics, persistence, or the timing through which shocks propagate to insurance demand.

Panel data, by construction, addresses both limitations: it preserves the time-series dimension within each country while also exploiting cross-country variation. This allows the analysis to identify relationships from within-country movements (controlling for time-invariant national characteristics) and to improve statistical efficiency by pooling information across economies, while still permitting heterogeneity in levels and, where appropriate, in responses.

European economies are exposed to shared macroeconomic and financial conditions, including monetary-policy regimes, global commodity-price cycles, international risk sentiment, and EU-wide policy initiatives. Such common forces can induce co-movements in insurance demand that are not attributable to domestic fundamentals alone. Panel data provide a structured way to account for these co-movements, for example through multi-factor specifications that separate common shocks from idiosyncratic country dynamics.

This matters for two reasons. First, controlling for common shocks reduces the risk of incorrectly attributing EU-wide events to domestic regressors. Second, it enables an economically meaningful decomposition of variation in insurance demand into components driven by (i) shared conditions and (ii) country-specific developments, which is particularly relevant when comparing markets that are

institutionally distinct yet economically interconnected.

Finally, the panel approach aligns with the substantive goals of this thesis: to develop a comparative macroeconomic account of private insurance demand across European economies. It allows the empirical analysis to address questions that are difficult to answer with isolated country-by-country time-series models, such as:

- Which determinants are robust across countries, and which are context-dependent?
- Do sentiment indicators contribute explanatory power beyond standard “hard” fundamentals in a multi-country setting?
- How does the persistence of insurance demand compare across markets with different levels of financial development?

For these reasons, panel data are a methodological necessity in this thesis. They provide an econometric structure in which insurance demand is modeled as a process that is simultaneously dynamic (within countries) and heterogeneous (across countries), while also being exposed to common external forces.

3.4.2 Panel construction and estimation strategy

The empirical strategy adopted in this thesis rests on five building blocks: (i) construction of a quarterly country panel, (ii) a baseline dynamic specification with distributed lags, (iii) allowance for serially correlated disturbances, (iv) penalized variable selection via the elastic net, and (v) post-selection refitting by OLS for interpretability.

Let countries be indexed by $i \in \{1, \dots, N\}$ and time (quarters) by $t \in \{1, \dots, T\}$. The dataset is a balanced panel: each country is observed over the same set of T quarters. Accordingly, the panel is aligned on a common quarterly calendar

and contains exactly $N \times T$ observations prior to the introduction of lags. After constructing lagged regressors, the regression-ready sample comprises admissible country–quarter observations $\{y_{i,t}, y_{i,t-1}, \dots, y_{i,t-4}, \mathbf{x}_{i,t}, \dots, \mathbf{x}_{i,t-4}, \mathbf{s}_{i,t}\}$, where $\mathbf{x}_{i,t}$ denotes the vector of macroeconomic fundamentals and $\mathbf{s}_{i,t}$ the vector of contemporaneous sentiment indicators.

Insurance penetration is modeled as a dynamic process featuring persistence, delayed responses to macroeconomic fundamentals, and contemporaneous effects of sentiment. The baseline specification is

$$y_{i,t} = \alpha_i + \sum_{k=1}^4 \phi_k y_{i,t-k} + \sum_{k=0}^4 \mathbf{x}'_{i,t-k} \boldsymbol{\beta}_k + \mathbf{s}'_{i,t} \boldsymbol{\gamma} + \varepsilon_{i,t} \quad (3.2)$$

Here, α_i captures time-invariant country heterogeneity (e.g., institutional and structural features). The coefficients $\phi_k, k = 1, \dots, 4$ measure the persistence of the dependent variable by capturing the effect of its own lags on current insurance penetration. The lagged dependent variables $y_{i,t-k}, k = 1, \dots, 4$ therefore allow for gradual adjustment dynamics and help absorb residual serial correlation that would otherwise remain in $\varepsilon_{i,t}$.

The $\mathbf{x}_{i,t}$ collects macroeconomic and financial determinants, included contemporaneously and with up to four lags to accommodate delayed transmission. The associated coefficient vectors $\boldsymbol{\beta}_k$ measure the marginal effect of the corresponding macroeconomic variables at lag k on the dependent variable. The $\mathbf{s}_{i,t}$ collects contemporaneous sentiment indicators, while the parameter vector $\boldsymbol{\gamma}$ captures the effect of these indicators on insurance penetration. The specification reflects the premise that expectations and confidence measures adjust rapidly, whereas “hard”

fundamentals may operate with longer lags.

The disturbance term $\varepsilon_{i,t}$ represents the idiosyncratic error component and is analyzed below, including potential serial dependence and conditional heteroskedasticity.

Country-specific unobserved heterogeneity is captured by α_i , for which two standard modeling approaches are available. Under a *random effects* (RE) specification, α_i is treated as a random component and consistency requires the orthogonality condition

$$\text{Cov}(\alpha_i, \mathbf{Z}_{i,t}) = \mathbf{0}, \quad (3.3)$$

where $\mathbf{Z}_{i,t}$ denotes the full vector of regressors (including lagged terms and controls). Under a fixed effects (FE) specification, α_i is allowed to be arbitrarily correlated with $\mathbf{Z}_{i,t}$; identification is then based on within-country (time-series) variation, typically via the within transformation.

In this thesis, both FE and RE versions of the baseline model were estimated. Model choice was guided by the Hausman (1978) specification test, which evaluates the consistency of the RE estimator by comparing it with FE estimates. Let $\hat{\beta}_{\text{FE}}$ and $\hat{\beta}_{\text{RE}}$ denote the corresponding slope estimates. The Hausman test statistic is

$$H = \left(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{RE}} \right)' \left[\text{Var}(\hat{\beta}_{\text{FE}}) - \text{Var}(\hat{\beta}_{\text{RE}}) \right]^{-1} \left(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{RE}} \right), \quad (3.4)$$

which is asymptotically distributed as $\chi^2(K)$ under the null hypothesis that the difference in estimates is not systematic (i.e., RE is consistent), where K is the number of tested slope coefficients.

The Hausman test rejects the random effects (RE) specification for the life insur-

ance model, implying that the maintained orthogonality condition discussed above is not supported by the data. Accordingly, the empirical analysis adopts the fixed effects (FE) model as the baseline specification, allowing time-invariant country characteristics that may be correlated with the regressors to be absorbed by α_i .

Diagnostic analysis of the residuals revealed the presence of autocorrelation in the cases of Czechia and Italy, as well as heteroskedasticity for Italy. Before selecting an appropriate correction, an additional diagnostic was performed to examine whether cross-sectional dependence was present in the panel. The Pesaran test (Pesaran, 2004; Pesaran, 2021) provides strong evidence against the presence of such dependence.

Consequently, the estimation was adjusted to employ cluster-robust standard errors. These were originally proposed by White (1984) and later formalized for panel data applications by Colin Cameron and Miller (2015). In addition, the MacKinnon and White (1985) variant was implemented to provide a finite-sample correction.

For the non-life insurance model, when both FE and RE specifications are estimated under an AR(1) within-country error process, a Hausman-type comparison fails to reject random-effects consistency, supporting the use of a random-intercept panel model for nonlife insurance demand.

Macroeconomic panel regressions at quarterly frequency often exhibit residual persistence. To capture this parsimoniously, the idiosyncratic disturbance is assumed to follow a country-specific AR(1) process,

$$\varepsilon_{i,t} = \rho, \varepsilon_{i,t-1} + u_{i,t}, \quad |\rho| < 1, \quad (3.5)$$

where $u_{i,t}$ is a mean-zero innovation with no serial correlation (within each country) and finite variance. Under this structure, ignoring serial correlation generally yields inefficient estimates and can distort inference through understated standard errors.

As a robustness check, we also estimated richer $AR(p)$ disturbance structures with $p = 2, 4$. For each specification, model choice was guided by information criteria (AIC/BIC) and residual diagnostics based on Ljung–Box tests on $\varepsilon_{i,t}$ and $\varepsilon_{i,t}^2$ at different lags. These diagnostics indicated occasional remaining autocorrelation and mild heteroskedasticity in some countries, but no pervasive pattern across the panel. In addition, normality is rejected at the panel level, driven primarily by one country (Norway), whose residuals exhibit heavier tails. Overall, $AR(1)$ delivers the best compromise between parsimony, fit, and residual adequacy, and is therefore retained as the baseline error structure.

3.4.3 Elastic Net for variable selection under multicollinearity

The candidate regressor set is large because it includes multiple lags of several macroeconomic variables as well as lagged dependent terms. Such lag-rich designs naturally induce multicollinearity (e.g., strong correlation among adjacent lags and across related macroeconomic indicators), which can destabilize estimation and render purely stepwise selection procedures sample-dependent.

To address this issue, we employ an Elastic Net (EN) procedure for variable selection. Let $\mathbf{y}$ denote the stacked dependent variable and let $\mathbf{Z}$ denote the stacked design matrix collecting all candidate regressors (including lags and fixed effects

as implemented). EN estimates coefficients $\boldsymbol{\theta}$ by solving

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta}} \left\{ \frac{1}{2n} \|\mathbf{y} - \mathbf{Z}\boldsymbol{\theta}\|_2^2 + \lambda \left(\alpha \|\boldsymbol{\theta}\|_1 + \frac{1-\alpha}{2} \|\boldsymbol{\theta}\|_2^2 \right) \right\}, \quad (3.6)$$

where n is the number of stacked observations, $\lambda \geq 0$ controls the overall degree of shrinkage, and $\alpha \in [0, 1]$ governs the mix between the LASSO penalty (via ℓ_1) and the ridge penalty (via ℓ_2).

The EN penalty combines two desirable properties:

- Variable selection: the ℓ_1 component can set some coefficients exactly to zero, yielding a sparse specification.
- Stability under collinearity: the ℓ_2 component stabilizes estimation when regressors are highly correlated.

Penalized estimators shrink coefficients by construction. While this is advantageous for selection and prediction, it complicates economic interpretation because coefficient magnitudes are biased toward zero. For this reason, the thesis adopts a two-step procedure:

1. Selection step: apply EN to select a subset of regressors, denoted by $\mathcal{S}$, i.e., the set of covariates with $\hat{\theta}_j \neq 0$.
2. Refitting step: re-estimate the mean equation by unpenalized OLS using only regressors in $\mathcal{S}$, obtaining post-selection coefficient estimates that are directly interpretable in the original scale of the model.

In implementing EN, lags of the dependent variable are treated as structural terms and are therefore protected from elimination. Concretely, these lags are left unpenalized via penalty factors (i.e., setting the corresponding entries of the penalty vector to zero), so they are always retained in Stage 1. This choice is motivated

by preliminary residual diagnostics, which indicate non-negligible autocorrelation that is parsimoniously absorbed by including y -lags in the mean equation.

After EN screening, the model is refit by unpenalized OLS on the selected set (together with the protected y -lags). Following this refit, we perform an additional backward stepwise pruning of mean covariates based on the AIC, permitting deletions only when the information criterion improves and residuals comply, so as to further simplify the specification while maintaining fit and interpretability.

Conceptually, the post-selection OLS model is:

$$y_{i,t} = \alpha_i + \mathbf{Z}_{i,t}^{(S)} \boldsymbol{\delta} + \varepsilon_{i,t}, \quad (3.7)$$

where $\mathbf{Z}_{i,t}^{(S)}$ collects only the selected regressors (including selected lags). The vector $\boldsymbol{\delta}$ contains the coefficients associated with the regressors retained after the selection procedure, capturing their marginal contribution to the dependent variable conditional on the selected specification. Inference is then conducted acknowledging the maintained AR(1) structure in $\varepsilon_{i,t}$ by adopting an estimation/inference procedure consistent with within-country serial correlation.

As a robustness check on the EN-based screening stage, we also estimated the full baseline model and applied backward stepwise elimination directly to that specification, using the AIC as the pruning criterion. Comparing the resulting stepwise-selected models with the EN-screened (and post-refit pruned) models provides a diagnostic on whether the main inferences are sensitive to the choice of selection mechanism, and helps verify that the EN procedure is not driving results mechanically through its regularization structure.

The panel models derived from the elastic net algorithm are presented in Chapter 4 under the subsection “Panel models.” The panel models obtained as part of the robustness check are reported in the same subsection, in the paragraph bearing the same title.

3.4.4 Interaction terms

In addition to additive effects, we allow for interaction terms to capture state dependence, for example, the idea that the marginal impact of a macro-financial determinant can vary with the institutional environment or the prevailing level of uncertainty. In the finance literature, Baltagi, Demetriades, and Law (2007) operationalize this logic by interacting openness measures (e.g., trade and financial openness) to test whether their effects are complementary rather than separable, while De Pooter (2020) show that the pass-through of monetary policy surprises to longer-term yields depends on the level of monetary policy uncertainty, i.e., shocks transmit differently across uncertainty states.

A further motivation for interaction terms comes from recent evidence that uncertainty effects are conditional on financial depth and credit conditions, rather than purely additive. In particular, Marozva and Magwedere (2025) explicitly study the interplay between economic policy uncertainty and financial market development in shaping FDI inflows, emphasizing that the marginal effect of uncertainty varies with the level of financial development. Similarly, Koirala (2024) document that the relationship between economic uncertainty and real household outcomes depends on households’ credit situations, highlighting a broader mechanism in which uncertainty operates through (and is amplified or dampened by) financial constraints. Taken together, these findings support specifying interaction terms

such as ‘uncertainty $\times$ financial development’ (or ‘uncertainty $\times$ credit/financial conditions’) in order to capture state-dependent transmission and to avoid misspecification when the effect of uncertainty is mediated by the financial environment.

The insurance-demand literature likewise supports modeling non-additive and state-dependent effects, providing a direct rationale for including interaction terms in multi-country regressions. For example, Chang and Berdiev (2013) show that the effect of natural disasters on insurance market development depends on the political-risk environment, emphasizing that disasters, political risk, and their interaction effects jointly shape insurance consumption. Similarly, Dong (2014) studies life insurance demand in Europe and finds that transparency does not only enter as a direct determinant; rather, transparency moderates how life insurance demand responds to adverse market outcomes (e.g., low solvency or profitability), consistent with an interaction such as Transparency $\times$ Market stress.

More broadly, Lee, Chiu, and Chang (2013) argue that linear specifications can be restrictive because the relationship between insurance demand and its determinants can change across risk regimes. Using a nonlinear panel framework (a panel smooth transition regression), they document regime-switching effects whereby country risk conditions alter the income elasticity of insurance demand. In effect, the concept is akin to allowing the marginal effect of income (or other fundamentals) to vary with a conditioning variable through terms such as Income $\times$ Country risk.

Taken together, these insurance-specific contributions motivate enriching the baseline model with interaction terms when theory suggests conditional transmission channels, and they reinforce treating interactions as first-class candidates in the selection-and-refit pipeline rather than as ad hoc add-ons. Motivated by these find-

ings, interaction terms in the present setting provide a disciplined way to model conditional responses, and to avoid misspecification when the true relationship is inherently non-additive.

Empirically, interaction effects are operationalized by augmenting the candidate regressor set with a targeted set of product terms. These interaction terms enter the same Elastic Net screening stage as all other potential determinants and are therefore retained only if they contribute incremental explanatory power under the cross-validated penalty. Any interaction that survives this selection-and-refit pipeline is interpreted as evidence that the marginal impact of one determinant on insurance demand varies systematically with the level of a second conditioning factor. To preserve hierarchical consistency, whenever an interaction term is retained, its associated main effects are included in the post-selection fixed-effects refit even if they were not selected by Elastic Net, ensuring that estimated interaction effects are interpreted relative to a well-defined baseline and are not confounded by omission of lower-order components.

The interaction terms that are investigated are the following, along with the basis for including them.

In life insurance, guided by economic theory and parsimony, the interaction set is restricted to four terms: (i) $\text{Income} \times \text{LT Interest Rate}$, (ii) $\text{Unemployment} \times \text{Income}$, (iii) $\text{Banking sector} \times \text{Consumer Confidence Index}$, and (iv) $\text{Banking sector} \times \text{Business Confidence Index}$. The first interaction captures heterogeneity in the response of life-insurance demand to the interest-rate environment across income levels, consistent with the idea that higher-income households face fewer liquidity con-

straints and may react more to the relative attractiveness of long-horizon savings. The second term allows labour-market conditions to condition the role of income: unemployment may dampen effective purchasing power and hence weaken the income channel, while also reflecting precautionary motives whose strength can vary with income. The third and fourth interactions model the financial-development channel as state-dependent: the effect of banking-sector depth on life-insurance demand is allowed to vary with household and business sentiment (CCI and BCI), reflecting that distribution capacity, credit availability, and willingness to commit to long-term contracts are typically stronger in more optimistic environments.

For the non-life insurance, the interaction set is restricted to: (i) Income $\times$ External trade, (ii) Unemployment $\times$ Income, (iii) External trade $\times$ Banking sector, (iv) External trade $\times$ World Uncertainty Index, and (v) Banking sector $\times$ Business Confidence Index. The first interaction captures that the income–nonlife relationship is likely to be stronger in more open economies, where higher income is more readily translated into commercial activity, logistics, and the accumulation of insurable assets. The second term allows labor-market stress to condition the income channel, reflecting that unemployment can depress effective purchasing power and reduce exposure (e.g., fewer insured vehicles and lower business activity), with potentially heterogeneous effects across income levels. The External trade $\times$ Banking sector interaction operationalizes a financial-transmission mechanism: deeper intermediation can amplify the extent to which trade openness translates into investment, firm activity, and hence demand for commercial non-life coverage. The External trade $\times$ World Uncertainty Index term introduces global risk as a moderator, recognizing that heightened world uncertainty may weaken (or alter) the trade–insurance

link through disruption of cross-border flows and a “wait-and-see” stance in investment and contracting. Finally, Banking sector $\times$ Business Confidence Index allows the role of the banking sector to be state-dependent on the business cycle, as distribution capacity, credit availability, and firms’ willingness to insure typically strengthen in periods of higher business confidence.

All interaction terms are constructed from the stationary transformations of the underlying series. To ensure interpretability within the fixed-effects framework and to reduce collinearity, each component entering an interaction is mean-centred at the country level prior to multiplication. Thus, interaction coefficients capture whether within-country deviations of one determinant condition the marginal effect of another around each country’s typical level.

The panel models incorporating interaction terms are presented in Chapter 4 under the subsection “Panel models,” in the paragraph titled “Interaction terms.”

3.5 Quantile Regression

For the τ th quantile, the model is expressed as shown in the following equation.

Equation 3.3: The quantile regression model

$$Y_t = \alpha^{(\tau)} + \sum_{\kappa} \beta_{\kappa}^{(\tau)} x_{\kappa,t} + \epsilon_t \quad (3.8)$$

Aside from τ , which represents the quantile being analyzed, all other variables are defined as specified in the multiple regression equation provided earlier. For simplicity, lagged dependent variables are incorporated as part of the x_{κ} s. This

model differs from the previously mentioned one in that the errors (ϵ_t) are assumed to follow a distribution $g_t(\epsilon)$, with the τ -quantile set to 0.

Koenker and Bassett (1978) introduced quantile regression as a natural extension of linear regression. They highlighted that linear regression's reliance on the assumption of a Gaussian distribution for both variables and residuals limits its applicability. Moreover, the presence of outliers can significantly distort parameter estimates, diminishing the reliability of linear regression as a statistical method. Quantile regression, on the other hand, provides a more robust alternative by estimating the conditional median or other quantiles, offering greater flexibility in handling data with non-normal error distributions and outliers.

This approach enables researchers to evaluate parameters for specific segments of a dataset, by assessing how each regressor affects different parts of the distribution, making it particularly useful in areas such as finance, where the relationships may vary across the distribution of outcomes. In the context of private insurance, this analytical tool has proven valuable. For example, Li (2007) employed a one-predictor-at-a-time approach to identify the factors influencing life insurance demand, highlighting income, financial development, and inflation as significant determinants. Similarly, Sriram, Shi, and Ghosh (2016) utilized quantile regression to analyze the cost efficiency of U.S. insurers in the non-life insurance sector.

Further uses of quantile regression in the field of private insurance include Kudryavtsev (2009), who compared the performance of Ordinary Least Squares (OLS), Generalized Least Squares (GLS), and quantile regression methods in determining insurance rates, finding that quantile regression demonstrated superior efficiency according to a simulation study. Schipper (2022) further illustrated the advantages of

quantile regression by assessing insurance claims at a consultancy firm. By comparing OLS, a linear regression model with non-constant variances, and quantile regression, he found that quantile regression provided the most consistent and reliable results. This body of work underscores the value of quantile regression in the insurance industry, particularly when dealing with skewed data, outliers, or varying effects across different segments of the distribution.

This research employs quantile regression to assess the impact of determining factors on life insurance penetration, focusing on various levels of the latter's performance. 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 enables a comprehensive understanding of how various factors impact life insurance demand across the entire spectrum of performance.

3.6 Granger causality

3.6.1 Bivariate Granger causality

Granger causality is a statistical concept used to determine whether one time series can predict another. It does not imply a direct cause-and-effect relationship. Still, it tests whether one variable's past values can improve the prediction of another variable beyond what its past values can already explain. This method, developed by Granger (1969), relies on non-singular vector autoregressive (VAR) models, which include lagged values of dependent and independent variables in the regression equation.

Suppose the inclusion of past values of the independent variable significantly en-

hances the predictive accuracy of the dependent variable. In that case, it is concluded that the independent variable "Granger-causes" the dependent variable. This approach is valuable for understanding dynamic relationships between variables in time-series data.

The null hypothesis posits that the lagged values of the independent variable do not predict the dependent variable. If the test results in a statistically significant rejection of the null hypothesis, then causality is considered present. However, several limitations are in place: it is sensitive to selecting appropriate lags, does not account for hidden confounders, and cannot determine causal mechanisms between the variables. Despite these constraints, it is widely used in time-series analysis to explore relationships between time-dependent variables, such as the interaction between macroeconomic indicators and private insurance.

Several studies have examined the dynamic relationships between economic growth and the insurance market. For example, Chang, Lee, and Chang (2014), Kugler and Ofoghi (2005), and Hu, Su, and Lee (2013) conducted an analysis in a bi-variate setting to explore the causal links between GDP, as a proxy for economic growth, and private insurance, as measured by insurance premiums.

Lee, Lee, and Chiu (2013) further advanced this field by introducing the concept of the half-life of deviations, which measures the number of periods required for a shock to dissipate by half. This measure provides insight into the speed at which time series data returns to long-run equilibrium after a perturbation, thereby enhancing our understanding of the dynamic interplay between macroeconomic factors and the insurance industry.

3.6.2 Multivariate Granger causality

Multivariate Granger causality extends the traditional bivariate approach by incorporating multiple variables into the analysis, allowing for a more comprehensive examination of causal relationships within complex systems. In this framework, a variable's causality is tested while simultaneously accounting for the influence of other related variables, thereby reducing the risk of spurious results that may arise due to omitted variable bias. This is particularly valuable in financial models, where numerous interdependent factors often influence outcomes. A prime example of this is the examination of macroeconomic factors affecting the demand for life insurance. Researchers in the field of the interrelation between macroeconomics and private insurance include Alhassan and Fiador (2014) and Pradhan (2017).

The findings from Granger causality studies have been mixed; depending on the sample and time period analyzed, evidence of unidirectional causality from the insurance market to economic growth has been attested, while other studies suggested the opposite direction of causality or feedback loops between the two variables. Additionally, some studies reported no causality at all. Pradhan (2017) provided a summary of this literature, highlighting the complex and context-dependent nature.

3.6.3 Panel Granger causality

Panel extensions of the Granger causality framework have also been developed to exploit the additional information contained in the cross-sectional dimension of panel datasets. In particular, the panel Granger causality test proposed by Dumitrescu and Hurlin (2012) allows researchers to examine predictive relationships while accounting for heterogeneity across the cross-sectional units. Even when

individual Granger causality tests are performed for each unit separately, the panel approach remains useful because it increases statistical power by combining information across the panel and provides formal inference regarding the existence of causality at the panel level. In contrast to individual tests, which rely only on the time dimension of each series, the panel procedure utilizes both the time and cross-sectional variation of the data and tests whether a causal relationship exists for at least a subset of the units in the panel.

Formally, the Dumitrescu–Hurlin test estimates the following model for each cross-sectional unit i :

$$Y_{i,t} = \alpha_i + \sum_{k=1}^p \gamma_{i,k} Y_{i,t-k} + \sum_{k=1}^p \beta_{i,k} X_{i,t-k} + \epsilon_{i,t}$$

where $i = 1, \dots, n$ indexes the cross-sectional units, t denotes time, and p is the chosen lag length. The coefficients $\beta_{i,k}$ capture the potential causal effect from X to Y . The term α_i captures unit-specific effects and reflects unobserved, time-invariant heterogeneity across the cross-sectional units. The coefficients $\gamma_{i,k}$ represent the autoregressive dynamics of the dependent variable, measuring the influence of its past values on its current level and thus controlling for persistence over time. Finally, the error term $\epsilon_{i,t}$ captures idiosyncratic shocks and all omitted factors affecting the dependent variable that are not explicitly included in the model. Together, these components ensure that the estimated causal effect is not driven by unobserved heterogeneity or internal dynamics, allowing for a proper assessment of Granger causality. The null hypothesis of the test states that no Granger causality exists for any unit in the panel,

$$H_0 : \beta_{i,k} = 0 \quad \forall i, k$$

while the alternative hypothesis allows causality to exist for at least some units. The test statistic is constructed by averaging the individual Wald statistics obtained from each unit:

$$\overline{W} = \frac{1}{n} \sum_{i=1}^n W_i.$$

This average statistic is then standardized to obtain a statistic that converges to the standard normal distribution under the null hypothesis. A rejection of the null hypothesis indicates that past values of X contain predictive information for Y for at least a subset of the cross-sectional units in the panel.

Before running the panel Granger tests, panel unit root tests were conducted using the Levin–Lin–Chu (Levin, Lin, and James Chu, 2002), Im–Pesaran–Shin (Im, Pesaran, and Shin, 2003), and Maddala–Wu (Maddala and Wu, 1999) methodologies. The results consistently reject the null hypothesis of a unit root across all variables and model specifications, indicating that the transformed series are stationary. This confirms the appropriateness of using first-differenced variables in subsequent panel regressions.

Two standardized statistics are reported for the Dumitrescu–Hurlin test. The first ($\bar{Z}$) relies on asymptotic properties and assumes a large time dimension, while the second ($\tilde{Z}$) incorporates a finite-sample correction that adjusts for the time dimension of the panel. Given the moderate time span of the data, the corrected

statistic ($\tilde{Z}$) is considered more reliable and is therefore used as the primary basis for inference.

3.6.4 Granger causality in the frequency domain

Geweke (1982) significantly contributed to the literature by proposing that the bivariate (or unconditional) Granger causality relationship could be examined through spectral analysis. He identified long-term relationships consistent with existing macroeconomic literature by analyzing deflated income, money supply, and inflation. In Geweke (1984), he furthered the scope by including a control variable (or conditional Granger causality relationship). Since then, this research stream has expanded considerably. Recent contributions include Ghysels, Hill, and Motegi (2016), who examined macroeconomic indicators and oil prices; Perez-Montiel and Manera (2022), who investigated the relationship between demand and GDP; and Fromentin (2022), who explored the connection between stock prices and macroeconomic fundamentals. No prior research has applied this approach to the nexus between insurance demand and macroeconomic data.

The bivariate Granger causality analysis typically follows these steps: First, bivariate Vector AutoRegression (VAR) models are formed, which incorporate lagged terms. Subsequently, model selection takes place using the Bayesian Information Criterion (BIC), as suggested by Schwarz (1978), to ensure that the irrelevant lags are eliminated, which also waste observations, while they reduce the estimations' robustness. Finally, the Granger test is performed to determine the presence of causality in both directions (or reverse causality).

where y is the response variable, x is the variable of interest, α and β are the

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_y \\ \alpha_x \end{bmatrix} + \sum_{k=1}^p \begin{bmatrix} \beta_{11,k} & \beta_{12,k} \\ \beta_{21,k} & \beta_{22,k} \end{bmatrix} \begin{bmatrix} y_{t-k} \\ x_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{bmatrix} \quad (3.9)$$

Equation 3.4: The Bivariate Granger causality model

regression coefficients. Time is indexed by t , k denotes the lag order, and the regression error terms affect the variables contemporaneously. When one (e.g., z) or more control variables are included, we get the multi-variate model of the method.

$$\begin{bmatrix} y_t \\ x_t \\ z_t \end{bmatrix} = \begin{bmatrix} \alpha_y \\ \alpha_x \\ \alpha_z \end{bmatrix} + \sum_{k=1}^p \begin{bmatrix} \beta_{11,k} & \beta_{12,k} & \beta_{13,k} \\ \beta_{21,k} & \beta_{22,k} & \beta_{23,k} \\ \beta_{31,k} & \beta_{32,k} & \beta_{33,k} \end{bmatrix} \begin{bmatrix} y_{t-k} \\ x_{t-k} \\ z_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \\ \varepsilon_{z,t} \end{bmatrix} \quad (3.10)$$

Equation 3.5: Conditional (multivariate) Granger causality model

Building on the foundation described above, Farnè and Montanari (2022) sought to determine whether causality at a given frequency systematically deviates from zero. 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.

Considering the bivariate stochastic process $Z_t = [X_t, Y_t]'$, we note that:

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

where $A_1, \dots, A_p$ are 2×2 coefficient matrices. Applying a frequency-domain trans-

formation, for each frequency ω , 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 :

$$\Sigma_2 = \begin{bmatrix} \sigma_2 & v_2 \\ v_2 & \gamma_2 \end{bmatrix},$$

and using the transform matrix:

$$S = \begin{bmatrix} 1 & 0 \\ -\frac{v_2}{\sigma_2} & 1 \end{bmatrix},$$

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):

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

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 $[X_t, Y_t]$ 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 $h_{Y \rightarrow X}(\omega)$, 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 $f_i = \frac{i}{T}$, $i = 1, \dots, \lfloor \frac{T}{2} \rfloor$, the $\hat{h}_{Y^* \rightarrow X^*}(2\pi f_i)$ will be computed and then the med $\left\{ \hat{h}_{Y^* \rightarrow X^*}(2\pi f_i), i = 1, \dots, \lfloor \frac{T}{2} \rfloor \right\}$. Finally, for a given significance level α , 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.

This research employs both bivariate and multivariate Granger causality analyses to investigate the relationship between life and non-life insurance penetration with GDP per capita. In the multivariate framework, inflation is included as a control variable. The analysis is based on a quarterly dataset that has been pre-processed to ensure stationarity. Additionally, the study examines the bivariate relationship in the frequency domain to capture potential dynamics across different time horizons.

3.7 Software and Computational Resources

All statistical analyses, including preliminary investigations not reported herein, were conducted in R (version 4.2.0; R Core Team, 2022), with particular acknowledgment of the *optim* function from the *stats* package, which served as the computational workhorse. A custom-built version of this function was developed to

accommodate models incorporating both ARMA terms and Student- t errors.² The primary R packages employed in this thesis were as follows:

`car` — Functions for regression diagnostics, effect displays, and hypothesis testing (Fox and Weisberg, 2019).

`dplyr` — Tools for selecting, filtering, transforming, summarizing, and grouping data (Wickham, François, 2023).

`e1071` — Miscellaneous functions for statistical analysis and probability distributions (Meyer, 2023).

`ggplot2` — Implementation of the grammar of graphics for creating publication-quality plots (Wickham, 2016).

`glmnet` — Efficient procedures for fitting lasso and elastic-net regularized generalized linear models (Friedman, 2024).

`grangers` — Inference on Granger-causality in the frequency domain (Farne' and Montanari, 2019).

`lmtest` — Diagnostic tests for linear models, including heteroskedasticity and autocorrelation tests (Zeileis and Hothorn, 2002).

`MASS` — Functions and datasets supporting modern applied statistical methods, including robust regression, discriminant analysis, and generalized linear models (Venables and Ripley, 2002).

`nlme` — Procedures for fitting linear and nonlinear mixed-effects models using

²The widely respected `rugarch` package, which is specialized for this type of study, permits the use of Student- t errors only within a (G)ARCH framework. The same limitation applies to the commercial EViews software.

maximum likelihood and restricted maximum likelihood estimation (Pinheiro and Bates, 2000).

plm — Estimation and testing of linear panel data models, including fixed and random effects (Croissant and Millo, 2023).

quantreg — Provides functions for quantile regression modeling and related inference in R (Koenker, 2024).

readxl — Import Excel files into R without requiring external dependencies (Wickham and Bryan, 2023).

rugarch — Provides tools for specifying, fitting, forecasting, and diagnosing univariate ARCH/GARCH-family volatility models in R (Galanos, 2025).

sandwich — Robust covariance matrix estimators for model objects, including heteroskedasticity and cluster robust standard errors (Zeileis, Köll, and Graham, 2024).

stats — Base R statistical functions for modeling, hypothesis testing, and optimization (R Core Team, 2022).

strucchange — Tools for testing, monitoring, and dating structural changes in linear regression models (Zeileis, Leisch, 2002).

tidyr — Functions for reshaping, pivoting, and cleaning datasets to maintain tidy data structures (Wickham, Vaughan, and Girlich, 2024).

tseries — Tools for time series analysis, including unit root tests and GARCH models (Trapletti and Hornik, 2025).

urca — Functions for unit root, cointegration, and related econometric tests (Pfaff, 2008a).

vars — Tools for vector autoregression (VAR), including Granger causality analysis (Pfaff, 2008b).

writexl — Excel writer for exporting data frames to .xlsx format (Ooms, 2024).

Chapter 4

Data and Results

This chapter presents the extensive primary research conducted to develop a comprehensive database, which forms the basis for a rigorous evaluation of the claims put forward in the literature review. It also reports the empirical findings derived from the data analysis.

4.1 Data

4.1.1 Studied countries

A preliminary survey encompassing 39 European countries was conducted to assess their capacity to provide quarterly data on insurance premiums production. However, a consolidated report from Insurance Europe, the federation representing the insurance associations across Europe, was not available.

In many countries, such data are published by the supervisory authorities respon-

sible for overseeing the insurance market, which is typically a department within the central bank charged with ensuring the solvency of regulated entities. These authorities primarily focus on maintaining the financial soundness of insurance undertakings in accordance with the prevailing regulatory framework, notably the Solvency II Directive for EU member states. As a result, the publication of market data is often not a priority.

For example, the Bank of Greece, which is responsible for supervising the domestic insurance market, does not publish detailed data beyond brief mentions in the Governor's Annual Reports. These reports typically present the total insurance premium production for the first nine months of each year but lack further analytical granularity. At the European level, the European Insurance and Occupational Pensions Authority (EIOPA) provides quarterly data on the overall volume of insurance premiums, which suffers the limitation it is relatively short, as it begins only in the third quarter of 2016 for most countries, or even later for some cases (see the "Solo Quarterly" of European Insurance and Occupational Pensions Authority (EIOPA) (2025)). Notably, even within this restricted framework, insurance undertakings that belong to corporate groups are reported separately without indicating their country of registration, further diminishing the dataset's analytical value. The time series for corporate groups begins in the second quarter of 2018 (see the "Group Quarterly" of European Insurance and Occupational Pensions Authority (EIOPA) (2025)). As a result, the two EIOPA datasets cannot be meaningfully combined to derive country-specific totals for insurance premiums.

Moreover, the jurisdiction of supervisory authorities, and thus their data collection efforts, is typically confined to insurance undertakings operating within the domestic market. This category includes entities structured as sociétés anonymes and

mutual cooperatives, as well as branches of non-EU foreign insurance companies. However, it excludes branches of foreign insurers operating under the Freedom of Establishment and those providing services under the Freedom to Provide Services (FOS) regime. Incorporating data from these two additional legal frameworks would enable a more comprehensive representation of the total market. However, such data are currently unavailable.

In response to the aforementioned limitations in data availability, this study conducted a survey of each country's insurance associations and regulatory authorities. This involved a systematic review of their official websites, supplemented, where necessary, by direct email inquiries. The objective was to evaluate the availability of quarterly data on insurance premium production. We are particularly indebted to the Association of British Insurers (ABI), which responded positively to our inquiry and demonstrated genuine willingness to collaborate. Unfortunately, due to significant differences in the classification of insurance premiums compared to the rest of Europe, their data could not be incorporated into the research database. The survey revealed that only 20 countries currently maintain this capability. Encouragingly, certain insurance markets also publish data on a monthly basis. Although this higher frequency was not utilized in the present study, given that macroeconomic indicators are predominantly reported on a quarterly basis, such monthly datasets represent a valuable resource for more detailed analyses in future research.

Unfortunately, data exploitation was not feasible for three of the twenty countries identified, as quarterly macroeconomic data for the relevant period were unavailable. Consequently, countries with the longest and most consistent time series were selected to form the research sample. Particular effort was made to include countries from Central and Eastern Europe, former Socialist states, recognized in

the literature as a distinct case (Born and Bujakowski, 2022; Havrylyshyn, Meng, and Tupy, 2016; Kjosevski, 2012; Ertl, 2017; Njegomir and Stojić, 2011; Njegomir and Stojić, 2012; Brokešová, Pastoráková, and Ondruška, 2014; Dragoş, 2014; Petkovski and Jordan, 2014).

As the practice of monitoring insurance markets using quarterly data is relatively recent, most countries exhibit only short time series. Consequently, several countries were excluded from the study due to an insufficient number of observations. Despite the brevity of the available series, it is reassuring to observe that autocorrelation and seasonality patterns remain relatively stable overall. Nonetheless, the presence of outliers occasionally disrupts these otherwise stable processes.

This research focuses on eight European countries: the Czech Republic (hereafter Czechia), Denmark, Greece, Italy, Latvia, Norway, Slovenia, and Spain. Notably, the dataset for Denmark does not include life insurance operations. The selected countries share several similarities. Except for Norway, all of them are members of the European Union (EU), while Norway participates in the European Economic Area (EEA) and is integrated into the Common Market. It is important to note that Norway's insurance (sub)class structure differs from that of the other countries examined. Five countries, Greece, Italy, Latvia, Slovenia, and Spain, are members of the eurozone, and the Danish krone is pegged to the euro. Additionally, Czechia is a candidate for eurozone accession. Czechia, Latvia, and Slovenia are also situated in Central and Eastern Europe and share a historical trajectory marked by emergence following political dissolution.

4.1.2 Insurance premiums

As outlined in the introduction, insurance premiums are collected to cover the costs associated with the risks specified in insurance contracts, the administrative expenses of insurance companies, and to allow for profit generation. Because premiums are set and collected in advance of any claims (i.e., insured loss events), there is inherent uncertainty regarding the eventual cost of these obligations. This uncertainty may persist for a considerable period, often exceeding one year, until the outstanding claims for a given underwriting year can be accurately quantified, typically following protracted negotiations or legal proceedings. Claims constitute the most significant expense for insurance companies; for instance, in 2018, insurers in Greece paid €2.1 billion in claims, accounting for 57% of the €3.7 billion in earned premiums (Hellenic Association of Insurance Companies, 2019).

Operating costs and profit margins tend to be stable and predictable, such that their variations do not materially threaten the financial stability of insurance enterprises. For example, the operating costs of insurance companies in Greece were €594 million in 2016, €616 million in 2017, and €568 million in 2018 (Hellenic Association of Insurance Companies, 2017; Hellenic Association of Insurance Companies, 2018; Hellenic Association of Insurance Companies, 2019).

Undoubtedly, unforeseen events beyond the aforementioned cost categories may occur, resulting in unexpected adverse effects. For instance, significantly poor investment performance can undermine the valuations of underlying assets, primarily when such assets serve as collateral for insurance provisions. Additionally, instability may arise from unexpected regulatory changes that alter the business models of insurance companies. A notable example is the European Solvency II directive

(Hodula, 2023), which rendered “traditional” life insurance products prohibitively expensive, thereby prompting a market shift toward investment-linked products.

This research acknowledges the significant disruptions faced by the private insurance sector; however, a detailed examination of these factors lies beyond the scope of the present study. Nevertheless, we underscore these topics as promising avenues for future research, offering valuable opportunities for scholars to advance the field of insurance economics.

Therefore, within the scope of this research, insurance premiums are considered reasonable proxies for the costs and risks borne by insurance companies in each country. It is assumed that the private insurance markets in all studied countries have attained a state of equilibrium, implying that any observed variations in insurance premiums are attributable exclusively to macroeconomic factors.

Direct written premiums, excluding reinsurance, serve as the primary quantitative metric utilized in this research. The data sources for these measures are detailed in Appendix C. It should be noted that the data series vary in length both across countries and within countries themselves, as observations for life and non-life insurance premiums often commence at different points in time.

As outlined in the introduction, comparisons between jurisdictions of varying sizes can be facilitated by employing two key ratios: the ratio of insurance premiums to GDP, referred to as insurance penetration, and the ratio of insurance premiums to population, known as insurance density. Insurance penetration measures the extent of insurance utilization within a country’s economy, while insurance density indicates the average insurance premiums paid per capita. Although the latter is less commonly applied, we note that Zheng, Liu, and Deng (2009) proposed

augmenting these indicators by incorporating the ratio of insurance density to GDP per capita to capture additional relevant information.

4.1.3 Explanatory variables

The variables presented below represent the determining factors influencing private insurance, as introduced in the literature review. Ideally, these variables should be allowed to vary freely, without imposed constraints, in order to capture the underlying market conditions most accurately.

a) Income is represented by GDP per capita. GDP is measured at chained volume prices, excluding the effects of inflation, providing a measure of economic output. Additionally, data on GDP at market prices were collected to calculate the insurance penetration ratio.

b) Inflation: For the countries that it is available, inflation is measured through the Harmonized Index of Consumer Prices (HICP), which tracks changes in the prices of products and services over time. The HICP offers an advantage over a country's CPI by enabling uniform comparisons across countries due to its consistent definition throughout the EU. Moreover, the HICP is employed by EU institutions and the ECB to monitor policy developments and guide decision-making. For instance, the ECB assesses whether its price stability objective is met by observing HICP values, which are expected to be low, stable, and predictable. Pursuant to a Governing Council decision, the medium-term target for the HICP is set at 2%, reflecting the objective established initially in 1998 and reaffirmed with minimal modification in 2003 and 2021 (European Central Bank, 2021; Höflmayr, 2021). According to unreported analyses, anticipated inflation data are fully correlated with actual

inflation figures; consequently, the former variable was excluded from this study.

c) Unemployment: This variable refers to the share of the labor force aged 20–64 actively seeking employment, using non-seasonally adjusted data. It provides insight into the health of the labor market and its potential impact on economic behavior.

d) Banking sector: The importance of financial intermediation is proxied through the ratio of total credit to the private non-financial sector to GDP. The former is analytically described in Dembiermont, Drehmann, and Muksakunratana (2013), while the credit receivers include non-financial corporations, households, and non-profit institutions serving households. Lenders include non-financial corporations, banks, central banks, general government, households, non-profit institutions serving households, internationally active banks, and other sectors. Credit instruments include loans, bonds, and short-term paper, while the following are excluded: equities and investment fund shares, insurance reserves, and trade credit. The valuation of credit instruments is at market prices. Data are sourced from the Bank for International Settlements (BIS) and the ECB.

e) Interest rate: This variable represents the interest rate on newly issued government bonds with a maturity of 10 years and government-guaranteed debt maturing in 10 years. It is calculated as a 3-month average of daily market prices, which differs from the interest rate at the time of issuance.

f) External trade: Data concerning the external trade of goods and services were selected, valued at current prices, and presented without seasonal adjustment. For comparability across countries, the ratio of foreign trade to GDP at current prices is used.

g) Population: This variable represents the total number of individuals residing in a country, serving as a proxy for market size and demographic dynamics. Further disaggregation was not undertaken, as the existing literature offers limited precedent, Chen, Wong, and Lee (2001), who focused on the U.S. market, being a notable exception, and because contemporary pricing practices have moved beyond gender-based differentiation (Aseervatham, Lex, and Spindler, 2016).

Furthermore, this research utilizes the following Business Trend Surveys (BTS) indicators:

h) Business Confidence Index (BCI): The BCI is a standardized economic indicator designed to gauge expectations about future business activity. It is based on opinion surveys conducted within the manufacturing sector, focusing on key variables such as production trends, order volumes, and finished goods inventories. The index has a long-term average of 100, which serves as a benchmark for interpreting sentiment: values above 100 indicate greater-than-average confidence in future business conditions, while values below 100 reflect increased pessimism. It is employed as a leading indicator for forecasting economic output, demonstrating varying levels of predictive accuracy (Santero and Westerlund, 1996; Suhányiová, Suhányi, and Kocišová, 2024). Consequently, it functions as a proxy for public sentiment concerning the overall state of the economy.

i) Consumer Confidence Index (CCI): The CCI is a key economic indicator that reflects future household consumption and saving behaviors. It is based on survey responses regarding individuals' expectations about their financial situation, perceptions of the overall economy, unemployment rates, and their ability to save. A value above 100 indicates higher consumer confidence, suggesting that consumers

are more likely to make significant purchases and less inclined to save, reflecting a generally positive outlook. Conversely, a value below 100 indicates a more pessimistic view, leading to higher saving tendencies and reduced spending in anticipation of potential economic challenges. Considerable evidence, e.g., Dées and Brinca (2011), suggests that the index serves its cause by providing a gauge for households' consumption. Still, revisions to the methodology of calculating the CCI have been proposed, which may prove beneficial, e.g., Gausden and Hasan (2020).

j) World Uncertainty Index (WUI): Some studies have explored the connection between uncertainty and private insurance (Gupta, 2019; Balcilar, 2020; Canh, Wongchoti, and Thanh, 2021), highlighting its significance. This research utilizes the WUI, a metric designed to quantify uncertainty by analyzing reports from each country's Economist Intelligence Unit (EIU). The Index tracks the frequency of references to uncertainty and related terms. According to Ahir, Bloom, and Furceri (2022), rising uncertainty primarily affects developing countries, reducing GDP and increasing stock market volatility. This suggests that growing uncertainty may have a profound impact on economic stability and, by extension, the life insurance market.

k) World Pandemic Uncertainty Index (WPUI): The COVID-19 pandemic brought about widespread social distancing and quarantine measures, significantly disrupting social and economic activities (Hale, 2023) and degrading economic sentiment (Zervoyianni, Dimelis, and Livada, 2023). We expect that private insurance was impacted, as its product distribution heavily relied on face-to-face interactions between insurance intermediaries and potential customers. Additionally, providing administrative services became more difficult due to restrictions on physical presence

in offices. However, the growing use of insurance aggregator websites, teleconferences, and digital services have reduced the dependency on in-person interactions, facilitating remote work and virtual transactions.

In response to the economic impact of the pandemic, EU member states implemented fiscal and monetary measures aimed at stabilizing economies and supporting recovery. Governments introduced discretionary fiscal stimulus packages to mitigate the immediate economic disruptions and protect households, businesses, and employment. Recognizing the extraordinary nature of the crisis, the EU activated the general escape clause within its fiscal framework, allowing member states temporary flexibility to deviate from standard fiscal rules and accommodate emergency spending needs. At the EU level, several coordinated initiatives were launched to complement national efforts. These included the reallocation of funding under the EU's cohesion policy to support crisis-related expenditures and the creation of the SURE program, a temporary loan-based instrument designed to assist member states in financing short-time work schemes and preventing mass unemployment. Additionally, a major recovery plan, known as Next Generation EU (NGEU), was established, with a total envelope of €750 billion. The central component of this plan was the Recovery and Resilience Facility (RRF), which provided grants and loans to support reforms and investments that foster economic resilience and promote the green and digital transitions across the EU (Anastasatou and Anyfantaki, 2023; Angelini, 2025).

Monetary policy also played a critical role. The European Central Bank (ECB) took decisive action to ensure liquidity in the financial system, preserve favorable financing conditions, and support credit flows. Among its key measures was the launch of the Pandemic Emergency Purchase Programme (PEPP), an asset purchase

program targeting both private and public sector securities. The ECB also expanded the range of eligible collateral in its refinancing operations and adjusted its policy tools to reduce borrowing costs for households, firms, and governments (Grynberg and Habib, 2021).

In light of the above, this research proposes expanding the study on the relationship between uncertainty and insurance by introducing the WPUI. This measures the frequency of references to “uncertainty” and its derivatives in proximity to the term “pandemic” in EIU reports, with each mention weighted by 1,000. This specialized factor is designed to capture the unique uncertainties and accompanying incentives introduced by the pandemic, as well as their effects on the insurance industry.

The data for the explanatory variables were obtained from Eurostat, the ECB, the Federal Reserve Bank of St. Louis, the OECD, Finance Norway, and the World Uncertainty Index website, as detailed in Appendix C. Summary statistics of these variables are presented in Appendix A. The data underwent processing to achieve stationarity, and visualizations of the transformed data are provided in Appendix D.

4.2 Results

This section presents and thoroughly analyzes the results derived from the applied data processing methods. The findings are discussed in detail, with emphasis on their implications and significance within the context of the research.

4.2.1 Ordinary Least Squares – Complete models

This statistical technique inserts all available explanatory variables into the model. For more details, please refer to the relevant paragraph of the Methodology chapter. Detailed results appear in Appendix E and G.

4.2.1.1 Life insurance

Czechia The results indicate that several macroeconomic and sentiment-related variables are significantly associated with insurance demand.

Among the structural (“hard”) factors, population exhibits a strong negative association with life insurance penetration, suggesting that demographic dynamics may contribute to diluting penetration. GDP per capita is also negatively associated, possibly reflecting a saturation effect or substitutability with other financial instruments in higher-income contexts. Unemployment is positively and significantly associated, a somewhat counterintuitive finding that may be linked to precautionary motives. The long-term interest rate also shows a positive and significant effect, possibly indicating a relationship between investment returns and insurance uptake.

Regarding sentiment factors, uncertainty exerts a significant negative influence on insurance penetration, consistent with the notion that increased unpredictability discourages long-term financial planning. However, business and consumer confidence indicators, as well as pandemic-related uncertainty, do not exhibit statistically significant associations.

Finally, the autoregressive terms capture persistence and temporal dynamics in insurance behavior. The first lag of insurance penetration is strongly negative and statistically significant, suggesting short-term mean reversion, while the third and

fourth lags are statistically insignificant, with the fourth lag approaching significance.

Greece Among the core economic variables, the long-term interest rate is positively and significantly associated with life insurance penetration, suggesting that higher returns on long-term instruments may encourage life insurance uptake. Other macroeconomic factors, including population size, GDP per capita, inflation, and unemployment, exhibit statistically insignificant effects, though their signs align with conventional expectations in some cases.

Regarding sentiment indicators, coefficients on business and consumer confidence, uncertainty, and pandemic-related uncertainty are all statistically insignificant. This suggests that, within Greece's context, these qualitative measures have limited explanatory power over variations in life insurance penetration when controlling for other factors.

All three autoregressive coefficients, from lag 1 to 3, are highly statistically significant and exhibit large negative values. This strong pattern of significance and consistent sign indicates substantial inertia in the series, with past values exerting a considerable influence on current levels of life insurance penetration. The negative signs suggest a cyclical adjustment process, where unusually high (or low) penetration rates in one period are followed by corrections in subsequent periods. This is consistent with the idea that the life insurance market adjusts gradually over time, possibly due to contractual rigidities, consumer inertia, or delayed policy responses to macroeconomic conditions.

Overall, the model emphasizes the importance of autoregressive dynamics and highlights the long-term interest rate as a key economic driver of life insurance

penetration in Greece, while other variables play a more limited or indirect role.

Italy Among the structural macroeconomic factors, population exhibits a marginally significant negative effect, suggesting that demographic size may exert downward pressure on life insurance uptake. Similarly, GDP per capita is positively associated with life insurance demand, though the coefficient is not statistically significant at conventional levels. The effect of unemployment is also negative and statistically significant, indicating that a stronger labor market increases the capacity or willingness to engage in long-term financial planning.

Other structural factors, including inflation, banking sector size, and long-term interest rates, do not exhibit statistically meaningful relationships in the Italian context.

Turning to sentiment-related variables, business confidence emerges as a significant and positive predictor of life insurance penetration, underscoring the role of macroeconomic expectations in shaping consumer behavior. In contrast, consumer confidence, uncertainty, and pandemic-related uncertainty do not appear to influence insurance demand significantly.

The dynamic structure of the model includes three autoregressive terms and two moving average components. All three AR terms are highly significant, with alternating signs that point to a complex autoregressive pattern. The second-order AR term is particularly large in magnitude and highly significant, suggesting a strong correction mechanism in the series. Among the MA terms, only the second lag is significant, indicating that some moving average effects contribute to short-term adjustments.

Overall, the model suggests that life insurance demand in Italy is shaped by business sentiment and persistent temporal dynamics, while traditional structural and uncertainty-related variables play a more limited role.

Latvia Among the structural (“hard”) factors, banking sector size is the only variable with a statistically significant coefficient, showing a negative relationship with life insurance penetration. This may indicate a crowding-out effect where greater access to banking services reduces household reliance on insurance instruments. Additionally, long-term interest rates are statistically significant and negatively signed, suggesting a possible disincentive effect on long-term insurance savings. Other economic fundamentals, such as GDP per capita, population, inflation, and unemployment, do not exhibit significant associations.

In the sentiment block, business confidence has a substantial and statistically significant adverse effect on life insurance penetration. This result suggests that during periods of economic optimism, households may perceive a reduced need for financial protection through life insurance products. Conversely, consumer confidence, uncertainty, and pandemic-related uncertainty do not significantly influence insurance behavior in this setting.

The temporal structure of the model is notably complex. Four of the five autoregressive terms are statistically significant, indicating strong serial dependence and cyclical adjustment in insurance demand over time. The fourth-order moving average term is also significant, reinforcing the presence of short-term correction patterns. These dynamics highlight the importance of modeling persistence and memory in insurance behavior.

Finally, the errors are modeled after a Student-t distribution with about 7 degrees

of freedom, accommodating heavier tails than the Gaussian alternative.

In summary, Latvia's model emphasizes the dominance of autoregressive and business sentiment effects, while structural macroeconomic variables play a comparatively minor role in explaining variation in life insurance penetration.

Norway Among the “hard” economic factors, GDP per capita shows a positive association with insurance penetration and is statistically significant. Unemployment and the size of the banking sector also have positive and statistically significant effects. In contrast, the long-term interest rate exerts a negative and statistically significant influence, suggesting that higher borrowing costs reduce demand for life insurance products.

Turning to sentiment-related variables, consumer confidence, uncertainty, and pandemic-related uncertainty do not exhibit statistically significant effects on life insurance penetration. This indicates that, in Norway, short-term shifts in consumer sentiment and perceptions of uncertainty may not substantially alter the underlying demand for life insurance.

Regarding the ARMA terms, the first lag of life insurance penetration is positive and statistically significant, while the fourth lag demonstrates a strong and statistically significant positive effect, highlighting substantial persistence in life insurance demand. The moving average term at lag 4 is negative but not statistically significant, implying limited relevance in capturing short-term error dynamics in this specification.

Slovenia The full specification model estimation for Slovenia includes two autoregressive terms to capture temporal dependence in life insurance penetration. Among

the AR components, the second lag is substantial, negative, and highly significant, suggesting a strong correction mechanism over time.

Turning to macroeconomic indicators, population has a negative and statistically significant effect. GDP per capita also enters with a significant negative coefficient, which may reflect saturation effects or suggest that increases in income are not directly translated into greater life insurance demand in the Slovenian context. Unemployment displays a negative coefficient that is marginally significant at the 10% level, again highlighting the potential sensitivity of insurance demand to labor market conditions.

Among the remaining economic fundamentals, long-term interest rates have a positive and significant coefficient, implying that life insurance demand may increase when interest rates are higher, possibly due to more attractive returns embedded in insurance contracts. Other hard factors, such as inflation and banking sector size, do not attain statistical significance.

Regarding sentiment variables, none of the estimated coefficients for business confidence, consumer confidence, uncertainty, or pandemic effects reach significance. This suggests that in Slovenia, such perceptions and shocks do not systematically influence the dynamics of life insurance penetration, at least not through the channels captured by this model.

In summary, Slovenia's model identifies a modest role for macroeconomic fundamentals, especially income, population, and interest rates, while the time series component captures meaningful autocorrelation, driven in large part by the second lag of the dependent variable.

Spain Among the structural determinants, none of the traditional macroeconomic variables, such as population size, GDP per capita, inflation, unemployment, and long-term interest rates, display statistically significant coefficients at conventional levels, except for unemployment. Notably, the BCI is negatively associated with life insurance penetration and statistically significant, suggesting a countercyclical pattern.

Regarding the dynamic structure, the third and eighth lags of life insurance penetration are retained, with the eighth lag exhibiting a large and highly significant positive coefficient, indicating strong path dependence in the series. The first moving average term is also significant, reinforcing the role of short-term autocorrelated shocks. Other sentiment or uncertainty-related variables do not yield significant results. Overall, the model highlights the importance of lagged dynamics and select sentiment indicators over traditional economic fundamentals in explaining life insurance penetration in Spain.

4.2.1.2 Non-life insurance

Czechia Among the structural factors, GDP per capita shows a significant adverse effect. Other structural indicators, such as population, inflation, unemployment, banking sector development, and external trade, do not exert a statistically significant influence on non-life insurance penetration.

Regarding sentiment indicators, consumer confidence emerges as a significant determinant, with a negative coefficient indicating that a higher tendency to save increases the proportion of non-life insurance to GDP. The uncertainty index also exerts a significant negative impact, indicating that heightened uncertainty reduces the engagement with non-life insurance. Pandemic-related uncertainty, while pos-

itive, remains statistically insignificant.

The model reveals strong autoregressive behavior, with all four lag terms being statistically significant at the 1% level. Notably, the first three lags exhibit significant negative coefficients, suggesting a high degree of persistence and potential inertia in insurance purchasing behavior.

Overall, the findings suggest a model where past values of non-life insurance penetration significantly influence short-term dynamics, while certain sentiment-driven variables, especially consumer confidence and uncertainty, play a more pronounced role than traditional macroeconomic fundamentals.

Denmark Among the structural factors, GDP per capita shows a large and statistically significant negative effect. The banking sector variable is positively associated with insurance penetration, suggesting that financial sector development facilitates insurance uptake. In contrast, external trade has a significant negative effect, suggesting that increased trade openness may be associated with structural shifts that reduce domestic insurance demand. Inflation and unemployment do not have a substantial impact.

Turning to sentiment indicators, consumer confidence has a significant adverse effect, consistent with the notion that an increased tendency to spend reduces the perceived need for insurance. The uncertainty index is significant, with a negative sign, suggesting a potential dampening effect of macroeconomic uncertainty on non-life insurance demand. Business confidence and pandemic-specific uncertainty do not exhibit considerable influence.

The autoregressive structure is complex, with multiple lags being significant. The

first lag of insurance penetration is strongly positive, indicating momentum in insurance uptake. However, subsequent lags alternate in sign and significance, reflecting cyclical adjustments and inertia in insurance behavior. Notably, the sixth lag is significantly negative, while the seventh is strongly positive, indicating oscillatory dynamics.

Overall, the model highlights the joint influence of income levels, financial development, consumer sentiment, and past insurance behavior in shaping non-life insurance penetration. The findings emphasize the need to account for both structural and psychological dimensions, as well as persistence and cyclicity, when analyzing insurance demand.

Greece Among the macroeconomic fundamentals, population exhibits a strong and statistically significant negative relationship with non-life insurance penetration. External trade is also negatively associated and statistically significant at the 5% level, indicating that increased openness may reduce the tendency to insure with a domestic insurer. Other macro variables, such as GDP per capita, inflation, unemployment, and the banking sector, do not attain statistical significance, suggesting limited direct impact on insurance demand in this specification.

Regarding sentiment indicators, neither business nor consumer confidence emerges as a significant predictor; however, consumer confidence and uncertainty approach marginally statistically significant levels, hinting at a potential role in influencing insurance behavior during uncertain periods. Pandemic-related uncertainty is not statistically significant.

The autoregressive structure of the model is pronounced, with all three lags of non-life insurance penetration being negative and highly significant. The magnitude

of these coefficients confirms the presence of strong temporal dependence and persistence in insurance behavior, implying that past values continue to exert a substantial influence on current outcomes.

Italy Among the "hard" factors, population has a positive and statistically significant effect on non-life insurance penetration, while GDP per capita exhibits a strong and highly significant negative relationship. Unemployment, banking sector development, and external trade all display positive and statistically significant coefficients, indicating that worsening labor market conditions, financial intermediation, and openness to trade support greater non-life insurance penetration. Inflation, by contrast, has no significant effect in this specification.

Among the sentiment-related factors, pandemic uncertainty is the only statistically significant variable, exerting a negative influence on non-life insurance activity. Other indicators, such as business confidence, consumer confidence, and uncertainty, are not statistically significant, suggesting that sentiment effects, while potentially important during crises, play a limited role in this setting.

The dynamic terms reveal extremely strong autoregressive persistence, with all three lags of non-life insurance penetration being negative and highly significant. Their coefficients are near unity in magnitude, indicating pronounced dependence on past values. The moving average component at lag 1 is also negative and significant, suggesting that short-term innovations also influence current values.

Latvia Among the macroeconomic fundamentals, GDP per capita emerges as a key driver, with a significant and negative coefficient. In contrast, inflation, unemployment, and external trade are statistically insignificant.

Among the sentiment variables, business confidence plays a prominent role. Its coefficient is positive and highly significant, suggesting that improvements in business sentiment are closely linked to higher levels of non-life insurance activity. Other sentiment indicators, as consumer confidence, uncertainty, and pandemic-related uncertainty, are statistically insignificant in this model.

The dynamic structure reveals a rich autoregressive component, with multiple lags of non-life insurance penetration included. The first five lags show a clear pattern of persistence, with lags 1 through 4 being statistically significant and negative, consistent with a gradual decay in the influence of past values. Lag 5 approaches marginal significance, while lags 6 and 8 show mixed results: lag 6 is not significant, but lag 8 is significant, hinting at potential cyclical or delayed effects.

Norway Several macroeconomic variables exhibit strong and statistically significant relationships with non-life insurance penetration. Population is positively associated with penetration, suggesting that larger markets support greater insurance activity. GDP per capita displays a negative and highly significant coefficient, indicating that higher income levels are associated with diluted non-life insurance penetration. Unemployment has a positive and significant impact, implying that insurance contracts may be retained even during adverse labor market conditions. The banking sector variable is also positive and significant, underlining the complementarity between financial sector development and insurance demand. External trade shows a positive and statistically significant coefficient, suggesting a link between trade openness and non-life insurance activity, albeit weaker than other macroeconomic drivers. Inflation does not exhibit a statistically significant effect.

Among the sentiment variables, consumer confidence is positive and statistically

significant, indicating that a higher tendency to spend supports greater non-life insurance penetration. Business confidence, uncertainty, and pandemic uncertainty are not statistically significant, suggesting that short-term shifts in these indicators do not have a measurable impact within the examined sample period.

The dynamic component of the model reveals a strong persistence effect. The first lag of non-life insurance penetration is positive and highly significant, indicating substantial path dependency in insurance demand. The second lag is positive but statistically insignificant, suggesting that past values beyond one period do not materially contribute to explaining current penetration once other factors are accounted for.

Slovenia Among the macroeconomic factors, population has a positive and statistically significant effect, indicating that higher population levels are associated with increased non-life insurance penetration. In contrast, GDP per capita is negatively and significantly related to insurance demand. Inflation is also negatively associated and highly significant, implying that price instability may reduce the attractiveness or affordability of non-life insurance. External trade displays a negative and statistically significant effect, which may reflect the exposure of Slovenia's economy to competition.

The remaining macroeconomic variables, unemployment and banking sector development, do not attain statistical significance. Similarly, none of the sentiment indicators (business confidence, consumer confidence, uncertainty, and pandemic-related uncertainty) appear to have a meaningful influence on non-life insurance penetration in this specification.

The dynamic structure of the model is particularly prominent. All three autoregres-

sive lags of non-life insurance penetration are negative and highly significant, indicating extremely strong persistence and mean-reverting tendencies in the series. Moreover, the moving average term at lag 1 is also highly significant, capturing residual autocorrelation effects not explained by the autoregressive terms alone.

Spain Among the macroeconomic variables, population is positively associated with insurance penetration and statistically significant, indicating that larger population levels contribute to greater overall insurance activity. Conversely, GDP per capita has a strong and highly significant negative effect. Inflation, unemployment, and external trade are statistically insignificant, while the banking sector variable is significant, with a negative coefficient, potentially reflecting structural distortions. In the domain of sentiment indicators, business confidence shows a significant and positive association with insurance penetration, suggesting that improvements in the economic outlook are conducive to insurance activity. In contrast, consumer confidence has a negative and highly significant effect, which indicates that the tendency to save rather than to spend favors this industry. Pandemic-related uncertainty is not statistically significant.

The dynamic component of the model is particularly pronounced. Lags 1 through 3 of insurance penetration are all negative and highly significant, capturing persistent autoregressive effects. Notably, the fourth lag is positive and significant, implying potential cyclical or delayed correction mechanisms. Additionally, the moving average term at lag 3 is also positive and highly significant, suggesting that past shocks continue to influence current values through residual memory.

4.2.2 Ordinary Least Squares – Variable selection models

4.2.2.1 Life insurance

Appendix F presents the best model for life insurance penetration in each country, as identified through the variable selection process. The relevant test statistics are found in Appendix G.

Czechia The determinants of life insurance penetration exhibit a clear structure with significant macroeconomic and lagged autoregressive effects. The model includes statistically significant coefficients for GDP per capita, population, unemployment, the banking sector, long-term interest rates, and uncertainty. Notably, the negative coefficient of GDP per capita suggests that in the Czech context, higher income per capita is not associated with greater insurance penetration. Similarly, the negative impact of the banking sector and uncertainty on insurance penetration suggests a substitutional relationship between financial intermediation and life insurance, where heightened perceived risk leads to a reduction in long-term financial commitments. Conversely, unemployment and interest rates show a positive association, reflecting precautionary demand and more attractive guaranteed returns during periods characterized by distress.

Autoregressive effects also play a substantial role in Czechia's insurance dynamics. The first lag of life insurance penetration is negative and highly significant, indicating a strong mean-reverting behavior or correction mechanism. Meanwhile, the fourth lag is positively associated, highlighting the existence of cyclical persistence in the data.

Greece The variable selection model identifies three statistically relevant explanatory variables for life insurance penetration: the unemployment rate, the long-term

interest rate, and the consumer confidence index. Among these, the unemployment rate is positively associated with penetration, although the effect does not reach conventional levels of statistical significance. The long-term interest rate shows a positive and statistically significant effect, suggesting that higher returns may be linked to increased demand for life insurance, potentially due to the attractiveness of guaranteed-return products. The consumer confidence index also enters the model with a positive and significant coefficient, indicating that sentiment plays a measurable role in shaping insurance demand.

In addition to these explanatory variables, the model includes three autoregressive terms, at lags one to three, all of which are negative and highly statistically significant. Their inclusion reflects the presence of substantial persistence and short-term reversal dynamics in the data. These autoregressive terms dominate the model in magnitude, underscoring the importance of accounting for temporal dependence when modeling life insurance penetration in Greece's context.

Italy The model for life insurance penetration is notably rich, incorporating a wide range of macroeconomic and dynamic components. Among the structural drivers, GDP per capita is positively associated with insurance uptake, suggesting that higher income levels lead to greater demand for long-term financial products. Unemployment, by contrast, exhibits a negative association, indicating that macroeconomic labor market distress tends to suppress insurance penetration. The Business Confidence Index emerges as a positive contributor, implying that improved expectations regarding economic prospects support engagement with life insurance products, possibly by enhancing perceptions of financial security and future stability.

Dynamic effects are particularly pronounced in Italy's model, with a layered autoregressive structure. The first lag of insurance penetration is strongly positive. In contrast, the second lag is negative and the third lag is again positive, reflecting a pattern of cyclical adjustment and inertia. This configuration highlights a complex interplay between short- and medium-term memory in insurance behavior. Furthermore, moving average terms are also present, with a negative first lag and a strongly positive second lag, indicating the presence of residual correction mechanisms and delayed responses to past shocks.

Latvia The model for life insurance penetration is relatively concise, yet it reveals distinct relationships with macroeconomic and behavioral variables. Among the structural determinants, the banking sector and business confidence variables show a negative association with insurance penetration, suggesting that deeper financial intermediation may substitute for the role of life insurance in household financial planning. Similarly, long-term interest rates exert an adverse effect, implying that higher rates may deter long-term commitments such as life insurance, potentially due to increased opportunity costs or reduced affordability. Inflation appears in the model as a positive factor, though modest in effect, possibly reflecting insurance's appeal as a hedge against the erosion of real wealth during inflationary periods. Finally, during the pandemic period, the insurance penetration receded slightly.

A rich autoregressive component characterizes the dynamic structure. The first three lags of life insurance penetration are all negative, indicating a prolonged corrective process and potential overreaction to past levels. In contrast, the fourth and fifth lags turn positive, highlighting a cyclical element in the adjustment dynamics. This back-and-forth pattern suggests oscillatory behavior, where deviations are followed by delayed corrections that reflect both inertia and behavioral reinforcement.

The model also includes a fourth-order moving average term with a negative sign, indicating that past shocks continue to influence current values through a smoothing mechanism. Overall, the model portrays insurance penetration as shaped by substitution effects within the financial system, characterized by complex, memory-driven decision-making.

Norway Among the “hard” economic factors, unemployment and the size of the banking sector have positive and statistically significant effects, indicating that weak labour market conditions and financial sector development support life insurance demand. The long-term interest rate shows a negative and statistically significant relationship, suggesting that higher borrowing costs reduce the attractiveness of life insurance products. GDP per capita is positive but not statistically significant in this specification.

Turning to sentiment-related variables, consumer confidence, uncertainty, and pandemic-related uncertainty do not display statistically significant effects. This suggests that shifts in sentiment and perceived uncertainty do not have a measurable short-term impact on life insurance penetration when controlling for macroeconomic fundamentals.

Regarding the dynamic terms, the fourth lag of life insurance penetration is positive and statistically significant, indicating strong persistence in demand over this horizon. The moving average term at lag 4 is negative but not statistically significant, implying limited relevance in capturing short-term error dynamics within this model specification.

Slovenia Among the structural variables, GDP per capita exhibits a negative association with life insurance penetration, suggesting that higher income levels do

not necessarily translate into increased participation in life insurance markets. This counterintuitive finding may reflect shifting financial preferences at higher income levels, where alternative investment opportunities become more appealing. Population enters the model with a pronounced adverse effect, underscoring the sector's limited capacity to scale with demographic size. Unemployment is also negatively associated, aligning with the view that labor market insecurity diminishes individuals' ability or willingness to commit to long-term financial products. In contrast, long-term interest rates exhibit a positive relationship, suggesting that higher returns increase the attractiveness of insurance-linked savings instruments. Lastly, the Business Confidence Index is positively correlated with life insurance penetration, indicating that favorable economic sentiment fosters demand for such products.

The dynamic component of Slovenia's model is dominated by a single autoregressive term, with the second lag of insurance penetration exhibiting a statistically significant positive effect. This suggests inertia and persistence in behavior, where past levels of insurance uptake significantly influence current levels of insurance uptake. The model excludes moving average components, suggesting that short-term deviations or past shocks do not substantially impact the current dynamics.

Spain The model for Spain retains two key macroeconomic variables: the unemployment rate and the business confidence index. The unemployment rate enters with a negative and statistically significant coefficient, consistent with the expected inverse relationship between employment conditions and capacity to purchase life insurance. The business confidence index, also negative and significant, suggests that pessimistic outlooks from firms may influence consumer financial behavior, possibly through broader perceptions of economic uncertainty or expected income

trajectories.

On the time series side, the model includes a combination of autoregressive and moving average components. Four autoregressive terms are retained, at lags 1, 2, 3, and 8, all of which are negative and statistically significant. Their inclusion points to strong mean-reverting behavior and delayed feedback effects in insurance purchasing patterns. Additionally, the model identifies two significant moving average terms at lags 1 and 8. Together, the ARMA structure suggests a high degree of temporal complexity in Spain's life insurance market, reinforcing the need for dynamic specifications to achieve accurate modeling.

Aggregate report An aggregate report on the signs of the statistically significant variables is available in Appendix H, which summarizes the frequency with which each explanatory variable was found to be statistically significant in the variable selection models for life insurance across the seven countries examined. The counts distinguish between positive and negative estimated effects and reflect significance at the 10% level.

Among the demographic and macroeconomic variables, unemployment appears most frequently as a significant determinant, with five significant instances in total, three of which indicate a negative association and two a positive one. This mixed pattern suggests that the relationship between unemployment and life insurance demand may vary across countries, potentially reflecting differences in labor market conditions and social protection systems. GDP per capita also shows a notable presence, appearing three times with two negative and one positive sign, while population is significant twice and exclusively with a negative sign. The banking sector variable is significant in three instances, predominantly with a negative sign,

suggesting that financial sector development may act as a substitute for certain insurance-related savings mechanisms in some national contexts.

Long-term interest rates exhibit the highest frequency of positive associations among the macroeconomic variables, appearing five times in total, with three positive and two negative signs. This distribution may reflect the dual role of interest rates in influencing both the attractiveness of savings-type insurance products and broader financial market conditions.

Turning to sentiment indicators, Business Confidence is significant four times and is evenly split between positive and negative signs, indicating heterogeneous effects across countries. Consumer Confidence appears only once and with a positive sign, suggesting a limited but potentially supportive role for household sentiment in life insurance demand. Uncertainty, proxied by the World Uncertainty Index, is significant in only one instance and with a negative sign, while Pandemic Uncertainty does not appear as a significant factor in any of the examined cases.

Overall, the results suggest that labor market conditions and interest rates emerge as the most recurrent determinants of life insurance demand within the examined models, while sentiment-based indicators display a more limited and heterogeneous influence. The variation in signs across countries further underscores the importance of country-specific economic and institutional contexts when interpreting the determinants of life insurance consumption.

4.2.2.2 Non-life insurance

Czechia The specification retains a subset of macroeconomic, sentiment, and autoregressive variables based on statistical relevance, aiming to strike a balance

between model fit and parsimony.

Among the macroeconomic fundamentals, GDP per capita is the only significant predictor, indicating that rising income levels are associated with lower levels of non-life insurance penetration. Population and banking sector development are included in the model but do not reach statistical significance, and external trade shows no explanatory power.

The model includes two sentiment variables. Consumer confidence exhibits a negative but insignificant effect, while uncertainty is negatively associated with insurance penetration and is statistically significant. This suggests that heightened uncertainty may reduce demand for non-life insurance, potentially due to income or liquidity concerns during volatile periods.

The autoregressive structure of the model is particularly strong. Lags 1 through 3 of non-life insurance penetration are negative, highly significant, and have nearly identical coefficients (approximately -1.48), indicating strong persistence. Lag 4 also contributes significantly, though with a smaller magnitude, suggesting a decaying but still relevant memory effect in the dynamic path of insurance demand.

Denmark Among the economic fundamentals, GDP per capita is strongly and negatively associated with insurance penetration. The banking sector variable enters positively and significantly, suggesting that financial development supports greater insurance activity. Conversely, external trade is negatively related to non-life insurance demand, and this relationship is statistically significant.

With regard to sentiment indicators, consumer confidence is negatively associated with insurance penetration and statistically significant, suggesting that the tendency

to save, rather than to spend, favors the non-life insurance industry. Uncertainty is significant and negatively signed, indicating that periods of heightened uncertainty may dampen demand for non-life insurance. Business confidence, however, is not statistically significant in this specification.

The model's dynamic structure is notably rich. The first lag of insurance penetration is positive and highly significant, indicating strong momentum in the evolution of insurance demand. Subsequent lags show a complex pattern of alternating signs, with significant negative effects at lags 2, 6, and 8, and significant positive effects at lags 3, 4, and 7. This irregular structure may reflect a combination of short-term adjustments and medium-term corrections in insurance behavior. The fifth lag is positive but not statistically significant.

Greece Among the macroeconomic variables, population has a statistically significant and negative effect on non-life insurance penetration. Inflation is also found to be negatively associated with insurance demand, with the coefficient being significant at the 5% level. Also, external trade shows a negative coefficient.

Turning to the sentiment factor, uncertainty exhibits a positive and significant effect, implying that periods of higher uncertainty may be associated with slightly increased demand for non-life insurance.

Finally, the autoregressive structure of the model reveals strong and statistically significant negative coefficients for all three lags of insurance penetration. This indicates a persistent dynamic pattern, where past values exert a substantial negative influence on current penetration rates, with the first lag having the most considerable effect. These dynamics underscore the inertia and potential mean-reverting behavior in the evolution of non-life insurance penetration over time.

Italy Among the macroeconomic fundamentals, population exerts a strong and positive effect on non-life insurance penetration, indicating that market size is a significant determinant of aggregate insurance activity. In contrast, GDP per capita is negatively associated with insurance demand and is highly significant.

Other economic factors retained in the model include unemployment, which is positively signed but not statistically significant, and the banking sector variable, which is positively associated and significant, suggesting that financial development supports the growth of the insurance market. External trade also contributes positively and significantly, reinforcing the role of economic openness in expanding non-life insurance activity.

The dynamic structure is particularly prominent. All three autoregressive terms are extremely strong and highly significant, indicating a high degree of persistence and potential mean-reverting behavior in insurance penetration over time. The presence of a moving average term at lag 1, which is also negative and statistically significant, suggests that short-run shocks have lingering effects on insurance behavior, reinforcing the need to account for both observed and unobserved temporal dependencies.

Latvia Among the economic fundamentals, GDP per capita is negatively and highly significantly associated with non-life insurance penetration. Unemployment also enters the model with a negative and statistically significant coefficient, indicating that weaker labor market conditions suppress insurance demand. External trade is positively associated with insurance penetration and statistically significant, highlighting the role of economic openness in fostering insurance growth. Inflation is included but does not reach conventional significance levels.

Sentiment is captured by the uncertainty index, which exerts a negative and statistically significant effect, suggesting that heightened macroeconomic uncertainty may lead to reductions in insurance activity, possibly reflecting more cautious spending.

The dynamic component of the model is extensive and central to its explanatory power. All included lags of insurance penetration are statistically significant, with consistently negative coefficients. The first three lags exhibit large magnitudes, reinforcing the strong degree of persistence in the series. Later lags (lags 4 through 6 and lag 8) remain significant, though smaller in magnitude, reflecting a decaying memory effect that captures both short-term inertia and medium-run cyclical corrections. The cumulative significance and direction of these lag terms confirm the presence of a pronounced autoregressive structure in Latvia's insurance market.

Norway Population has a positive and statistically significant coefficient, confirming that larger markets tend to sustain greater insurance penetration. GDP per capita is negative and highly significant, suggesting that as income levels increase, non-life insurance penetration is diluted. Unemployment exerts a positive and significant effect, implying that non-life insurance policies may be retained during periods of higher joblessness. The banking sector variable is also positive and significant, reflecting the close link between financial development and insurance demand. External trade shows a positive coefficient and is statistically significant, indicating a potential, though weaker, relationship between trade openness and non-life insurance penetration.

The sole sentiment variable in the model, consumer confidence, is positive and highly significant, indicating that an increased tendency to spend fosters greater demand for non-life insurance.

The first lag of non-life insurance penetration is positive and highly significant, underscoring a strong persistence effect in the series. The second lag is positive but statistically insignificant, suggesting that longer-term autoregressive effects play a limited role once other explanatory factors are accounted for.

Slovenia Among the macroeconomic fundamentals, population has a positive and statistically significant association with insurance penetration, highlighting the scale effect in expanding insurance coverage. In contrast, GDP per capita is negatively associated with penetration and is highly significant. Inflation is also statistically significant and negatively signed, suggesting that price instability adversely affects the affordability of non-life insurance. External trade displays a negative and statistically significant effect, possibly reflecting external vulnerabilities or structural trade dependencies that displace domestic insurance demand. Unemployment and banking sector variables are statistically insignificant in this model.

Sentiment factors, including business confidence, consumer confidence, uncertainty, and pandemic-related uncertainty, do not exhibit significant effects. Their inclusion reflects potential behavioral influences, but the lack of statistical significance suggests these factors may not play a central role in driving non-life insurance activity.

The dynamic structure of the model is particularly robust. The first three lags of insurance penetration are all negative and highly significant, indicating exceptionally strong persistence and possible mean-reverting tendencies. Additionally, a moving average term at lag 1 is retained and is strongly negative, capturing short-run innovations not explained by the autoregressive terms alone. Notably, the variable selection model is identical to the complete model, as it was not possible to exclude

any variables without violating the assumptions underlying multiple regression analysis.

Spain Among the structural determinants, population has a positive and statistically significant effect, consistent with a volume-based increase in insurance penetration as the market size expands. GDP per capita shows a strong and highly significant negative effect. The banking sector variable is retained in the model but remains statistically insignificant.

Sentiment indicators play a notable role. Business confidence is positively and significantly associated with non-life insurance penetration, suggesting that favorable macroeconomic expectations stimulate insurance activity, possibly by boosting firm-level investment and household financial planning. At the same time, consumer confidence is negatively associated with penetration. It is also highly significant, indicating that a greater tendency to save increases the perceived need for precautionary financial instruments such as insurance.

The dynamic structure of the model is characterized by strong autoregressive and moving average components. Lags 1 through 3 of non-life insurance penetration are all negative and highly significant, underscoring the persistence of past behavior in shaping current outcomes. Notably, the fourth lag is positive and statistically significant, suggesting cyclical rebound effects or delayed adjustments in demand. The model also includes a moving average term at lag 3, which is positive and highly significant, capturing lingering effects from prior shocks that the autoregressive structure has not fully absorbed.

Aggregate report An aggregate report on the signs of the statistically significant variables (see Appendix H) summarizes the frequency with which each explanatory

variable was found to be statistically significant in the variable selection models for non-life insurance across the seven countries examined. As in the life insurance analysis, the counts distinguish between positive and negative estimated effects and reflect significance at the 10% level.

Among the demographic and macroeconomic determinants, GDP per capita emerges as the most consistent factor, appearing seven times and exclusively with a negative sign. This uniformity suggests a systematic inverse relationship between income levels and non-life insurance penetration within the examined specifications. Population is also frequently significant, appearing five times, predominantly with a positive sign. This pattern indicates that demographic scale may contribute positively to the development of non-life insurance markets, likely reflecting broader exposure to insurable risks and increased demand for property and liability coverage.

The banking sector variable appears three times and consistently with a positive sign, suggesting that financial sector development may complement non-life insurance activity. External trade is also significant in six instances but displays an equal number of positive and negative signs, indicating heterogeneous effects across countries and potentially reflecting differences in economic structure and openness.

In contrast, inflation appears only twice and exclusively with a negative sign, suggesting that macroeconomic instability may weaken non-life insurance activity in certain cases. Unemployment is significant only twice and displays a balanced distribution between positive and negative signs, pointing to a limited and context-dependent role for labor market conditions.

Regarding sentiment indicators, Consumer Confidence and Uncertainty appear more frequently than Business Confidence. Consumer Confidence is significant three times, predominantly with negative signs, while the World Uncertainty Index appears four times, mainly with negative effects, indicating that heightened uncertainty may dampen non-life insurance demand in several countries. Business Confidence, by contrast, appears only once and with a positive sign. As in the life insurance case, Pandemic Uncertainty does not emerge as a statistically significant factor in any of the models.

Overall, the results suggest that income levels, demographic scale, and financial sector development are among the most recurrent determinants of non-life insurance activity, while sentiment indicators play a secondary and more heterogeneous role. The variation in signs across several variables further highlights the importance of country-specific economic structures and institutional characteristics in shaping the dynamics of non-life insurance markets.

4.2.3 A Brief Note on the Comparison Between Western and CEE Countries

Following Truett and Truett (1990), this analysis compares income elasticity estimates, where statistically significant, between Western European (WE) and Central and Eastern European (CEE) countries.

Life insurance In the only WE country where income elasticity was statistically significant (Italy), the estimated value was 0.440. Conversely, in two CEE countries (Czechia and Slovenia), the corresponding estimates were -0.804 and -0.523 . These results suggest that income growth is associated with increased life insurance

penetration in WE countries, consistent with findings in the literature. In contrast, the negative elasticities observed in CEE countries imply that life insurance may be perceived as an investment choice during challenging times, with demand increasing during periods of financial strain.

Non-life insurance In the four WE countries (Denmark, Italy, Norway, and Spain) where income elasticity was found to be statistically significant, the estimated values were -0.727 , -0.705 , -0.371 , and -0.848 , with an average of -0.663 . For the CEE countries (Czechia, Latvia, and Slovenia), the corresponding values were -0.232 , -1.644 , and -0.876 , averaging -0.917 . These findings indicate that income elasticity is higher in absolute magnitude in the CEE countries compared to their WE counterparts. This observation is consistent with existing literature, which suggests that non-life insurance demand in emerging markets tends to be more sensitive to changes in income levels.

4.2.4 Quantile Regression

This analysis employs quantile regression to examine how the variables retained after the selection process influence insurance penetration across different points of the conditional distribution (see Appendix I). The results underscore that the effects of the explanatory variables vary considerably across quantiles, highlighting the importance of modeling distributional heterogeneity rather than relying solely on average effects derived from conventional regression techniques.

4.2.4.1 Life insurance

Czechia Among the explanatory variables, none of the macroeconomic fundamentals appear as statistically significant determinants across the examined quantiles.

Population, GDP per capita, Unemployment, Banking sector development, and the long-term interest rate exhibit coefficients whose signs vary across quantiles but remain statistically insignificant, suggesting that their effects on life insurance penetration in Czechia are not robust within the quantile regression framework. Similarly, the Uncertainty indicator does not emerge as a statistically significant factor at any quantile, indicating a limited role for global uncertainty in shaping the dynamics of the Czech life insurance market during the examined period.

In contrast, the lagged dependent variables show consistent statistical significance across several quantiles, highlighting the importance of dynamic adjustment in life insurance penetration. The first lag of insurance penetration is negative and statistically significant across all quantiles, with the magnitude of the effect becoming particularly pronounced at the upper tail of the distribution. This pattern suggests the presence of short-run correction dynamics in the evolution of life insurance penetration. The fourth lag, by contrast, is positive and statistically significant at the lower and median quantiles and again at the upper quantile, indicating that past levels of insurance penetration exert a delayed positive influence on current outcomes.

Overall, the results indicate that the dynamics of life insurance penetration in Czechia are driven primarily by its own lagged values rather than by contemporaneous macroeconomic or sentiment indicators. The presence of significant lagged effects across multiple quantiles points to a strong persistence in the development of the life insurance market.

Greece Among the explanatory factors, unemployment displays increasing and predominantly positive coefficients across quantiles, though it only reaches statistical

significance at the 75% quantile. This suggests that increases in unemployment are associated with high performances in life insurance penetration, potentially reflecting labor market-driven precautionary behavior.

The autoregressive structure exhibits consistent and robust statistical significance across all quantiles. The first three lags of life insurance penetration show strongly negative and highly significant coefficients throughout, underscoring the importance of temporal inertia and short-term correction mechanisms in the evolution of insurance demand. Notably, the magnitude of these effects generally declines at higher quantiles, particularly for lags 1 and 2, suggesting a less pronounced mean-reverting behavior. However, the third lag shows a slight resurgence in magnitude at the highest quantile, suggesting more complex delayed feedback effects when the life insurance market performs optimally.

Italy Among the macroeconomic variables, unemployment emerges as a statistically significant determinant across several quantiles. The coefficient is positive and significant at the lower and middle quantiles (0.1, 0.25, 0.5, and 0.75), indicating that increases in unemployment are associated with higher levels of life insurance penetration across a broad range of the distribution. However, this relationship does not remain statistically significant at the upper quantile, suggesting that the influence of labor market conditions weakens when insurance penetration reaches its highest levels.

GDP per capita becomes statistically significant only at the upper quantile (0.9), where the coefficient is negative. This result suggests that, at higher levels of insurance penetration, increases in income may be associated with a reduction in life insurance penetration.

Turning to sentiment indicators, Business Confidence is statistically significant only at the upper quantile. The positive coefficient at the 0.9 quantile indicates that improvements in business sentiment are associated with higher life insurance penetration when the market is operating at relatively elevated levels.

The dynamic structure of the model is captured by the lagged values of insurance penetration, which show strong and consistent significance. The first lag is positive and highly significant across all quantiles, indicating a pronounced persistence in life insurance penetration over time. The second lag is negative and significant at the lower-middle and median quantiles (0.25 and 0.5), suggesting the presence of short-run adjustment dynamics. The third lag is positive and significant at the median and upper quantiles (0.5 and 0.9), indicating that earlier levels of insurance penetration continue to exert a delayed positive influence on current outcomes.

Overall, the results highlight the importance of labor market conditions and dynamic persistence in shaping life insurance penetration in Italy, while income and business sentiment appear to exert an influence primarily at higher levels of the distribution.

Latvia Among the explanatory variables, the banking sector variable appears as a statistically significant determinant at the lower and upper quantiles. The estimated coefficients are negative at both the 0.1 and 0.9 quantiles, indicating that greater banking sector development is associated with lower life insurance penetration at both the lower and upper ends of the distribution. This pattern may suggest a substitutive relationship between banking sector activity and life insurance products within the Latvian financial system.

Business Confidence also emerges as statistically significant at the lower-middle

quantile (0.25), where the coefficient is positive. This result indicates that improvements in business sentiment are associated with higher life insurance penetration when the latter lies in the lower-middle range of the distribution.

The dynamic structure of the model is reflected in the lagged values of insurance penetration, several of which are statistically significant. The first lag is negative and statistically significant across all quantiles, although the level of significance declines toward the upper end of the distribution. This pattern indicates strong short-run adjustment dynamics in the evolution of life insurance penetration. The second lag is negative and significant at the lower quantiles (0.1 and 0.25) and remains weakly significant at the median quantile, suggesting that earlier deviations continue to exert downward adjustment effects in the short run. The third lag is also negative and significant at the lower quantiles (0.1 and 0.25), reinforcing the presence of pronounced dynamic corrections in the lower part of the distribution.

Overall, the results highlight the importance of dynamic persistence in shaping life insurance penetration in Latvia, with lagged values exerting strong and consistent effects. In addition, banking sector development and business sentiment appear to influence insurance penetration at specific parts of the distribution, indicating that their effects are heterogeneous across different levels of market development.

Norway Among the macroeconomic variables, unemployment becomes statistically significant only at the upper quantile (0.9), where the coefficient is negative. This result indicates that higher unemployment is associated with lower life insurance penetration, suggesting that adverse labor market conditions may constrain insurance demand.

The banking sector variable also appears as statistically significant at the median

and upper-middle quantiles (0.5 and 0.75). The estimated coefficients are positive, indicating that greater development of the banking sector is associated with higher levels of life insurance penetration at these points of the distribution. This pattern suggests a complementary relationship between banking sector development and life insurance activity in Norway, particularly when insurance penetration lies around the middle and upper-middle parts of the distribution.

The dynamic structure of the model is captured by the fourth lag of insurance penetration, which is positive and statistically significant across all quantiles. The magnitude of the coefficient remains relatively stable throughout the distribution, indicating a consistent and persistent influence of past insurance penetration on current outcomes. This finding points to a strong degree of persistence in the development of the Norwegian life insurance market, with past levels exerting a lasting positive effect on current penetration levels.

Slovenia Among the macroeconomic variables, GDP per capita emerges as a statistically significant determinant at several quantiles. The estimated coefficients are negative and significant at the 0.25, 0.75, and 0.9 quantiles, indicating that higher income levels are associated with lower life insurance penetration across a substantial part of the distribution, particularly at the upper quantiles. This pattern suggests that as income decreases, households may hold on to life insurance products.

Unemployment appears as statistically significant only at the lower-middle quantile (0.25), where the coefficient is negative. This result indicates that increases in unemployment are associated with lower life insurance penetration, reflecting the potential constraining effect of weaker labor market conditions on insurance demand.

The long-term interest rate also becomes statistically significant at the upper quan-

tiles (0.75 and 0.9), where the estimated coefficients are positive. This finding suggests that higher long-term interest rates are associated with greater life insurance penetration when the market operates at relatively higher levels, possibly reflecting the sensitivity of savings-type life insurance products to changes in the interest rate environment.

Finally, the second lag of insurance penetration appears as statistically significant at the 0.25, 0.5, and 0.75 quantiles. The coefficients are negative, indicating the presence of dynamic adjustment mechanisms in the evolution of life insurance penetration. This pattern suggests that deviations in previous periods tend to be followed by corrective movements in subsequent periods, contributing to the stabilization of insurance penetration over time.

Spain Among the explanatory variables, the first lag of insurance penetration is statistically significant at the 0.25, 0.5, and 0.75 quantiles. The coefficients are negative, indicating that increases in life insurance penetration in the previous period are associated with downward adjustments in subsequent periods across the middle part of the distribution.

The second lag of insurance penetration displays a stronger and more consistent influence. It is negative and statistically significant from the 0.25 quantile onward, with the magnitude of the effect becoming more pronounced at the upper quantiles. This pattern suggests that past deviations in insurance penetration tend to be followed by corrective movements, particularly when penetration levels are relatively high.

Similarly, the third lag of insurance penetration is negative and statistically significant at the 0.25, 0.5, and 0.75 quantiles, reinforcing the presence of dynamic

adjustment processes in the evolution of the Spanish life insurance market. These results indicate that the development of life insurance penetration is strongly influenced by its own past values across several periods.

Finally, the eighth lag of insurance penetration appears as statistically significant at the lower quantile (0.1), where the coefficient is positive. This result suggests that earlier historical levels of insurance penetration exert a delayed positive influence when the dependent variable lies at the lower end of its distribution.

Overall, the results indicate that the dynamics of life insurance penetration in Spain are driven primarily by lagged adjustments rather than by contemporaneous macroeconomic or sentiment indicators. The consistent significance of several lagged terms across the distribution highlights the importance of persistence and gradual adjustment in the evolution of the Spanish life insurance market.

4.2.4.2 Non-life insurance

Czechia Among the explanatory variables, the banking sector variable appears as statistically significant at the lower quantiles. The coefficients are positive and significant at the 0.1 and 0.25 quantiles, indicating that greater banking sector development is associated with higher levels of non-life insurance penetration when the latter lies in the lower part of the distribution. This result suggests a complementary relationship between banking sector activity and non-life insurance markets during periods of relatively low insurance penetration.

The dynamic structure of the model is strongly reflected in the lagged values of insurance penetration. The first lag of insurance penetration is negative and highly significant across all quantiles, indicating the presence of strong short-run adjust-

ment dynamics. Similarly, the second and third lags are also negative and statistically significant throughout the distribution, reinforcing the presence of persistent corrective mechanisms in the evolution of non-life insurance penetration. The consistency and magnitude of these coefficients suggest that deviations in previous periods are followed by substantial downward adjustments across the entire distribution.

Overall, the results indicate that the evolution of non-life insurance penetration in Czechia is driven primarily by its own past values, reflecting strong dynamic persistence and adjustment processes, while the banking sector appears to influence the market mainly at lower levels of insurance penetration.

Denmark Among the macroeconomic variables, GDP per capita emerges as a statistically significant determinant across most quantiles. The estimated coefficients are negative and significant from the 0.25 quantile onward, with the magnitude remaining relatively stable across the middle and upper parts of the distribution. This pattern indicates that lower income levels are associated with higher non-life insurance penetration across a large portion of the distribution, suggesting that decreases in income may coincide with retaining risk-management mechanisms.

The banking sector variable is statistically significant only at the lower quantile (0.1), where the coefficient is positive. This result indicates that greater development of the banking sector is associated with higher levels of non-life insurance penetration when the dependent variable lies at the lower end of the distribution.

The dynamic structure of the model is reflected in the first lag of insurance penetration, which is positive and statistically significant across all quantiles. This consistent significance indicates a strong degree of persistence in the evolution of

non-life insurance penetration in Denmark, with past levels exerting a positive influence on current outcomes throughout the distribution.

Greece Among the macroeconomic variables, population appears as statistically significant at the median quantile (0.5), where the coefficient is negative. This result indicates that increases in population are associated with lower levels of non-life insurance penetration when the dependent variable lies around the middle of its distribution.

Inflation emerges as statistically significant at the upper quantile (0.9), where the coefficient is negative. This result indicates that higher inflation is associated with lower non-life insurance penetration when the market operates at relatively higher levels, reflecting the potential adverse effects of macroeconomic instability on insurance demand.

External trade also becomes statistically significant at the median quantile, with a negative coefficient. This finding suggests that greater trade openness is associated with lower non-life insurance penetration at this point of the distribution.

The dynamic structure of the model is strongly reflected in the lagged values of insurance penetration. The first, second, and third lags are negative and highly statistically significant across all quantiles. This consistent pattern indicates strong adjustment dynamics in the evolution of non-life insurance penetration in Greece, with past increases in penetration followed by corrective movements in subsequent periods. The persistence and magnitude of these lagged effects highlight the importance of dynamic processes in shaping the development of the Greek non-life insurance market.

Italy Among the explanatory variables, the banking sector variable appears as a statistically significant determinant across all quantiles. The estimated coefficients are positive and significant throughout the distribution, indicating that greater development of the banking sector is consistently associated with higher levels of non-life insurance penetration in Italy. The stability of this relationship across quantiles suggests a complementary interaction between banking activity and the non-life insurance market.

The dynamic structure of the model is strongly reflected in the lagged values of insurance penetration. The first, second, and third lags are all negative and highly statistically significant across all quantiles. This consistent pattern indicates the presence of strong adjustment dynamics in the evolution of non-life insurance penetration, with increases in penetration in previous periods followed by corrective movements in subsequent periods. The magnitude and persistence of these lagged effects highlight the importance of dynamic processes in shaping the development of the Italian non-life insurance market.

Latvia Among the explanatory variables, GDP per capita appears as a statistically significant determinant across several quantiles. The estimated coefficients are negative and significant at the 0.25, 0.5, and 0.75 quantiles, indicating that lower income levels are associated with higher non-life insurance penetration across the middle part of the distribution.

The dynamic structure of the model is reflected primarily in the lagged values of insurance penetration. The second lag of insurance penetration is negative and statistically significant across all quantiles, indicating a consistent adjustment mechanism in the evolution of non-life insurance penetration. This result suggests that

increases in insurance penetration in previous periods are followed by corrective movements in subsequent periods across the entire distribution.

In addition, the third lag of insurance penetration becomes statistically significant at the median quantile (0.5), where the coefficient is negative. This finding further supports the presence of dynamic adjustment processes in the development of the Latvian non-life insurance market, particularly around the central part of the distribution.

Norway Among the macroeconomic variables, GDP per capita emerges as a statistically significant determinant across all quantiles. The estimated coefficients are negative and highly significant throughout the distribution, indicating that higher income levels are consistently associated with lower non-life insurance penetration. The stability of this relationship across quantiles suggests that the inverse association between income and non-life insurance penetration persists across both lower and higher levels of market development.

Unemployment becomes statistically significant only at the 0.25 quantile, where the coefficient is positive. This finding suggests that increases in unemployment are associated with higher non-life insurance penetration when the dependent variable lies in the lower-middle part of the distribution.

The banking sector variable is also statistically significant across all quantiles. The coefficients are positive and significant throughout the distribution, indicating that greater development of the banking sector is associated with higher levels of non-life insurance penetration. This pattern suggests a complementary relationship between banking activity and the non-life insurance market in Norway.

External trade is statistically significant at the lower quantiles (0.1 and 0.25), where the coefficients are negative. This result indicates that greater trade openness is associated with lower non-life insurance penetration when the dependent variable lies at the lower end of the distribution.

Finally, the first lag of insurance penetration is positive and statistically significant across all quantiles. This result indicates strong persistence in the evolution of non-life insurance penetration in Norway, with past levels exerting a consistent positive influence on current outcomes across the entire distribution.

Slovenia The results indicate that the dynamic structure of the model plays the dominant role in explaining the evolution of non-life insurance penetration. The second lag of insurance penetration is negative and highly statistically significant across all quantiles. This consistent pattern suggests the presence of strong adjustment dynamics, whereby increases in insurance penetration in previous periods are followed by corrective movements in subsequent periods throughout the distribution.

The third lag of insurance penetration is also statistically significant across all quantiles. The estimated coefficients are negative, reinforcing the presence of persistent dynamic adjustment mechanisms in the Slovenian non-life insurance market. The magnitude and consistency of these effects suggest that past levels of insurance penetration exert a substantial influence on current outcomes.

In addition, the first lag of insurance penetration is statistically significant at several quantiles (0.1, 0.25, 0.5, and 0.9), with negative coefficients. This result further supports the presence of strong short-run adjustment processes in the development of non-life insurance penetration.

Overall, the results highlight that the evolution of non-life insurance penetration in Slovenia is driven primarily by its own lagged dynamics rather than by contemporaneous macroeconomic or sentiment variables.

Spain Among the explanatory variables, GDP per capita emerges as a statistically significant determinant across all quantiles. The estimated coefficients are negative throughout the distribution, indicating that higher income levels are associated with lower non-life insurance penetration. The consistency of this relationship across quantiles suggests that the inverse association between income and non-life insurance penetration persists across both lower and higher levels of market development.

The dynamic structure of the model is reflected in several lagged values of insurance penetration. The first lag is negative and statistically significant across all quantiles, indicating that increases in insurance penetration in the previous period are followed by downward adjustments in subsequent periods. A similar pattern is observed for the second lag, which is also negative and statistically significant across the entire distribution, reinforcing the presence of strong adjustment dynamics.

The third lag of insurance penetration becomes statistically significant at the median and upper quantiles (0.5, 0.75, and 0.9), where the coefficients remain negative. This result further supports the presence of dynamic corrective mechanisms influencing the evolution of the Spanish non-life insurance market.

In contrast, the fourth lag of insurance penetration is positive and statistically significant from the 0.25 quantile onward. This pattern suggests that earlier historical levels of insurance penetration exert a delayed positive influence on current out-

comes, indicating the coexistence of short-term adjustment effects and longer-term persistence in the development of the Spanish non-life insurance market.

4.2.5 Elastic net algorithm

In this section, we present the empirical results of the proposed two-stage algorithm. We discuss the post-selection refit estimates under explicit ARMA (and, where indicated, ARCH/GARCH) disturbances in the main text, while the full set of detailed results is reported in Appendix J, while the test statistics appear in Appendix G.

4.2.5.1 Life insurance

Czechia The OLS refit based on the Elastic Net–screened specification indicates very strong persistence in life insurance penetration. The first three autoregressive terms are all negative and highly statistically significant, with sizeable magnitudes. This pattern suggests that deviations in penetration tend to be followed by pronounced corrections over subsequent quarters, consistent with a highly dynamic adjustment process. The intercept is small and statistically insignificant.

Among macroeconomic drivers, inflation enters with mixed timing effects: inflation at lag 2 is positive and significant, while inflation at lag 4 is negative and significant, implying that inflationary conditions may initially coincide with higher penetration but later relate to lower penetration. Banking sector development (lag 2) and long-term interest rates (lag 4) are both positive and statistically significant, whereas population lags are negative, with the lag-4 term significant, pointing to a negative association between the scale effect captured by population and penetration dynamics in this specification. GDP per capita at lag 4 is positive but only marginally significant at the 10% level.

Sentiment indicators are retained and statistically meaningful: Consumer Confidence and Business Confidence enter contemporaneously and are negative, with Business Confidence showing stronger significance. Taken together, the table depicts a model in which inertia and short-run correction (via the lagged dependent terms) dominate the dynamics, while macro-financial conditions (inflation timing, interest rates, banking sector) and sentiment contribute additional explanatory power in shaping quarterly movements in life insurance penetration.

Greece The OLS refit based on the Elastic Net–screened specification suggests a strongly mean-reverting dynamic in life insurance penetration. The first three autoregressive terms are all negative and statistically significant, indicating that increases in penetration tend to be followed by corrections over the subsequent quarters. The intercept is positive and marginally significant, pointing to a weak positive drift once the dynamic and covariate effects are accounted for.

Among macroeconomic drivers, unemployment enters both contemporaneously and with lags, with a positive current effect but negative effects at lags 2 and 3, implying a short-run association that reverses as labor-market conditions propagate through the system. Banking sector development (lag 2) is positive and statistically significant, while the long-term interest rate (lag 4) is negative and significant, indicating that higher rates are associated with lower life insurance penetration with a delayed impact. Overall, the results highlight that dynamic adjustment dominates, while labor-market conditions and financial variables provide additional explanatory power for quarterly movements in life insurance penetration.

Italy The Elastic Net–screened refit for life insurance penetration is estimated under an ARMA–GARCH disturbance specification, indicating that both serial depen-

dence and conditional heteroskedasticity are material in this case. The mean equation includes a statistically significant intercept and a positive, highly significant fourth lag of insurance penetration, pointing to persistence at the one-year horizon once the ARMA structure is accounted for. In addition, the moving-average terms MA(1) and MA(2) are strongly significant, confirming non-negligible short-run error dynamics captured by the ARMA component.

Regarding macro-financial determinants, GDP per capita at lag 4 enters with a negative and highly significant coefficient, while unemployment at lag 4 is positive and significant. Long-term interest rates are retained at lags 1 and 3 and both appear negative and statistically significant, implying that higher interest-rate conditions are associated with lower life insurance penetration over short to medium horizons. On the volatility side, the GARCH component exhibits extremely high persistence, with (β_1) close to unity, consistent with pronounced volatility clustering and slow decay of variance shocks. Overall, the results suggest that life insurance penetration dynamics are shaped by delayed macroeconomic effects and strong disturbance persistence in both the mean (via MA terms) and the variance (via GARCH).

Latvia The OLS refit based on the Elastic Net–screened specification points to very strong dynamics in life insurance penetration. The first four autoregressive terms are all negative and highly statistically significant, indicating pronounced mean reversion: increases in penetration are typically followed by sizable corrections over the subsequent quarters. The intercept is negative but statistically insignificant, suggesting no meaningful drift once the dynamic structure and covariates are taken into account.

Among macroeconomic drivers, the banking sector enters both contemporaneously

and with a lag. The contemporaneous banking sector coefficient is negative and statistically significant, while the lag 2 term is positive and significant, implying an offsetting short-run pattern across horizons. GDP per capita at lag 1 is positive and statistically significant, consistent with higher income levels being associated with higher life insurance penetration after a short delay. Unemployment at lag 2 is negative but not statistically significant in this specification. Overall, the results indicate that quarterly movements are dominated by dynamic adjustment, with selective contributions from income and banking-sector conditions.

Norway The OLS refit based on the Elastic Net–screened specification indicates that life insurance penetration is shaped by both delayed persistence and shorter-horizon correction. The autoregressive terms at lags 3 and 4 are statistically significant with opposite signs: lag 3 is negative, while lag 4 is positive and larger in magnitude, suggesting a dynamic pattern in which movements in penetration partly reverse over three quarters but exhibit persistence at the one-year horizon. The intercept is negative and highly significant, indicating a downward shift once covariates and dynamics are accounted for.

Among macroeconomic factors, banking sector development has a positive and significant impact, while unemployment at lag 1 is also positive and significant. Population effects are consistently negative across multiple lags, with the lag 4 term being strongly significant, indicating a robust negative association between the scale proxy and penetration dynamics in this specification. Interest rates appear with several lags: the contemporaneous long-term rate is negative but not significant, whereas the lag 1 term is weakly significant and positive, implying some sensitivity to the timing of rate changes. GDP per capita and inflation lags are retained but are not statistically significant.

Sentiment indicators contribute additional explanatory power: Business Confidence and Uncertainty enter contemporaneously with positive and statistically significant coefficients, while Pandemic Uncertainty is positive but not significant. Overall, the results suggest that quarterly movements in life insurance penetration reflect a combination of dynamic adjustment (particularly around the one-year horizon) and selected macro-financial and sentiment conditions, with population effects and confidence/uncertainty measures standing out among the non-dynamic covariates.

Slovenia The OLS refit based on the Elastic Net–screened specification suggests that life insurance penetration exhibits a pronounced dynamic structure with alternating persistence across horizons. The autoregressive terms at lag 1 and lag 4 are positive and highly statistically significant, whereas lag 3 is negative and significant, implying a pattern in which increases in penetration tend to persist in the short run and at the one-year horizon but partially reverse around three quarters. The intercept is negative and weakly significant, indicating a modest downward shift once covariates and dynamics are controlled for.

Macroeconomic effects are strong and precisely estimated. GDP per capita enters contemporaneously with a large negative coefficient, while its lagged terms at lag 2 and lag 4 are positive and highly significant, pointing to a non-monotonic timing profile in the income–penetration relationship. Unemployment is negative and highly significant contemporaneously but becomes positive and significant at lag 4, suggesting delayed reversal effects in labor-market conditions. The long-term interest rate enters positively and very strongly, and banking sector development at lag 2 is also positive and significant, underscoring the role of financial conditions in shaping penetration dynamics. Inflation is retained but is not statistically significant in this specification.

Sentiment variables add further explanatory content: Business Confidence is positive and highly significant, while Uncertainty is negative and marginally significant. Overall, the results indicate that quarterly movements in life insurance penetration in Slovenia reflect a combination of strong macro-financial influences and a rich autoregressive pattern, with particularly prominent roles for income, interest rates, and confidence, alongside timing-dependent effects across lags.

Spain The OLS refit based on the Elastic Net–screened specification indicates strong mean reversion in life insurance penetration. The first three autoregressive terms are all negative and highly statistically significant, implying that increases in penetration are typically followed by sizable corrections over the next quarters. The intercept is positive but statistically insignificant, suggesting no clear drift once the dynamic structure and covariates are accounted for.

Macroeconomic effects are mainly channeled through labor-market conditions and interest rates. Unemployment at lag 1 and lag 4 enters positively and significantly, while long-term interest rates at lag 3 and lag 4 are also positive and statistically significant, pointing to delayed sensitivity of life insurance penetration to financing conditions. Inflation is significant contemporaneously but its lag 1 effect is not, indicating that price dynamics matter primarily in the current quarter in this specification.

Sentiment indicators contribute meaningfully: Business Confidence is negative and highly significant, Consumer Confidence is positive and significant, and Uncertainty is negative and significant. Overall, the results suggest that quarterly movements in life insurance penetration are dominated by short-run corrective dynamics, with additional explanatory power from unemployment and interest-rate

conditions as well as contemporaneous sentiment measures.

4.2.5.2 Non-life insurance

Czechia The OLS refit based on the Elastic Net–screened specification for non-life insurance penetration is dominated by very strong dynamic adjustment. The first three autoregressive terms are all negative and extremely precisely estimated, indicating pronounced mean reversion: increases in non-life penetration are followed by sizable corrections over the subsequent quarters. The intercept is small and statistically insignificant, suggesting no systematic drift once dynamics and covariates are controlled for.

Among macroeconomic drivers, GDP per capita enters with a negative and statistically significant coefficient, while banking sector is positive and significant both contemporaneously and at lag 1, pointing to a robust association between financial deepening and non-life penetration. Population at lag 1 is positive and significant, whereas inflation at lag 4 is only marginally significant. External trade enters negatively at lag 1 (significant) and lag 2 (marginal), implying that higher trade openness is associated with lower non-life penetration over short horizons in this specification.

Sentiment indicators are also retained and statistically meaningful: Consumer Confidence and Pandemic Uncertainty are positive and significant, while Uncertainty is negative and significant. Taken together, the results suggest that quarterly movements in non-life insurance penetration are largely governed by strong corrective dynamics, with additional explanatory power from income, banking-sector conditions, external trade, and contemporaneous sentiment and uncertainty measures.

Denmark The Elastic Net–screened refit for non-life insurance penetration is estimated with explicit ARMA disturbances, indicating substantial residual dependence beyond the included regressors. In the mean equation, non-life penetration displays positive persistence at both the short horizon and the one-year horizon: Insurance penetration lag 1 and lag 4 are positive and statistically significant. The intercept is negative and significant, suggesting a downward shift once macro-financial drivers and dynamic effects are controlled for.

Among macroeconomic determinants, GDP per capita enters with a large negative and highly statistically significant coefficient, while the banking sector variable is positive and strongly significant, pointing to a robust association between financial deepening and higher non-life penetration in this specification. The ARMA component is pronounced: both AR(1) and AR(2) are negative and highly significant, and MA(1) is very close to unity and extremely precisely estimated, confirming strong short-run error dynamics. Overall, the results suggest that non-life penetration is shaped by persistent dynamics in the dependent variable and macro-financial conditions, while a substantial share of remaining serial dependence is captured through the ARMA error structure.

Greece The Elastic Net–screened refit for non-life insurance penetration is estimated with explicit ARMA disturbances and exhibits extremely strong dynamic adjustment. All four autoregressive terms are negative and highly statistically significant, implying pronounced mean reversion: increases in non-life penetration are followed by sizable corrections over subsequent quarters. The intercept is positive and statistically significant, indicating a level shift once macroeconomic controls and the dynamic structure are accounted for.

Among macroeconomic drivers, banking sector development enters positively and is strongly significant, whereas GDP per capita at lag 2, unemployment at lag 3, population at lag 4, and external trade at lag 1 all enter with negative and statistically significant coefficients. Inflation is retained but not statistically significant in this specification. Uncertainty is negative and significant, suggesting that higher uncertainty is associated with lower non-life penetration contemporaneously.

The ARMA component is also substantial: the coefficients on MA(1)–MA(3) are all highly significant, with MA(3) close to unity, indicating strong short-run dependence in the disturbances beyond what is captured by the regressors and lagged dependent variables. Overall, the results point to a model in which non-life penetration dynamics are dominated by strong corrective persistence, with additional explanatory power from banking-sector conditions, income, labor-market variables, external trade, and uncertainty, while remaining serial dependence is absorbed by the moving-average error structure.

Italy The OLS refit based on the Elastic Net–screened specification for non-life insurance penetration in Italy is dominated by extremely strong dynamic adjustment. The first three autoregressive terms are all negative, and highly statistically significant, implying pronounced mean reversion: increases in non-life penetration are followed by almost one-for-one corrections over the next quarters. The intercept is small and statistically insignificant, indicating no systematic drift once dynamics and covariates are controlled for.

Among non-dynamic covariates, the banking sector variable enters positively and is statistically significant, suggesting that financial deepening is associated with higher non-life penetration contemporaneously. Population at lag 4 is positive and

significant, pointing to a delayed scale-related effect in this specification. On the sentiment side, Business Confidence is negative and strongly significant, indicating that higher business sentiment coincides with lower non-life penetration after controlling for macro-financial conditions and the strong autoregressive structure. Overall, the results suggest that non-life penetration dynamics are primarily governed by rapid corrective adjustments, with additional explanatory power from banking-sector conditions, delayed population effects, and contemporaneous business sentiment.

Latvia The Elastic Net–screened refit for non-life insurance penetration is estimated under an ARMA–GARCH disturbance specification, implying that both serial dependence and conditional heteroskedasticity are relevant. The mean dynamics are rich: the coefficients on Insurance penetration lag 1–lag 4 are all statistically significant, with alternating signs across horizons, indicating a mix of short-run correction and longer-horizon persistence in quarterly penetration movements. In addition, the moving-average terms MA(1) and MA(2) are highly significant and negative, confirming strong short-run dependence in the disturbance component beyond what is captured by the lagged dependent variables and covariates.

Macroeconomic covariates also contribute to the mean equation. GDP per capita enters with a negative and highly significant coefficient, whereas External trade is positive but not statistically significant once dynamics are controlled for. On the variance side, the GARCH term exhibits strong persistence, with β_1 close to unity, consistent with volatility clustering and slow decay of variance shocks. The ARCH term α_1 is estimated at zero and is not statistically significant, suggesting that conditional variance persistence is captured primarily through the lagged variance component rather than immediate shock effects.

Overall, the results indicate that non-life insurance penetration is characterized by pronounced dynamic adjustment and highly persistent conditional variance, with GDP per capita providing additional explanatory power after accounting for serial correlation and volatility clustering.

Norway The OLS refit based on the Elastic Net–screened specification for non-life insurance penetration suggests a predominantly persistent short-run dynamic. Insurance penetration lag 1 is positive and highly statistically significant, indicating that increases in non-life penetration tend to carry over to the next quarter. The additional lags (lag 2 and lag 4) are positive but not statistically significant, implying that most of the dynamic signal is concentrated at the one-quarter horizon. The intercept is negative and statistically significant, pointing to a downward shift once covariates and dynamics are taken into account.

Macroeconomic effects are clearly present. GDP per capita enters with a negative and highly significant coefficient, and its lag 4 term is also negative and significant, indicating that higher income levels are associated with lower non-life penetration both contemporaneously and with a one-year delay in this specification. Banking sector development is positive and strongly significant, consistent with financial deepening supporting non-life penetration. External trade at lag 3 is positive and significant, suggesting that trade activity is associated with higher penetration at a delayed horizon. Overall, the results indicate that non-life penetration dynamics combine short-run persistence with meaningful macro-financial contributions, particularly from income, banking-sector conditions, and lagged external trade.

Slovenia The OLS refit based on the Elastic Net–screened specification for non-life insurance penetration is characterized by very strong mean reversion. The first

three autoregressive terms are all negative, large in magnitude, and highly statistically significant, indicating that increases in non-life penetration are typically followed by sizeable corrections over the subsequent quarters. The intercept is small and statistically insignificant, suggesting no systematic drift once dynamics and covariates are taken into account.

Among macroeconomic drivers, the banking sector variable enters positively and significantly, pointing to a supportive role of financial deepening for non-life penetration contemporaneously. Inflation at lag 4 is negative but only marginally significant, indicating a weak delayed association with penetration in this specification. External trade at lag 3 enters with a negative and statistically significant coefficient, suggesting that higher trade activity is associated with lower non-life penetration at a delayed horizon. Overall, the results imply that quarterly movements in non-life insurance penetration are dominated by strong corrective dynamics, with additional explanatory power from banking-sector conditions and delayed external and inflation effects.

Spain The OLS refit based on the Elastic Net–screened specification for non-life insurance penetration indicates a dynamic pattern that combines short-run correction with longer-horizon persistence. Insurance penetration lag 1 and lag 2 are negative and highly statistically significant, implying that increases in penetration tend to be followed by corrections over the next quarters, whereas lag 4 is positive and highly significant, pointing to persistence at the one-year horizon. The intercept is small and statistically insignificant, suggesting no systematic drift once dynamics and covariates are taken into account.

Macroeconomic covariates are strongly informative in this specification. GDP per

capita enters with negative and highly significant coefficients both contemporaneously and at lag 2, indicating that higher income levels are associated with lower non-life penetration. Unemployment is negative and significant contemporaneously, but positive and significant at lag 1, while the lag 3 term is not significant, suggesting non-monotonic timing in labor-market effects. Population at lag 2 is positive and significant, whereas the lag 4 term is not, and inflation at lag 3 is negative and significant. Banking sector development at lag 3 is positive and highly significant, while external trade at lag 2 is positive but only marginally significant.

On the sentiment side, Consumer Confidence is retained but not statistically significant in this specification. Overall, the results suggest that quarterly movements in non-life insurance penetration in Spain reflect a combination of strong macroeconomic effects (income, labor-market conditions, population, inflation, banking) and a dynamic adjustment process featuring short-run correction alongside persistence at the one-year horizon.

4.2.5.3 Panel models

In the paragraphs that follow, we present the panel regression models obtained from the Elastic Net screening stage. Specifically, we report the post-selection specifications that retain the covariates selected by EN and summarize the corresponding refitted panel estimates, so that the discussion focuses on the empirically supported determinants of insurance penetration in the multi-country setting.

Life insurance The results of the fixed effects panel regression model for life insurance penetration after the Elastic Net screening procedure can be found in Appendix J. The specification retains a limited set of explanatory variables capturing

financial sector development and interest rate dynamics, together with autoregressive terms of the dependent variable.

Among the economic determinants, the banking sector variables display consistently positive coefficients. The contemporaneous banking sector indicator and its first and second lags suggest that financial sector development is positively associated with life insurance penetration. In contrast, the long-term interest rate exhibits a negative effect. Both the first and second lags of the long-term interest rate carry negative coefficients, indicating that higher long-term rates are associated with lower levels of life insurance penetration.

The dynamic structure of the model is captured by the lagged dependent variables. The first three lags of insurance penetration enter with negative coefficients, while the fourth lag shows a large positive coefficient. This pattern indicates the presence of dynamic adjustment in life insurance penetration, suggesting that past levels of the dependent variable play an important role in explaining its current evolution.

Overall, the results highlight the importance of financial sector development, interest rate conditions, and the persistence of insurance market dynamics in explaining variations in life insurance penetration across the panel.

Non-life insurance The random effects panel refit based on the Elastic Net–screened specification indicates extremely strong persistence in non-life insurance penetration. Insurance penetration lag 4 is positive and overwhelmingly statistically significant, implying that non-life penetration is highly persistent at the one-year horizon once time-invariant country heterogeneity is controlled for. The intercept is small and statistically insignificant.

Macroeconomic covariates are strongly informative. GDP per capita enters with a negative and highly statistically significant contemporaneous effect, while its lag 4 term is positive and highly significant, pointing to a pronounced timing pattern in which income is associated with lower non-life penetration in the short run but higher penetration at the one-year horizon. The banking sector variable enters with a positive coefficient, while its lags 1 to 3 remain positive and statistically significant as well, indicating a robust and persistent association between financial deepening and non-life penetration dynamics.

Sentiment indicators also matter in the multi-country setting: Consumer Confidence is negative and highly significant, and Uncertainty is negative and significant, suggesting that tendency to spend and elevated uncertainty are associated with lower non-life penetration contemporaneously. Overall, the results highlight a model in which non-life penetration is dominated by strong annual persistence, while macro-financial conditions, particularly banking-sector development and the timing of income effects, and sentiment measures provide additional explanatory power.

The estimated AR(1) parameter for the idiosyncratic error component is $\rho = -0.305$, indicating moderate negative first-order serial correlation in the within-country disturbances. In practical terms, after controlling for the selected covariates and the dynamic terms of non-life insurance penetration, residual shocks tend to partially reverse in the subsequent period rather than persist in the same direction. This suggests an oscillatory adjustment pattern, positive deviations from the fitted path are, on average, followed by negative deviations (and vice versa), which is consistent with short-run correction dynamics around the model-implied trajectory.

Robustness check – Life insurance The results, presented in Appendix J, report the robustness specification for life insurance penetration based on a fixed effects panel model in which variable selection was performed using a backward elimination procedure guided by the AIC. The model preserves the dynamic structure of the baseline specification by retaining the four lagged terms of insurance penetration, while cluster-robust standard errors are computed at the country level to account for heteroskedasticity and serial correlation within panels.

The estimates confirm the strong persistence of life insurance penetration over time. In particular, the fourth lag of the dependent variable remains positive and highly statistically significant, indicating that past insurance activity plays an important role in determining current levels of life insurance penetration. The first three lags display negative coefficients, although only the second lag is statistically significant at conventional levels.

Among the explanatory variables, indicators related to the development of the banking sector exhibit a positive association with life insurance penetration. Both the contemporaneous value of the banking sector variable and its second lag are statistically significant, suggesting that financial sector development may facilitate the expansion of insurance markets.

Long-term interest rates appear to exert a negative influence on life insurance penetration. The coefficients of the first three lags of the long-term interest rate are negative and statistically significant, indicating that increases in interest rates may reduce the demand for life insurance products, possibly reflecting changes in household financial allocation or substitution toward alternative financial instruments.

A comparison between the robustness specification and the baseline model reveals

a high degree of consistency in the estimated relationships. In both specifications, variables related to the development of the banking sector exhibit a positive and statistically significant association with life insurance penetration. In particular, the contemporaneous value of the banking sector variable and its second lag remain significant across both models, indicating that financial sector development plays a stable and robust role in supporting the expansion of life insurance markets.

Similarly, the coefficients associated with long-term interest rates display a consistent negative effect in both specifications. The first and second lags of the long-term interest rate remain statistically significant and retain comparable magnitudes, suggesting that increases in interest rates may dampen demand for life insurance products, possibly reflecting substitution toward alternative financial instruments or changes in household portfolio allocation.

The dynamic structure of insurance penetration also remains largely unchanged across the two models. In both cases, the fourth lag of insurance penetration is positive and highly statistically significant, confirming the strong persistence of life insurance activity over time. The first three lags display negative coefficients in both specifications, although their statistical significance varies slightly between the two models.

Overall, the backward elimination specification produces results that are broadly consistent with those obtained from the Elastic Net screening model. The similarity of the estimated coefficients and their statistical significance across the two approaches provides additional support for the robustness of the main findings regarding the determinants of life insurance penetration.

Robustness check – Non-life insurance As a robustness check, the determinants of non-life insurance penetration were estimated using a Random Effects panel model with a country-specific random intercept. To account for potential serial correlation in the disturbances, an AR(1) error structure was specified within each country. A backward variable elimination procedure based on the AIC was applied in order to obtain a parsimonious specification. The fourth lag of the dependent variable was retained in all candidate models and was protected from elimination, as it captures the dynamic persistence of insurance penetration and helps address residual autocorrelation.

Because information-criterion-based model comparison requires likelihoods estimated under a common framework, the selection procedure was conducted using Maximum Likelihood estimation. The final specification was subsequently re-estimated using Restricted Maximum Likelihood in order to obtain less biased estimates of the variance components associated with the random effects and the error structure.

The results confirm the strong persistence of non-life insurance penetration, as indicated by the large and highly significant coefficient of the fourth lag of the dependent variable. This finding suggests that past insurance activity plays a dominant role in shaping current levels of non-life insurance penetration. Among the economic determinants, the development of the banking sector exhibits a strong positive association with insurance penetration, both in its contemporaneous value and in several lagged terms. This result highlights the complementary relationship between banking development and insurance markets.

Economic conditions also appear to influence insurance activity through a dynamic

mechanism. The contemporaneous coefficient of GDP per capita is negative, while its fourth lag is positive and statistically significant. This pattern suggests that increases in income may initially be associated with adjustments in household financial allocation, while the positive effect of income growth on insurance demand materializes with a delay as households gradually incorporate insurance products into their financial planning.

Finally, sentiment and uncertainty indicators also contribute to explaining insurance activity. Higher levels of consumer confidence and uncertainty are associated with lower non-life insurance penetration, while pandemic-related uncertainty appears to exert a small positive effect.

The AR(1) error parameter ($\rho = -0.311$) indicates a moderate negative autocorrelation in the residuals, suggesting that short-term shocks tend to partially reverse in subsequent periods. Overall, the robustness specification confirms the main relationships identified in the baseline model.

Life insurance with interaction terms The results reported in Appendix J present the fixed effects panel specification for life insurance penetration obtained after the Elastic Net screening procedure, including interaction terms between selected explanatory variables. The model also incorporates country fixed effects in order to control for time-invariant heterogeneity across countries, while cluster-robust standard errors are employed to account for potential heteroskedasticity and serial correlation within panels.

The estimates indicate a positive and statistically significant relationship between the development of the banking sector and life insurance penetration. Both the contemporaneous value of the banking sector variable and its second lag exert a

positive effect, suggesting that the expansion of financial intermediation supports the development of life insurance markets.

Long-term interest rates appear to exert a negative influence on life insurance penetration. The first and second lags of the long-term interest rate display negative and statistically significant coefficients, indicating that higher interest rates may reduce demand for life insurance products.

The model further incorporates an interaction term between the banking sector and the Consumer Confidence Index. The coefficient of this interaction term is negative and highly statistically significant, implying that the positive impact of financial sector development on life insurance penetration weakens as consumer confidence increases.

Finally, the dynamic structure of the model reveals a strong persistence in life insurance penetration. In particular, the fourth lag of the dependent variable is positive and highly significant, highlighting the importance of long-term dynamics in the evolution of insurance markets.

A comparison with the baseline fixed effects specification reported earlier indicates that the main findings remain largely unchanged after the inclusion of interaction terms. In both models, variables related to the development of the banking sector display a positive and statistically significant relationship with life insurance penetration, confirming the importance of financial sector development for the expansion of insurance markets. Similarly, the lagged values of long-term interest rates retain a negative effect, suggesting that increases in interest rates may reduce the demand for life insurance products.

The dynamic structure of insurance penetration also remains broadly consistent across the two specifications. In particular, the fourth lag of the dependent variable continues to exhibit a positive and highly significant coefficient, confirming the strong persistence of life insurance penetration over time.

Overall, the similarity of the main coefficients across the two specifications indicates that the core determinants of life insurance penetration remain stable, while the interaction term enriches the analysis by revealing an additional dimension through which financial development and consumer sentiment jointly influence insurance market outcomes.

Non-life insurance with interaction terms The random-effects panel model obtained after the elastic net screening and the backward AIC selection indicates very strong persistence in non-life insurance penetration, with the second and especially the fourth lag of the dependent variable retained, suggesting that current penetration is largely anchored to its annual (four-quarter) level while still allowing for some additional short-run adjustment. Among the macroeconomic determinants, income (GDP per capita) enters as an important driver, with its impact distributed across lags, while unemployment appears with a delayed positive association. The financial channel remains prominent: the banking sector is positively related to non-life penetration both contemporaneously and through short lags. External trade is also retained with a positive main effect.

Sentiment and uncertainty indicators contribute additional explanatory power, with consumer confidence and uncertainty entering with negative associations once the full set of controls is considered. The interaction terms highlight that the role of external trade is not uniform across economic conditions: the negative interaction

between income and external trade implies that the marginal effect of external trade weakens at higher income levels. Likewise, the negative external trade–banking interaction suggests diminishing marginal effects when both openness and banking depth are simultaneously elevated, consistent with non-linear or saturation-type dynamics in financially developed and highly open environments.

Finally, the AR(1) error parameter is $\rho = -0.367$, indicating moderate negative first-order serial correlation in the within-country disturbances. This pattern implies that after conditioning on the selected covariates and interaction structure, residual shocks tend to partially reverse in the subsequent period, consistent with short-run correction around the model-implied trajectory.

A comparison between the two specifications, which are the product of the elastic net algorithm, indicates that the main determinants of non-life insurance penetration remain broadly consistent across the two models, while the inclusion of interaction terms provides additional insights into the mechanisms through which macroeconomic and financial variables influence insurance demand.

In both specifications, the development of the banking sector emerges as one of the most important determinants of non-life insurance penetration. The contemporaneous value of the banking sector variable exhibits a strong and positive effect in both models, while several of its lagged values remain statistically significant. This finding confirms the close relationship between financial sector development and the expansion of insurance markets, suggesting that a more developed banking system may facilitate insurance distribution and financial intermediation.

Similarly, GDP per capita plays a significant role in explaining non-life insurance penetration. In the baseline specification, the contemporaneous effect of GDP per

capita is negative while its fourth lag is positive and highly significant, indicating the presence of delayed economic effects on insurance market development. The interaction specification confirms this pattern while also revealing additional dynamic effects through the inclusion of the third lag of GDP per capita.

The sentiment-related variables remain stable across the two models. Both the Consumer Confidence Index and the Uncertainty index display negative and statistically significant coefficients in both specifications, suggesting that a tendency to save and increased uncertainty are associated with lower levels of non-life insurance penetration.

The dynamic structure of insurance penetration also remains highly persistent. In the baseline model, the fourth lag of insurance penetration is positive and extremely significant, indicating strong persistence in the evolution of non-life insurance markets. The interaction model preserves this result while also identifying a small but significant contribution of the second lag of the dependent variable.

The extended specification further reveals important interaction effects between macroeconomic and financial variables. In particular, the interaction between GDP per capita and external trade is negative and statistically significant, suggesting that the positive effect of economic development on non-life insurance penetration weakens in economies with higher levels of trade openness. Similarly, the negative interaction between external trade and the banking sector indicates that the positive influence of financial sector development may be moderated in more externally oriented economies.

Overall, the comparison between the two models indicates that the core determinants of non-life insurance penetration remain robust across specifications, while

the interaction model enriches the analysis by capturing additional channels through which economic development, financial intermediation, and international trade jointly influence insurance market dynamics.

4.2.6 Evaluation of the Variable Selection and Quantile Regression Approaches

Following a rigorous and comprehensive analytical procedure that ensured a meticulous examination of country-specific factors, the resulting parameter estimates revealed variability in statistical significance, sign, and magnitude. Given that the analysis covers seven countries in the case of life insurance and eight in the case of non-life insurance, a considerable number of coefficients proved statistically insignificant, which explains the relatively limited frequencies reported in Appendix H tables which summarize the signs frequencies in the univariate (per country) OLS regressions.

For Life insurance, the statistically significant effects appear relatively sparse and heterogeneous. For instance, the Long-term interest rate exhibits a predominantly positive association with insurance penetration (three positive versus two negative instances), whereas Unemployment more frequently displays a negative relationship (three negative versus two positive instances). Similarly, GDP per capita shows mixed results, appearing once with a positive sign and twice with a negative sign. Among the sentiment indicators, Business Confidence appears equally often with positive and negative signs, while Consumer Confidence is recorded only once as statistically significant and with a positive sign.

In contrast, the results for Non-life insurance reveal somewhat clearer patterns for

certain variables. GDP per capita, for example, appears consistently with a negative sign in seven statistically significant cases, while Population is more often associated with a positive sign (four positive versus one negative instance). The Banking sector variable also tends to display a positive association (three positive instances). At the same time, some variables exhibit balanced or ambiguous effects; External trade appears equally often with positive and negative signs, while indicators such as Consumer Confidence and Uncertainty display mixed signs, suggesting that their influence may be more context-dependent across countries.

Overall, these results highlight the substantial cross-country heterogeneity in the determinants of insurance penetration and suggest that the influence of several explanatory factors is not uniform across national contexts. Such heterogeneity has been widely documented in previous scholarly work, underscoring the diverse effects of influencing factors (Dragoş, 2014). Furthermore, the signs and significance levels of the regression coefficients were occasionally inconsistent or counterintuitive (Headen and Lee, 1974). Notably, all proposed explanatory variables appeared at least once across the models assessing insurance penetration in the eight countries under investigation, though inflation and the pandemic uncertainty never achieved statistical significance. However, no single factor dominated the models, as none appeared in all of them. The remainder of this section presents a consolidated overview of the statistically significant findings, synthesizing results across all countries studied and summarizing the outcomes for both employed methodologies (see Appendix H).

Below, the life insurance and the non-life insurance models are commented. What is told for the life ones and applies to the non-life ones is not repeated.

4.2.6.1 Life insurance

The population variable appears in two models, both with a negative coefficient. In both cases, the parameter follows a predominantly downward trend across quantiles, which suggests that population decline is generally associated with higher life insurance penetration.

The predominant factor in the literature, at least historically, has been income (GDP per capita), which appeared in three of the seven models. The parameter signs were primarily negative, and in most cases, the parameter values decreased from one quantile to the next. While much of the literature reports a positive relationship between income and insurance consumption, some studies have identified a negative association, e.g., Anderson and Nevin (1975), Alhassan and Biekpe (2016), Trinh (2023), and Hwang and Greenford (2005). Moreover, there are cases where GDP was found to be statistically insignificant, further complicating the picture (e.g., Beck and Webb (2002) and Sen (2008)). Our findings are consistent with these divergent perspectives, underscoring the nuanced relationship between income and life insurance consumption.

Inflation, a commonly discussed factor in the literature, did not appear in any model, indicating its relatively limited explanatory power for insurance penetration in this context. One possible explanation is the consistently low inflation observed during the studied period. Average inflation across the studied countries ranged from approximately 2% to 4%, with the vast majority of observations falling between 0% and 5%, levels that likely did not significantly disrupt consumers' financial planning. Although some countries experienced periods of exceptionally low, or even negative, inflation, the overall trend was one of stability. Consequently, inflation

likely had a limited impact on the life insurance market during this time and was largely disregarded by consumers.

Unemployment appears in five models, all of them achieving statistical significance, exhibiting a positive sign in two cases and a negative sign in three. In the quantile regression results, the unemployment parameter displays varying magnitudes across quantiles, rendering this aspect of the analysis inconclusive. These findings reflect the literature's hesitation to use unemployment as a reliable predictor, due to its often counterintuitive effects. However, the insights associated with the income parameter suggest that life insurance tends to perform better in contracting economies, which may help explain the observed positive relationship between unemployment and insurance consumption.

One possible explanation for the positive correlation between unemployment and life insurance penetration is that insured individuals may go to great lengths to maintain their life insurance contracts, even during recessions. Unemployed persons, particularly those not facing severe financial hardship, may prioritize preserving existing policies or seek private insurance to replace coverage previously provided by social security systems. Additionally, unemployment may prompt a shift toward freelancing or self-employment, where employer-sponsored insurance is typically unavailable, thus increasing the demand for private life insurance. Another contributing factor could be employers pursuing efficiency gains through technology, resulting in layoffs of workers performing low-value-added tasks. In such cases, salary budgets may be reallocated to a smaller number of highly specialized employees with higher compensation packages, which may include life insurance benefits. Moreover, rising unemployment can exacerbate income inequality, as indicated by the Gini coefficient. Recent research by Dragoş, Codruţa, and Dragoş

(2019), which examined 32 European countries between 2002 and 2012, identified a positive relationship between unemployment and income disparity, further supporting the potential link between unemployment and life insurance penetration.

The banking sector variable appears in three models, where the negative sign was more frequent, which implies a somewhat competitive relationship between it and life insurance. The quantile regression results provide inconclusive evidence regarding the trend of the parameter. However, the absence of statistical significance in some models also supports the recent conclusion by Srbinoski (2021) that financial development can reduce the need for precautionary savings, thereby indirectly affecting life insurance demand. Once financial development surpasses a certain threshold, the growth of the banking sector may become decoupled from the expansion of life insurance services.

The long-term interest rate appears as statistically significant in five models, whose signs are distributed between three positive and two negative ones. This finding aligns with the segment of the literature that reports a positive relationship (Beenstock, Dickinson, and Khajuria, 1986), and with some studies presenting opposing evidence (Dragoş, Codruţa, and Dragoş, 2019). Moreover, the quantile regression results predominantly support a positive association between interest rates and life insurance penetration. This suggests that during periods of financial distress, often marked by rising interest rates, consumers may view life insurance as a reliable savings vehicle.

The Business Confidence Index (BCI) appears in four models, with its estimated sign evenly split between positive and negative values. However, the quantile regression results reveal that the magnitude of the BCI coefficient does not exhibit

a consistent pattern across quantiles. As a result, no definitive conclusion can be drawn regarding the relationship between business confidence and life insurance demand.

The CCI appears in one model, bearing a positive relationship with life insurance penetration. This suggests that the life insurance sector is not significantly affected by the indicator.

The Uncertainty Index parameter appears in four models, but only once bearing statistical significance, and bears a negative sign. The quantile regression analysis reveals no consistent pattern across quantiles. These findings align with the literature, which highlights the complex relationship between uncertainty and life insurance. For example, Gupta (2019) found that increases in economic policy uncertainty (EPU) significantly reduce life insurance premiums, while decreases in EPU do not produce long-term effects. In their study, replacing EPU with the S&P volatility index (VIX) showed that life insurance premiums declined as volatility decreased. On the other hand, Balcilar (2020) concluded that EPU significantly raises life insurance premiums in both the short and long term, underscoring the nuanced impact economic uncertainty can have on the life insurance market. It is reminded that the dependent variable in this research is life penetration, not life insurance premiums as in the two referenced studies.

Additionally, Canh, Wongchoti, and Thanh (2021) examined the relationship between life insurance consumption and global economic policy uncertainty (GEPU) across multiple countries, controlling for factors such as income and inflation. Their findings similarly indicate that lower economic uncertainty fosters growth in the life insurance market. It is unfortunate that EPU was available for only three

of the studied countries: Greece, Italy, and Spain.

The Pandemic Uncertainty Index did not appear in any models with a statistically significant parameter. This suggests that teleworking and state aid were able to mitigate the pandemic's effects to a significant extent.

4.2.6.2 Non-life insurance

The population variable appears in five of the models, with a positive coefficient in all but one. In two cases, the parameter exhibits a predominantly upward trend across quantiles, suggesting that population increase is generally associated with higher non-life insurance penetration. These results align with the recommendations in the literature.

Income, typically proxied by GDP per capita and widely regarded as the predominant factor in the literature, appeared in seven out of the eight estimated models. The corresponding coefficients were uniformly negative, although their magnitudes generally increased across quantiles. This pattern suggests that policyholders tend to retain their insurance coverage even during periods of economic downturn. The negative relationship aligns with previous findings that associate recessions with heightened insurance fraud. For instance, Eriksen and Carson (2017) found that declines in house prices were significantly associated with increases in arson incidents. Consequently, the elevated cost burden resulting from fraudulent claims compels insurers to transfer these costs to policyholders.

Inflation, a staple of the literature, appeared in only two of the eight models, both with a negative sign. The quantile regression results revealed that the parameters' trajectories were downwards in magnitude. The above results confirm the advice

in the literature.

Unemployment appeared in two models, its sign being equally distributed between a positive and a negative one. In the quantile regression results, the unemployment parameter displays a downward magnitude across the quantiles, as expected. These results confirm the literature's hesitation to include it as an explanatory variable.

The banking sector variable appears in three models, all with a positive sign. The quantile regression results provide inconclusive evidence regarding the trend of the parameter. The results generally align with the existing literature.

The external trade regressor appeared as being statistically significant in six models, with its signs distributed between three positive and three negative ones. At the same time, the quantile regression reports did not provide any conclusive evidence on its trajectory, whether it is upward or downward in magnitude. It becomes evident that the external trade is a factor that promotes competition, which, in turn, has varying effects in each domestic market.

The BCI appeared only once, with a positive sign, while its parameter value followed a generally upward trajectory. It is suggested that business confidence did not have a significant impact on the non-life insurance industry during the studied period.

Also, the CCI appeared in three models, and the most frequent sign was the negative one. Also, its parameter followed a downward trend in magnitude across the quantiles. Although it is understood that the CCI did not significantly impact the sample during the studied period, it is suggested that an increased attitude toward saving rather than spending favors non-life insurance penetration.

The Uncertainty Index parameter appeared in four models, with its signs being distributed between one positive and three negative ones. The quantile regression analysis reveals no consistent pattern across quantiles.

As was the case for the life insurance models, the Pandemic Uncertainty Index did not appear in any non-life ones with a statistically significant parameter.

4.2.7 Robustness Test

To assess the robustness of the empirical findings, this section compares the results obtained from two distinct linear estimation techniques: Ordinary Least Squares (OLS) and Quantile Regression (QR). While OLS provides estimates of the conditional mean of the dependent variable, QR allows for a more comprehensive examination of the conditional distribution by estimating effects at different quantiles. The comparison of the results obtained from these two approaches serves as a robustness check of the estimated relationships. The aggregate results of this comparison are presented in Appendix M. For the models provided by the variable selection process, we noted that in only three occasions the variables' signs changed. In all cases, it was an intercept, one for Czechia's life models and for both models for Spain. The models derived from the variable selection OLS were compared with the outcomes of the median quantile regression ($\tau = 0.5$) across the countries studied (see tables in Appendices F and I). A consistent pattern was observed: the estimated coefficients exhibited the same sign across both methods in almost all models. This alignment in directionality suggests that the core relationships identified by OLS are not sensitive to deviations from normality or the presence of outliers, as quantile regression is more robust to such issues.

4.2.7.1 Life insurance

Out of the 58 instances where a variable was retained, 13 cases (approximately 22%) exhibited a sign reversal between OLS and QR. These reversals are concentrated in variables such as the intercept (3 reversals), GDP per capita (2), and autoregressive terms (2), suggesting that their estimated effects may be sensitive to the underlying distributional assumptions or influenced by outliers and skewness in the data. Also, the majority of reversals were found in Latvia (3).

4.2.7.2 Non-life insurance

Out of the 89 instances where a variable was retained, 17 cases (approximately 19%) exhibited a sign reversal between OLS and QR. These reversals are concentrated in variables such as the intercept (3 reversals), BCI, Uncertainty, and the second autoregressive terms (2), suggesting that their estimated effects may be sensitive to the underlying distributional assumptions or influenced by outliers and skewness in the data. Also, the majority of reversals were found in Denmark (6) and Slovenia (5).

Although this comparison does not constitute a complete robustness test in a strict econometric sense, the consistency in signs across methodologies provides supportive evidence that the key relationships are not artifacts of the estimation technique. Therefore, the main empirical conclusions are stable under alternative modeling approaches.

4.2.8 Granger causality

This segment of the research utilized life and non-life insurance penetration, respectively, along with inflation and GDP per capita, with the latter being calculated based on nominal (current) GDP rather than the inflation-adjusted real GDP. For each insurance branch, a table summarizes the results of the multivariate and bivariate Granger causality tests conducted to investigate the temporal dynamics between GDP per capita and insurance penetration across the analyzed countries. The multivariate model incorporates inflation as a control variable, whereas the bivariate model examines the relationship without additional controls.

4.2.8.1 Life insurance

Table 4.1: Life insurance penetration, Bi- and Multi-variate Granger causality tests results, p-values

Country	Cause	Effect	Multivariate	Bivariate
Czechia	LIP	GDPpc	0.016**	0.066*
	GDPpc	LIP	0.000***	0.000***
Greece	LIP	GDPpc	0.000***	0.000***
	GDPpc	LIP	0.030**	0.019**
Italy	LIP	GDPpc	0.002***	0.000***
	GDPpc	LIP	0.005***	0.003***
Latvia	LIP	GDPpc	0.010**	0.000***
	GDPpc	LIP	0.069*	0.009***
Norway	LIP	GDPpc	0.066*	0.045**
	GDPpc	LIP	0.050*	0.874
Slovenia	LIP	GDPpc	0.097*	0.195
	GDPpc	LIP	0.001***	0.178
Spain	LIP	GDPpc	0.437	0.237
	GDPpc	LIP	0.343	0.330

LIP: Life insurance penetration, GDPpc: Nominal GDP per capita
p-value under 10% (*), 5% (**), 1% (***)

Czechia The Granger causality tests show bidirectional causality between life insurance penetration (LIP) and GDP per capita. GDP per capita strongly causes LIP in both multivariate and bivariate settings, while LIP also Granger-causes GDP per capita, albeit more weakly.

Greece A bidirectional relationship is evident between life insurance penetration

and GDP per capita. Both directions of causality are highly significant, suggesting a strong dynamic interaction between income levels and the development of the life insurance market.

Italy The results indicate robust bidirectional causality between life insurance penetration and GDP per capita. Both directions are highly significant across multivariate and bivariate models, underscoring a strong feedback mechanism.

Latvia The results suggest a two-way relationship between life insurance penetration and GDP per capita, though the strength varies. LIP significantly causes GDP per capita in both specifications, while GDP per capita also Granger-causes LIP, particularly in the bivariate test.

Norway Evidence is displayed of bidirectional causality. Life insurance penetration Granger-causes GDP per capita in both specifications, while GDP per capita only shows causality in the multivariate model and is insignificant in the bivariate test.

Slovenia The results suggest a predominantly bidirectional relationship in the multivariate specification. In the bivariate setting, the relationships are not statistically significant at the conventional levels.

Spain No evidence of Granger causality is found in either direction. This suggests that changes in GDP per capita and life insurance penetration evolve independently without dynamic feedback.

Overall, the Granger causality tests reveal substantial heterogeneity across countries. Strong bidirectional causality is observed in Greece, Italy, and Czechia,

where income levels and life insurance penetration reinforce each other over time. Latvia also shows evidence of two-way causality, though with varying levels of significance. Norway and Slovenia exhibit weaker and more asymmetric results, with causality running predominantly from life insurance penetration to income in Norway and from income to penetration in Slovenia. In contrast, Spain stands out as the only case where no causal links are detected, suggesting a decoupling of income dynamics and the life insurance market.

4.2.8.2 Non-life insurance

Table 4.2: Non-life insurance penetration, Bi- and Multi-variate Granger causality tests results, p-values

Country	Cause	Effect	Multivariate	Bivariate
Czechia	NLIP	GDPpc	0.000***	0.000***
	GDPpc	NLIP	0.773	0.611
Denmark	NLIP	GDPpc	0.006***	0.001***
	GDPpc	NLIP	0.028**	0.887
Greece	NLIP	GDPpc	0.102	0.000***
	GDPpc	NLIP	0.000***	0.782
Italy	NLIP	GDPpc	0.000***	0.000***
	GDPpc	NLIP	0.013**	0.017**
Latvia	NLIP	GDPpc	0.004***	0.000***
	GDPpc	NLIP	0.107	0.027**
Norway	NLIP	GDPpc	0.010**	0.010**
	GDPpc	NLIP	0.387	0.447
Slovenia	NLIP	GDPpc	0.000***	0.000***
	GDPpc	NLIP	0.011**	0.102
Spain	NLIP	GDPpc	0.003***	0.000***
	GDPpc	NLIP	0.325	0.061*

NLIP: Non-life insurance penetration, GDPpc: Nominal GDP per capita
p-value under 10% (*), 5% (**), 1% (***)

Czechia The results indicate strong unidirectional causality from non-life insurance penetration (NLIP) to GDP per capita, highly significant in both the multivariate and bivariate models. No evidence is found for the reverse relationship, suggesting that insurance dynamics lead economic activity but not vice versa.

Denmark NLIP Granger-causes GDP per capita in both specifications, while GDP per capita also causes NLIP, but only in the multivariate setting. This points to predominantly one-way causality from insurance to income, with some weak feedback in the richer specification.

Greece GDP per capita strongly Granger-causes NLIP in the multivariate model, while NLIP significantly drives GDP per capita only in the bivariate test.

Italy Robust bidirectional causality is displayed between NLIP and GDP per capita. Both directions are significant in the multivariate framework, while the bivariate tests confirm the feedback effect from income to insurance demand.

Latvia Non-life insurance penetration significantly Granger-causes GDP per capita across both models. The reverse relationship is weaker, appearing only in the bivariate setting, indicating that causality runs primarily from insurance to income.

Norway Clear unidirectional causality from NLIP to GDP per capita is exhibited, significant in both test specifications. GDP per capita does not Granger-cause NLIP, highlighting the dominant role of insurance in driving income dynamics.

Slovenia Strong bidirectional causality is evident in the multivariate model, while only the insurance-to-income direction remains significant in the bivariate case. This points to a feedback relationship, though income effects are less stable across model specifications.

Spain Evidence of NLIP Granger-causing GDP per capita in both models is shown. The reverse effect is marginal, reaching significance in the bivariate case only, suggesting a mostly one-way dynamic from insurance to income.

Across the countries examined, non-life insurance penetration more frequently Granger-

causes GDP per capita than the reverse. Strong bidirectional causality is observed in Italy and Slovenia, while Denmark and Greece show partial feedback effects. In contrast, Czechia, Latvia, Norway, and Spain are dominated by insurance-to-income causality, with Spain showing only weak reverse effects.

4.2.8.3 Panel data

The results of the Dumitrescu–Hurlin panel Granger causality test reveal distinct dynamics between life and non-life insurance penetration and economic growth. In the life insurance segment, the null hypothesis of no causality is rejected in both directions at conventional significance levels, indicating the presence of bi-directional causality between economic growth and life insurance penetration. This finding supports the feedback hypothesis, suggesting that economic expansion fosters the development of life insurance markets while, in turn, the life insurance sector contributes to economic growth through savings mobilization and long-term investment.

In contrast, the results for non-life insurance provide only weak evidence of causality. Specifically, economic growth appears to Granger-cause non-life insurance penetration, whereas no reverse causality is detected. This implies a unidirectional relationship consistent with a demand following pattern, where non-life insurance development responds to economic conditions but does not exert a significant influence on economic growth.

The multivariate Dumitrescu–Hurlin panel Granger causality test, which controls for inflation, confirms the robustness of the relationship between life insurance penetration and economic growth. Specifically, the null hypothesis of no causality is rejected in both directions, indicating the presence of a bi-directional relationship

that persists even after accounting for macroeconomic conditions. This finding suggests that the interaction between life insurance development and economic growth is structural in nature and not driven by omitted variable bias related to inflation.

In contrast, the results for non-life insurance differ markedly from the bivariate case. Once inflation is included as a control variable, the previously observed causality from economic growth to non-life insurance penetration disappears, and no significant relationship is detected in either direction. This indicates that the earlier evidence of causality was not robust and may have been driven by common macroeconomic factors rather than a direct causal link. Consequently, non-life insurance appears to follow economic conditions without exerting an independent effect on economic growth.

Table 4.3: Panel Granger causality test (Dumitrescu–Hurlin)

Panel	Cause	Effect	Bivariate		Multivariate	
			$p(\bar{Z})$	$p(\tilde{Z})$	$p(\bar{Z})$	$p(\tilde{Z})$
Life	GDPpc	LIP	0.037**	0.025**	0.061*	0.043**
	LIP	GDPpc	0.025**	0.016**	0.020**	0.012**
Non-life	GDPpc	NLIP	0.067*	0.048**	0.145	0.110
	NLIP	GDPpc	0.350	0.313	0.185	0.146

LIP: Life insurance penetration; NLIP: Non-life insurance penetration; GDPpc: Nominal GDP per capita.

$p(\bar{Z})$ and $p(\tilde{Z})$ denote p-values based on the asymptotic and small-sample corrected statistics, respectively.

Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2.9 Granger causality in the frequency domain

4.2.9.1 Income towards Life insurance

The following figures present the Granger causality spectrum from income, proxied by GDP per capita, to life insurance penetration. The corresponding visualizations are provided in Appendix K. The horizontal axis represents the frequency domain, while the vertical axis measures the magnitude of the Granger causality spectrum. The solid blue line depicts the estimated frequency-specific causality, and the red dashed horizontal line indicates the 5% significance threshold, denoting the minimum value required for statistical significance.

Czechia The spectrum remains above the significance threshold until the frequency of 0.3, implying that the influence of GDP per capita on life insurance penetration is most pronounced after a lag of approximately 3.5 quarters (calculated as the reciprocal of the frequency, $1/0.3$). Beyond this range, the spectrum falls below the threshold, indicating no significant short-term effect. This pattern suggests that income affects life insurance penetration primarily over longer cycles rather than at high (short-run) frequencies.

Greece The Granger causality spectrum remains statistically significant across the entire frequency domain. The spectrum peaks at a frequency of 0.5, corresponding to a lag of two quarters, indicating that the predictive effect of income on life insurance penetration is most pronounced at short- to medium-term horizons.

Italy The Granger causality spectrum is concentrated within the frequency band of 0.15 to 0.35, corresponding to lags of approximately 3 to 6.5 quarters. Additionally, significance is observed at the lower edge of the spectrum, indicating a long-term causal relationship. These findings imply that GDP per capita significantly influences life insurance penetration both at medium- and long-term horizons.

Latvia The spectrum is significant up to the 0.3 frequency mark, implying that the relationship is primarily long-term, with effects materializing after approximately 3.5 quarters.

Norway The spectrum displays a pronounced peak around the frequency of 0.25, corresponding to a lag of four quarters. Statistical significance is maintained between the 0.2 and 0.3 frequency

range, reinforcing the presence of a long-term causal effect. A secondary, smaller peak appears at 0.5 (a lag of two quarters), indicating a modest short-term influence. This dual-peaked structure suggests that the causal relationship operates at multiple temporal scales, with particularly strong effects over the annual cycle.

Slovenia The spectrum remains above the significance threshold until the 0.3 frequency mark, providing evidence of a predictive relationship over longer horizons (beyond 3.5 quarters). The maximum is observed at a frequency of approximately 0.2, corresponding to a lag of five quarters.

Spain. The causality spectrum lies predominantly below the significance threshold, suggesting a generally weak linkage. The only exception occurs around the frequency of 0.25, where the spectrum briefly exceeds the threshold within the 0.2–0.3 range. This indicates a localized effect at a lag of approximately four quarters, without broader evidence of systematic causality.

4.2.9.2 Life insurance towards Income

The reverse direction of causality, from life insurance penetration to GDP per capita, is illustrated in the subsequent figures, also included in Appendix K. The interpretation framework remains the same: the x-axis represents frequency, the y-axis the magnitude of the causality spectrum, and the red dashed line denotes the 5% significance threshold.

Czechia The spectrum exceeds the significance threshold across all frequencies, indicating pervasive Granger causality from life insurance penetration to GDP per capita. The spectrum exhibits a generally downward trajectory across frequencies, suggesting that the predictive effect is stronger at medium- to long-term horizons.

Greece The spectrum remains above the threshold up to the 0.2 frequency mark, indicating that the transmission effect from life insurance penetration to GDP per capita is most pronounced in the long term.

Italy The spectrum lies generally above, though close to, the significance threshold, with two distinct peaks at frequencies of approximately 0.25 and 0.5. These correspond to lags of four and two quarters, respectively, suggesting that the causal effect is strongest over short- and medium-term horizons.

Latvia The spectrum exhibits a distinct peak at 0.25 and remains above the threshold within the frequency range 0.15–0.35, corresponding to lags of seven to three quarters. This pattern suggests that the causal effect of life insurance penetration on GDP per capita is relevant across both medium- and long-term horizons.

Norway The spectrum remains above the threshold up to the 0.25 frequency mark, implying a significant causal effect materializing after four quarters. The declining trajectory from lower to higher frequencies indicates that no influence is evident at shorter horizons.

Slovenia The spectrum remains consistently above the significance threshold across all frequencies. The upward slope suggests that the influence is more pronounced at short-term horizons compared to longer-term ones.

Spain. The spectrum exceeds the significance threshold only at the 0.5 frequency mark, corresponding to a lag of two quarters. This result implies that the effect of life insurance penetration on GDP per capita is limited to a short-term channel.

The frequency-domain Granger causality results reveal notable cross-country heterogeneity in the dynamic interplay between income and life insurance penetration. In several cases, including Czechia, Latvia, Norway, and Slovenia, the predictive effect of GDP per capita on life insurance demand is concentrated at low frequencies, indicating that income influences operate predominantly over long-term horizons. By contrast, Greece exhibits statistically significant causality across the entire frequency domain, with the strongest effects materializing at short- to medium-term lags of around two quarters. Italy demonstrates a mixed pattern, with significance both at medium frequencies (3–6 quarters) and at the long-run edge of the spectrum, suggesting a dual channel of influence. Spain shows only limited and localized significance, implying a weak and unsystematic income effect.

When considering the reverse direction, life insurance penetration appears to exert a significant impact on GDP per capita in most countries, albeit with varying temporal structures. In Czechia and Slovenia, the effect is pervasive, spanning the entire frequency domain. Greece, Norway, and Latvia display significant effects primarily at longer horizons, while Italy's spectrum suggests relevance at both short- and medium-term lags. In Spain, however, the influence of life insurance on income

is confined to a narrow short-term channel of two quarters.

Overall, these results indicate that while income generally acts as a long-term driver of life insurance penetration, the feedback from insurance markets to economic output can be more immediate, with some countries (e.g., Italy and Spain) exhibiting short-run effects. This asymmetry underscores the complex and potentially bidirectional nature of the income–insurance nexus across said European economies.

Table 4.4: Summary of frequency-domain Granger causality between income and life insurance penetration

Country	Income → Life insurance	Life insurance → Income
Czechia	Long-term (up to 3.5 quarters)	All horizons (short to long)
Greece	All horizons; strongest at short-medium (2 quarters)	Long-term (up to 0.2 frequency)
Italy	Medium (3–6 quarters) and long-term	Short- and medium-term (2–4 quarters)
Latvia	Long-term (after 3.5 quarters)	Medium- to long-term (3–7 quarters)
Norway	Long-term (4 quarters) + secondary short-term (2 quarters)	Long-term (4 quarters)
Slovenia	Long-term (5 quarters)	All horizons; stronger at short-term
Spain	Weak overall; localized effect at 4 quarters	Short-term (2 quarters only)

4.2.9.3 Income towards Non-life insurance

Appendix L presents the figures illustrating the Granger causality spectrum from GDP per capita to non-life insurance penetration. The graphical format follows the structure described in the preceding sections, with frequency on the x-axis and the magnitude of the Granger causality spectrum on the y-axis. The horizontal dashed line denotes the 5% statistical significance threshold.

Czechia The causality spectrum closely parallels the significance threshold across the frequency domain, providing no robust evidence of predictive influence from GDP per capita on non-life insurance penetration. Nonetheless, two local peaks are observed at frequencies of approximately 0.25 and 0.5, corresponding to transmission lags of four and two quarters, respectively. Although isolated, these peaks reach statistical significance and suggest dynamics at short- and medium-term horizons.

Denmark The Granger causality spectrum consistently exceeds the significance threshold across the entire examined frequency range. The spectrum assumes a chevron-like shape, reaching its lowest points around the 0.1 to 0.2 frequency marks.

Greece The spectrum remains above the significance threshold up to the 0.3 frequency mark, peaking at approximately 0.2, which corresponds to a lag of five quarters. This indicates that the predictive effect of income on non-life insurance penetration is strongest at long-term horizons, with significance sustained even further into lower frequencies. These results suggest that income variations affect non-life insurance demand primarily with a delay of more than one year, highlighting a long but meaningful causal relationship.

Italy The causality spectrum generally lies below the significance threshold, except for distinct peaks at frequencies of 0.25 and 0.5, corresponding to lags of four and two quarters, respectively. This implies that, although the overall evidence is weak, income influences on non-life insurance penetration are most apparent at short- to medium-term horizons.

Latvia The spectrum exceeds the significance threshold across all frequencies, though it lies closer to the threshold at 0.25 and higher frequencies. This pattern indicates that the predictive effect of GDP per capita on non-life insurance penetration is statistically significant, with stronger effects observed at longer lags.

Norway The spectrum remains consistently above the significance threshold across the entire frequency domain, declining gradually as frequency increases. This trajectory suggests that the influence of GDP per capita on non-life insurance penetration is strong at shorter lags and becomes even more pronounced over longer horizons.

Slovenia The spectrum lies predominantly below the significance threshold, with exceptions at

frequencies of 0.25 and 0.5, corresponding to lags of four and two quarters, respectively. These localized peaks indicate that income may exert short-term and medium-term effects on non-life insurance demand, despite the overall weakness of the relationship.

Spain The spectrum generally aligns with the significance threshold across most frequencies, suggesting only a marginal dynamic relationship. Two exceptions are observed: a stronger peak at 0.25 and a smaller one between 0.4 and 0.5, corresponding to lags of four and two quarters, respectively. This indicates that any significant income effects are concentrated around the two-quarter and one-year horizons.

4.2.9.4 Non-life insurance towards Income

The subsequent figures, also presented in Appendix L, illustrate the reverse causality spectrum, specifically the impact of non-life insurance penetration on GDP per capita. The format remains consistent with the previous figures, with frequency on the x-axis, the magnitude of the Granger causality spectrum on the y-axis, and the 5% significance threshold represented by a dashed horizontal line.

Czechia The spectrum remains entirely below the significance threshold, indicating no robust evidence of causality. Two local peaks occur at approximately 0.1 and 0.35 (lags of ten and three quarters, respectively), but neither reaches statistical significance. These suggest that if any influence exists, it would manifest primarily over long-term horizons.

Denmark The spectrum remains below the significance threshold across the frequency range. Its maximum occurs near the 0.15 frequency mark, corresponding to a lag of seven quarters, implying that any potential influence would be concentrated at longer horizons, though not statistically confirmed.

Greece The spectrum does not cross the significance threshold at any frequency. Only at very high frequencies, near 0.5, does the curve approach the threshold. This pattern suggests that any potential impact of non-life insurance penetration on GDP per capita would be confined to very short-term horizons, if present at all.

Italy The spectrum remains consistently above the significance threshold across the entire frequency

domain, with notable peaks at 0.15 and 0.35 (lags of seven and three quarters). These results indicate a statistically significant influence of non-life insurance penetration on GDP per capita over both medium- and long-term horizons.

Latvia A distinct peak above the threshold is observed around the 0.25 frequency mark, with significance sustained between 0.2 and 0.3. These frequencies correspond to lags of three to five quarters, indicating a long-term causal effect, whereby changes in non-life insurance penetration affect economic performance after about one year.

Norway The spectrum remains above the threshold up to the 0.2 frequency mark and exhibits a downward trajectory from 0.1 to 0.5. This pattern suggests that non-life insurance penetration significantly influences GDP per capita over long horizons, with diminishing impact at higher frequencies.

Slovenia The spectrum lies below the significance threshold for most of the frequency domain, except for a pronounced peak at 0.15 (a lag of seven quarters). This indicates that the effect of non-life insurance penetration on economic output is most evident over the long term.

Spain The spectrum exceeds the significance threshold until approximately the 0.1 frequency mark, corresponding to transmission lags of more than ten quarters. Outside this range, the spectrum hovers near the threshold, suggesting that the influence of non-life insurance on GDP per capita is confined to very long-term horizons.

The frequency-domain Granger causality results for non-life insurance again reveal substantial cross-country heterogeneity. In the income-to-insurance direction, Denmark and Norway display strong and pervasive effects across all frequencies, with the magnitude particularly pronounced at longer horizons. Greece and Latvia also show robust long-term causality, though Greece's effect peaks at a five-quarter lag, while Latvia's significance extends across the entire spectrum. Italy, Slovenia, Spain, and Czechia exhibit weaker evidence overall, with causality emerging only at specific frequencies corresponding to short- to medium-term lags (two to four quarters).

In the reverse direction, from non-life insurance penetration to GDP per capita, significant effects are more limited but remain evident in certain cases. Italy and Latvia present clear medium- to long-term causality, while Norway and Spain display long-horizon influences (above seven quarters).

Slovenia exhibits significance at a lag of seven quarters, again highlighting long-term effects. In contrast, Czechia, Denmark, and Greece provide no robust evidence of feedback effects from non-life insurance to economic growth, with only isolated or near-threshold peaks observed. Taken together, these findings suggest that income is a stronger and more consistent driver of non-life insurance penetration than the reverse. Nevertheless, in countries such as Italy, Latvia, and Norway, non-life insurance penetration also appears to contribute meaningfully to economic performance, particularly at medium- to long-term horizons.

Table 4.5: Summary of frequency-domain Granger causality between income and non-life insurance penetration

Country	Income → Non-life insurance	Non-life insurance → Income
Czechia	No robust evidence; isolated short/medium peaks (2–4 quarters)	No significant effects; isolated long-term peaks (3–10 quarters, not significant)
Denmark	Strong, all frequencies; chevron shape	No significant effects; maximum at long horizon (7 quarters)
Greece	Long-term (peak at 5 quarters; significance up to 0.3 frequency)	No significant effects; near threshold only at short-term (2 quarters)
Italy	Weak overall; localized short/medium-term peaks (2–4 quarters)	Significant across all frequencies; strongest at 3–7 quarters
Latvia	Significant across spectrum; weaker beyond 0.25	Significant at 3–5 quarters (long-term effect)
Norway	Strong across spectrum; effect grows at longer horizons	Significant up to 0.2 frequency; long-term effect (≥ 5 quarters)
Slovenia	Weak overall; isolated peaks at 2–4 quarters	Long-term effect at 7 quarters
Spain	Marginal overall; peaks at 2 and 4 quarters	Long-term effect (> 10 quarters)

4.2.10 A note on the results obtained from Granger-causality testing

Careful readers may notice discrepancies between the two approaches used to assess Granger causality. For instance, a standard time-domain test can fail to reject the null of no causality, whereas a

frequency-domain test identifies statistically significant causal influence. This subsection clarifies why such divergences can arise.

Although Granger causality is conventionally assessed in the time domain using vector autoregressions and Wald-type tests, the literature has long emphasized that causality can also be examined in the frequency domain (Granger, 1969; Geweke, 1982). The distinction between these approaches often accounts for seemingly contradictory outcomes: time-domain tests deliver a global assessment of predictive content across all frequencies, while frequency-domain diagnostics permit inference at specific horizons. As Breitung and Candelon (2006) demonstrated, a variable may exert significant causal influence in the short run but not in the long run, or vice versa, leading to rejection in one framework and acceptance in the other. Moreover, finite-sample limitations and lag-length selection can materially affect the power and size of standard Granger tests, and structural breaks or regime shifts may obscure relationships in aggregated tests (Bai and Perron, 2003). To address these concerns, researchers often complement baseline results with robustness checks (e.g., alternative lag orders, rolling or recursive estimation) and employ procedures that are less sensitive to integration and cointegration orders, such as the Toda–Yamamoto approach (Toda and Yamamoto, 1995). Overall, divergence between analytical and time-domain Granger results should not be viewed as inconsistency, but rather as evidence that causal effects may be frequency-specific, sample-dependent, or regime-varying.

Importantly, recent theoretical and simulation work by Wei (2021) provided a critical refinement: the power of the frequency-domain Granger causality test is intimately tied to the characteristic roots of the underlying VAR model. When a root lies near unity, the test attains especially high power at frequencies close to 0 (or π), precisely where low- or high-frequency dynamics dominate. This insight helps explain why the test may succeed in detecting causality at specific horizons but fail at others, even within the same dataset. It underscores the need to interpret frequency-domain findings with careful consideration of the underlying series' persistence and oscillatory properties, and to assess robustness across frequency bands, especially those associated with near-unit-root dynamics.

Chapter 5

Conclusions, Policy Recommendations, and Suggestions for Further Research

5.1 Limitations of the research

This research examined the interdependence between the macroeconomic environment and the insurance sector. However, the analysis is not exhaustive. A more comprehensive approach could yield more robust findings by incorporating additional macroeconomic variables that influence insurance demand. For example, a detailed examination of employment composition across the primary, secondary, and tertiary sectors could provide insights into how different occupational structures impact life insurance consumption. Additionally, analyzing the structure of economic activities using the Statistical Classification of Economic Activities (NACE) could help elu-

cidate the relationship between industry-specific performance and insurance consumption, provided that sufficient historical data are available. Similarly, incorporating ad hoc measures, such as tourism-related indicators, including air transport volume and hotel overnight stays, particularly in countries where tourism constitutes a significant economic sector, could offer a more nuanced understanding of how international and domestic travel patterns affect insurance demand. Also, the inclusion of data on major historical natural disasters would be particularly valuable, as such events have been shown to influence both non-life and life insurance demand even across national boundaries (Fier and Carson, 2015).

Furthermore, as previously noted, factors beyond macroeconomic variables also influence insurance markets. However, the limited availability of quarterly data constrained their inclusion in this study. As higher-frequency data become increasingly accessible, researchers will be better positioned to develop and test more sophisticated hypotheses. It is imperative to conduct country-specific impact analyses, as the determinants of insurance consumption vary across countries. As insurance consumption is influenced by the availability of high-quality insurance products at competitive prices, and given the inherently dynamic nature of these demand factors, it is essential to acknowledge that no definitive conclusions can be drawn. Consequently, findings should be constantly updated to support an understanding of the underlying forces shaping the insurance market.

5.2 Evaluation of the contribution

An evaluation of the performance of the Business Tendency Survey indicators used in this study, namely the Business Confidence Index, Consumer Confidence Index,

World Uncertainty Index, and World Pandemic Uncertainty Index, reveals that they contributed positively to the explanatory power of many models, both of individual countries and panel data models. Among these, the BCI emerged as particularly influential, frequently included in the life insurance penetration models as a statistically significant regressor. Its frequency of inclusion matched or even exceeded that of traditional macroeconomic indicators such as inflation and population. The World Uncertainty Index also appeared with similarly high frequency in the non-life insurance penetration models, surpassing several traditional “hard” factors such as inflation, unemployment, and the banking sector. These findings underscore the relevance of public opinion-based indicators as valuable tools for capturing and interpreting patterns in insurance consumption.

In the panel-regression results, life insurance penetration is positively associated with the size and development of the banking sector and is also related to consumers’ propensity to spend, as captured by the Consumer Confidence Index (CCI). By contrast, life penetration exhibits a negative association with the long-term interest rate, consistent with the idea that higher long-term yields may weaken the relative attractiveness of life-insurance products and discourage longer-horizon contractual saving. Turning to non-life insurance penetration, the set of positively contributing factors includes income measured with a one-year lag, the unemployment rate, banking-sector development, and external trade intensity, suggesting that market size, financial depth, and the scale of economic activity and exposures are important correlates of non-life coverage. Negative associations, in turn, emerge for contemporaneous (more recent) income, consumers’ propensity to spend (CCI), and heightened uncertainty, indicating that short-run fluctuations in spending sentiment and uncertainty conditions are linked to lower non-life penetration within the pooled

cross-country setting.

A number of common patterns emerge from the quantile regression results for life insurance across the examined countries. First, the most consistent finding is the dominant role of the dynamic structure. Lagged values of life insurance penetration are statistically significant in almost all countries and across multiple quantiles, indicating strong persistence and adjustment dynamics. In many cases, the presence of alternating signs across lags suggests mean-reverting behavior and gradual correction mechanisms, highlighting the importance of past market developments in shaping current outcomes. Second, macroeconomic fundamentals do not exhibit a uniform or robust influence. Variables such as GDP per capita, unemployment, and interest rates appear only sporadically as statistically significant determinants, and their effects are often confined to specific quantiles. This indicates that their impact is conditional on the level of insurance penetration and varies across different parts of the distribution, rather than being systematic.

Third, the results provide clear evidence of heterogeneity across both countries and quantiles. The same variable may have different signs, levels of significance, or no effect at all depending on the country and the position within the distribution. This finding supports the view that life insurance demand is shaped by country-specific institutional, financial, and structural characteristics, which cannot be adequately captured by homogeneous modeling approaches. Fourth, sentiment and financial variables play a secondary but non-negligible role. They are significant only in certain countries and at specific quantiles, suggesting that their influence is context-dependent and becomes relevant only under particular market conditions.

The quantile regression results for non-life insurance reveal several consistent pat-

terns across countries. First, as in the case of life insurance, the dominant feature of the results is the strong role of dynamic adjustment mechanisms. Lagged values of non-life insurance penetration are statistically significant in all countries and across most quantiles, indicating that the evolution of the market is largely driven by its own past values. In many cases, the negative coefficients of the first lags point to pronounced short-run correction dynamics, while higher-order lags occasionally introduce delayed positive effects, suggesting the coexistence of persistence and mean-reverting behavior. Second, compared to life insurance, macroeconomic and financial variables appear more frequently as statistically significant determinants. In particular, GDP per capita and banking sector development emerge as key factors in several countries. However, their effects are not uniform. GDP per capita is often negatively associated with non-life insurance penetration, while the banking sector generally exhibits a positive and robust influence, indicating a complementary relationship between financial development and insurance markets.

Third, the results provide strong evidence of heterogeneity across both countries and quantiles. The same variable may exert different effects depending on the level of insurance penetration and the country under consideration. This heterogeneity is particularly evident in the case of macroeconomic variables, whose influence is often confined to specific parts of the distribution rather than being pervasive. Fourth, the importance of sector-specific and structural factors is more pronounced in the non-life insurance market. Variables such as external trade, and exposure to economic instability play a role in shaping demand, reflecting the closer link between non-life insurance and economic activity. Overall, while non-life insurance demand is also characterized by strong persistence and dynamic adjustment, it appears to be more sensitive than life insurance to macroeconomic and financial

conditions. At the same time, the effects of these variables remain heterogeneous and distribution-dependent. This reinforces the value of quantile regression as a tool for uncovering such non-linearities and heterogeneity, which are not captured by conventional mean-based approaches.

The quantile regression analysis reveals a consistent and overarching pattern across both life and non-life insurance markets: insurance demand is fundamentally driven by dynamic persistence, while the influence of macroeconomic, financial, and sentiment variables is heterogeneous, conditional, and distribution-dependent.

5.3 Policy implications

The empirical findings of this study yield several important policy implications for both the insurance sector and the broader macroeconomic environment.

First, the presence of bidirectional Granger causality between GDP per capita and insurance penetration in several countries highlights the mutually reinforcing relationship between economic growth and insurance market development. This finding suggests that policies aimed at fostering macroeconomic stability, such as maintaining sustainable growth, low inflation, and predictable fiscal conditions, can have indirect yet significant benefits for the expansion of insurance markets. At the same time, a well-developed insurance sector can contribute to economic resilience by facilitating risk transfer, mobilizing long-term savings, and supporting investment activity.

Second, the strong persistence observed in both life and non-life insurance penetration implies that insurance markets evolve gradually and are influenced by their own

past trajectories. This path dependence suggests that policy interventions should adopt a long-term perspective, focusing on structural improvements rather than short-lived measures. In this context, enhancing financial literacy and increasing public awareness of insurance products is of central importance. In particular, life insurance should be promoted not only as a protection mechanism but also as a long-term savings and wealth transfer instrument. Public information campaigns, especially during periods of economic uncertainty, could help stabilize demand by reinforcing consumer confidence.

Third, the heterogeneous and distribution-dependent effects identified through the quantile regression analysis indicate that policy measures should be carefully targeted. Since the impact of macroeconomic and financial variables varies across countries and across different levels of insurance market development, a “one-size-fits-all” approach is unlikely to be effective. Instead, policymakers should tailor their strategies to the specific characteristics of each market, taking into account institutional frameworks, financial development, and the maturity of the insurance sector.

Fourth, the role of financial development, particularly the banking sector, emerges as a key determinant, especially in the non-life insurance market. The evidence of complementarity between banking activity and insurance penetration suggests that policies promoting financial sector integration can yield positive spillovers. In this respect, maintaining a supportive and well-regulated environment for bancassurance and other forms of collaboration between financial institutions can enhance market efficiency and broaden access to insurance products.

Fifth, the findings regarding macroeconomic variables such as long-term interest

rates and external trade underscore the importance of policy predictability and transparency. Given the sensitivity of insurance products, particularly life insurance, to interest rate movements, monetary authorities should aim to provide clear forward guidance and avoid abrupt policy shifts that could disrupt long-term investment strategies. Similarly, the link between external trade and non-life insurance demand suggests that policies promoting stable and open economic relations can indirectly support insurance market development.

Finally, the limited and context-dependent role of sentiment indicators suggests that while expectations and confidence matter, their effects are neither uniform nor dominant. Nevertheless, in periods of heightened uncertainty, policymakers should complement structural measures with communication strategies that enhance transparency and reduce ambiguity in economic policymaking.

Overall, the results of this study emphasize that insurance demand is shaped by a complex interplay of macroeconomic conditions, financial development, and dynamic adjustment mechanisms. As such, effective policy design requires a combination of macroeconomic stability, institutional support, and targeted interventions that account for country-specific characteristics and distributional heterogeneity. It is hoped that the findings of this research will contribute to the understanding of these relationships and stimulate further academic and policy-oriented work in the fields of insurance economics and macro-financial analysis.

Appendices

A Summary statistics

Table A.1: Summary statistics, Czechia

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.009	0.002	0.008	0.007	0.010	0.285	-0.838	0.006	0.012
Penetration Nonlife	0.016	0.002	0.015	0.015	0.017	0.691	-0.672	0.014	0.020
Population	10,590.058	148.062	10,515.500	10,505.750	10,554.250	1.357	-0.039	10,479.000	10,899.000
GDP per capita	4.273	0.441	4.379	3.861	4.677	-0.133	-1.551	3.560	4.972
Inflation	3.754	4.374	2.505	1.418	3.326	1.958	2.862	0.100	17.578
Unemployment	3.350	1.581	2.550	2.133	4.592	0.780	-1.016	1.700	6.567
Banking sector	49.748	1.277	49.800	48.700	50.550	0.149	-0.940	47.700	52.300
LT Interest rate	2.136	1.370	1.805	0.998	3.248	0.601	-0.882	0.303	5.113
Business Confidence	99.565	1.239	99.676	98.579	100.553	-1.264	2.845	94.569	101.148
Consumer Confidence	100.511	2.350	100.722	98.696	102.618	-0.395	-1.117	95.964	103.872
Uncertainty	1.942	1.873	2.000	0.000	3.000	0.855	-0.068	0.000	7.000
Pandemic uncertainty	2.077	7.342	0.000	0.000	0.000	5.339	31.267	0.000	49.745
External trade	1.518	0.100	1.545	1.499	1.579	-1.051	0.155	1.275	1.656

StDev: Standard Deviation, Q1: First Quartile, Q3: Third Quartile, Min: Minimum Value, Max: Maximum Value

LT: Long-term, Business Confidence: Business Confidence Index, Consumer Confidence: Consumer Confidence Index, Uncertainty: World Uncertainty Index, Pandemic Uncertainty: World Pandemic Uncertainty Index

Table A.2: Summary statistics, Denmark

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Nonlife	0.026	0.001	0.026	0.025	0.027	-0.210	-0.642	0.023	0.028
Population	5,722.507	150.574	5,729.050	5,585.075	5,833.125	0.102	-1.276	5,479.000	5,991.400
GDP per capita	13.231	0.988	12.982	12.471	13.903	0.798	-0.136	11.852	16.048
Inflation	1.863	1.954	1.201	0.605	2.493	2.202	5.042	0.097	9.236
Unemployment	4.872	1.096	4.833	4.158	5.717	-0.069	-0.601	2.400	7.033
Banking sector	168.916	18.407	170.550	163.625	184.075	-0.522	-0.584	131.700	198.700
LT Interest rate	1.518	1.384	1.420	0.345	2.524	0.392	-0.967	-0.493	4.547
Business Confidence	100.166	1.429	100.274	99.773	101.024	-1.636	4.337	94.142	102.468
Consumer Confidence	100.365	1.233	100.798	99.879	101.201	-1.531	2.278	96.290	101.931
Uncertainty	3.059	2.870	2.000	1.000	4.000	1.409	1.584	0.000	12.000
Pandemic uncertainty	1.297	4.394	0.000	0.000	0.000	3.955	16.621	0.000	26.529
External trade	0.625	0.113	0.602	0.539	0.683	0.756	-0.535	0.463	0.892

Table A.3: Summary statistics, Greece

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.011	0.002	0.011	0.010	0.012	0.244	-0.201	0.007	0.015
Penetration Nonlife	0.012	0.001	0.012	0.011	0.013	0.194	-0.664	0.009	0.015
Population	10,842.550	202.738	10,787.400	10,701.175	11,056.075	0.008	-1.448	10,525.500	11,122.900
GDP per capita	4.630	0.498	4.472	4.219	4.911	0.716	-0.710	3.793	5.668
Inflation	1.717	2.902	1.304	-0.456	2.934	1.139	1.744	-2.380	11.676
Unemployment	15.857	6.282	15.883	10.558	21.775	0.074	-1.396	6.167	26.133
Banking sector	93.167	24.364	101.800	80.050	112.975	-0.729	-0.859	47.200	120.600
LT Interest rate	6.808	5.398	4.967	3.805	8.376	1.710	2.953	0.697	25.400
Business Confidence	98.857	2.919	99.561	96.618	101.164	-0.446	-0.897	91.757	103.788
Consumer Confidence	98.019	2.152	98.147	96.259	99.524	0.199	-0.491	93.996	103.763
Uncertainty	2.903	2.819	2.000	0.000	4.000	1.109	1.170	0.000	13.000
Pandemic uncertainty	2.716	7.723	0.000	0.000	0.000	3.069	9.034	0.000	39.667
External trade	0.449	0.114	0.417	0.367	0.505	0.953	0.340	0.273	0.781

Table A.4: Summary statistics, Italy

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.053	0.011	0.053	0.045	0.060	0.098	-0.261	0.027	0.082
Penetration Nonlife	0.022	0.003	0.022	0.020	0.024	-0.420	-0.941	0.017	0.027
GDP per capita	7.635	0.395	7.626	7.365	7.927	-0.203	0.075	6.359	8.385
Population	59,649.051	518.879	59,763.700	59,098.250	60,109.400	-0.282	-1.367	58,572.900	60,339.100
Inflation	1.906	2.309	1.184	0.483	2.521	2.082	4.717	-0.485	11.746
Unemployment	8.083	1.860	8.100	6.500	9.625	-0.043	-1.136	4.600	11.500
Banking sector	79.357	9.292	79.950	73.475	86.500	-0.576	-0.528	58.400	92.300
LT Interest rate	3.258	1.498	3.667	1.863	4.397	-0.103	-1.124	0.637	6.613
Business Confidence	100.249	1.250	100.459	99.668	100.977	-0.809	0.736	96.363	102.630
Consumer Confidence	99.546	1.542	99.717	98.730	100.519	-0.300	-0.123	96.036	103.193
Uncertainty	3.958	3.437	3.000	1.000	6.000	1.102	1.191	0.000	15.000
Pandemic uncertainty	1.970	7.143	0.000	0.000	0.000	4.167	17.403	0.000	40.073
External trade	0.569	0.061	0.559	0.537	0.596	0.675	0.993	0.438	0.749

Table A.5: Summary statistics, Latvia

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.005	0.002	0.005	0.004	0.006	1.180	3.879	0.002	0.012
Penetration Nonlife	0.013	0.004	0.013	0.010	0.015	0.619	2.024	0.003	0.029
Population	1,981.169	93.285	1,961.300	1,900.950	2,039.000	0.665	-0.686	1,859.200	2,188.000
GDP per capita	3.551	0.591	3.459	3.105	4.087	0.006	-1.140	2.399	4.561
Inflation	3.857	5.803	1.992	0.300	4.088	1.730	2.096	-3.750	21.746
Unemployment	9.544	3.650	8.700	6.667	11.500	0.970	-0.257	5.667	18.633
Banking sector	57.728	15.041	57.100	46.315	68.120	0.246	-1.016	35.380	85.440
LT Interest rate	3.438	3.597	2.690	0.802	5.232	1.241	0.751	-0.257	13.670
Business Confidence	100.300	2.875	100.899	99.804	101.766	-1.927	4.075	89.041	103.759
Consumer Confidence	100.334	3.174	101.419	98.763	102.701	-1.167	0.532	91.380	103.745
Uncertainty	4.000	3.786	3.000	1.000	6.000	0.861	-0.257	0.000	15.000
Pandemic uncertainty	1.356	4.028	0.000	0.000	0.000	3.093	8.888	0.000	19.313
External trade	0.979	0.152	0.991	0.942	1.046	-0.264	0.761	0.586	1.335

Table A.6: Summary statistics, Norway

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.029	0.009	0.028	0.023	0.032	1.602	5.593	0.013	0.071
Penetration Nonlife	0.067	0.006	0.067	0.063	0.071	-0.108	0.105	0.049	0.081
Population	4,992.118	354.488	5,002.000	4,638.250	5,315.500	0.026	-1.453	4,467.000	5,590.000
GDP per capita	28.004	2.866	28.175	26.166	30.061	-0.326	-0.474	21.376	34.045
Inflation	2.446	1.433	2.238	1.456	3.127	0.845	1.382	-1.427	6.741
Unemployment	2.660	0.576	2.600	2.275	3.100	0.293	-0.446	1.467	4.100
Banking sector	102.565	18.930	107.400	84.500	116.525	-0.153	-0.953	68.500	139.400
LT Interest rate	3.380	1.644	3.462	1.886	4.380	0.307	-0.939	0.607	6.753
Business Confidence	100.081	1.166	100.214	99.296	100.871	-0.595	0.563	96.236	102.641
Consumer Confidence	10.266	17.223	15.150	1.125	22.975	-1.051	0.285	-36.900	31.200
Uncertainty	2.696	2.605	2.000	1.000	4.000	1.505	2.240	0.000	13.000
Pandemic uncertainty	2.051	7.366	0.000	0.000	0.000	3.948	14.731	0.000	39.160
External trade	1.046	0.399	0.854	0.707	1.315	0.791	-0.530	0.640	2.073

Table A.7: Summary statistics, Slovenia

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.015	0.002	0.015	0.014	0.016	-0.181	-1.104	0.012	0.017
Penetration Nonlife	0.036	0.006	0.034	0.032	0.041	0.547	-1.187	0.028	0.046
Population	2,090.263	22.626	2,093.350	2,065.925	2,108.050	0.053	-1.661	2,062.400	2,124.700
GDP per capita	5.049	0.405	5.106	4.696	5.320	-0.089	-1.043	4.229	5.763
Inflation	2.510	3.295	1.600	-0.011	3.173	1.178	0.236	-0.921	10.667
Unemployment	5.044	1.821	4.517	3.675	6.075	0.778	-0.712	2.833	9.133
Banking sector	44.713	7.631	41.925	39.405	49.477	0.818	-0.220	33.890	63.300
LT Interest rate	1.271	1.152	0.955	0.392	1.788	0.710	-0.729	-0.180	3.487
Business Confidence	100.842	1.937	101.690	99.206	102.082	-1.030	0.776	94.568	103.450
Consumer Confidence	100.468	2.631	100.787	98.275	102.976	-0.186	-1.341	95.629	104.302
Uncertainty	4.263	2.767	4.000	2.250	6.000	0.181	-0.980	0.000	10.000
Pandemic uncertainty	2.030	5.742	0.000	0.000	0.000	3.458	13.208	0.000	30.436
External trade	1.592	0.125	1.576	1.509	1.633	0.759	0.257	1.356	1.889

Table A.8: Summary statistics, Spain

	Mean	StDev	Median	Q1	Q3	Skewness	Kurtosis	Min	Max
Penetration Life	0.024	0.007	0.023	0.020	0.027	2.915	12.125	0.015	0.066
Penetration Nonlife	0.029	0.003	0.028	0.028	0.030	0.886	-0.180	0.025	0.036
Population	45,571.348	2,307.395	46,464.950	44,205.825	46,816.050	-0.927	-0.300	40,478.400	49,018.700
GDP per capita	6.264	0.373	6.236	5.980	6.537	0.103	-0.550	5.316	7.147
Inflation	2.379	2.024	2.555	0.969	3.437	0.808	2.015	-1.069	10.059
Unemployment	13.686	5.021	12.617	9.717	17.583	0.548	-0.887	6.667	24.567
Banking sector	116.725	30.622	105.700	91.775	145.275	0.410	-1.288	71.000	167.600
LT Interest rate	3.311	1.673	3.793	1.652	4.506	-0.365	-1.025	0.100	6.427
Business Confidence	100.393	1.608	100.833	99.783	101.473	-1.367	2.021	94.499	102.807
Consumer Confidence	99.454	2.797	100.190	97.237	101.602	-0.543	-0.760	93.248	104.026
Uncertainty	3.530	2.758	3.000	1.000	5.000	0.901	0.616	0.000	12.000
Pandemic uncertainty	1.048	4.443	0.000	0.000	0.000	5.672	34.842	0.000	34.025
External trade	0.609	0.072	0.603	0.557	0.652	0.440	0.206	0.453	0.820

B Stationarity tests

Table B.1: Stationarity test, ADF p-values, Czechia

Variable	None	Drift	Trend
Penetration Life	0.05	0.60	0.00
Penetration Nonlife	0.69	0.00	0.00
Population	0.29	0.69	0.11
GDP per capita	0.37	0.29	0.02
Inflation	0.12	0.17	0.77
Unemployment	0.03	0.58	0.93
Banks	0.90	0.09	0.09
LT Interest rate	0.73	0.34	0.48
Business Confidence	0.82	0.01	0.01
Consumer Confidence	0.68	0.03	0.02
Uncertainty	0.03	0.04	0.26
Pandemic uncertainty	0.00	0.12	0.70
External trade	0.39	0.05	0.01

LT: Long-term, Business Confidence: Business Confidence Index, Consumer Confidence: Consumer Confidence Index, Uncertainty: World Uncertainty Index, Pandemic Uncertainty: World Pandemic Uncertainty Index

Table B.2: Stationarity test, ADF p-values, Denmark

Variable	None	Drift	Trend
Penetration Nonlife	0.69	0.03	0.00
Population	0.00	0.60	0.09
GDP per capita	0.15	0.64	0.01
Inflation	0.01	0.01	0.37
Unemployment	0.91	0.01	0.00
Banking sector	0.15	0.73	0.00
Business Confidence	0.83	0.00	0.00
Consumer Confidence	0.88	0.00	0.00
Uncertainty	0.05	0.01	0.26
Pandemic uncertainty	0.03	0.41	0.91
External trade	0.17	0.80	0.01

Table B.3: Stationarity test, ADF p-values, Greece

Variable	None	Drift	Trend
Penetration Life	0.69	0.00	0.00
Penetration Nonlife	0.72	0.00	0.00
Population	0.15	0.13	0.00
GDP per capita	0.41	0.06	0.67
Inflation	0.00	0.09	0.47
Unemployment	0.80	0.27	0.02
Banking sector	0.34	0.78	0.01
LT Interest rate	0.15	0.08	0.02
Business Confidence	0.91	0.00	0.00
Consumer Confidence	0.74	0.01	0.00
Uncertainty	0.03	0.01	0.23
Pandemic uncertainty	0.00	0.21	0.59
External trade	0.90	0.09	0.00

Table B.4: Stationarity test, ADF p-values, Italy

Variable	None	Drift	Trend
Penetration Life	0.70	0.00	0.00
Penetration Nonlife	0.60	0.00	0.00
Population	0.09	0.55	0.03
GDP per capita	0.61	0.11	0.00
Inflation	0.05	0.24	0.76
Unemployment	0.39	0.48	0.00
Banking sector	0.05	0.97	0.02
LT Interest rate	0.11	0.04	0.50
Business Confidence	0.88	0.00	0.00
Consumer Confidence	0.63	0.00	0.00
Uncertainty	0.05	0.00	0.01
Pandemic uncertainty	0.02	0.35	0.89
External trade	0.97	0.06	0.01

Table B.5: Stationarity test, ADF p-values, Latvia

Variable	None	Drift	Trend
Penetration Life	0.33	0.00	0.00
Penetration Nonlife	0.20	0.00	0.00
Population	0.01	0.00	0.03
GDP per capita	0.69	0.13	0.00
Inflation	0.00	0.02	0.93
Unemployment	0.59	0.12	0.00
Banking sector	0.15	0.92	0.00
LT Interest rate	0.18	0.42	0.30
Business Confidence	0.88	0.01	0.01
Consumer Confidence	0.97	0.02	0.01
Uncertainty	0.11	0.06	0.41
Pandemic uncertainty	0.05	0.42	0.87
External trade	0.84	0.04	0.04

Table B.6: Stationarity test, ADF p-values, Norway

Variable	None	Drift	Trend
Penetration Life	0.22	0.00	0.00
Penetration Nonlife	0.81	0.00	0.00
Population	0.01	0.50	0.04
GDP per capita	0.47	0.12	0.00
Inflation	0.15	0.01	0.14
Unemployment	0.70	0.03	0.03
Banking sector	0.96	0.02	0.00
LT Interest rate	0.16	0.13	0.70
Business Confidence	0.98	0.00	0.00
Consumer Confidence	0.00	0.05	0.00
Uncertainty	0.01	0.00	0.32
Pandemic uncertainty	0.00	0.24	0.49
External trade	0.17	0.59	0.09

Table B.7: Stationarity test, ADF p-values, Slovenia

Variable	None	Drift	Trend
Penetration Life	0.53	0.01	0.00
Penetration Nonlife	0.46	0.00	0.00
Population	0.07	0.61	0.02
GDP per capita	0.32	0.11	0.00
Inflation	0.19	0.20	0.91
Unemployment	0.00	0.24	0.14
Banking sector	0.00	0.00	0.00
LT Interest rate	0.98	0.42	0.43
Business Confidence	0.65	0.06	0.01
Consumer Confidence	0.67	0.20	0.05
Uncertainty	0.29	0.00	0.02
Pandemic uncertainty	0.01	0.21	0.82
External trade	0.97	0.01	0.01

Table B.8: Stationarity test, ADF p-values, Spain

Variable	None	Drift	Trend
Penetration Life	0.16	0.00	0.00
Penetration Nonlife	0.68	0.00	0.00
Population	0.16	0.05	0.00
GDP per capita	0.34	0.08	0.02
Inflation	0.03	0.01	0.06
Unemployment	0.68	0.31	0.21
Banking sector	0.66	0.54	0.02
LT Interest rate	0.22	0.20	0.21
Business Confidence	0.79	0.00	0.00
Consumer Confidence	0.80	0.00	0.00
Uncertainty	0.02	0.00	0.07
Pandemic uncertainty	0.00	0.26	0.53
External trade	0.92	0.10	0.00

Table B.9: ADF Test p-values for treated data, specification: levels

Variable	Czechia	Denmark	Greece	Italy	Latvia	Norway	Slovenia	Spain
Penetration Life	0.010	–	0.010	0.010	0.010	0.031	0.010	0.010
Penetration Nonlife	0.010	0.010	0.073	0.010	0.010	0.011	0.010	0.010
Population	0.010	0.010	0.066	0.019	0.010	0.028	0.010	0.010
GDP per capita	0.010	0.010	0.019	0.010	0.010	0.010	0.010	0.010
Inflation	0.010	0.010	0.033	0.010	0.010	0.010	0.015	0.010
Unemployment	0.010	0.043	0.019	0.010	0.010	0.010	0.010	0.010
Banks	0.010	0.010	0.010	0.010	0.010	0.010	0.026	0.010
LT Interest rate	0.010	0.010	0.010	0.010	0.010	0.031	0.010	0.010
Business Confidence	0.010	0.010	0.010	0.010	0.013	0.015	0.025	0.010
Consumer Confidence	0.010	0.010	0.016	0.010	0.010	0.025	0.037	0.010
Uncertainty	0.010	0.010	0.010	0.010	0.019	0.032	0.010	0.043
Pandemic uncertainty	0.010	0.010	0.016	0.010	0.010	0.010	0.010	0.010
External trade	0.010	0.041	0.010	0.010	0.010	0.036	0.039	0.010

C Data sources

Table C.1: Sources of data on premium

Country	Time period	Source
Czechia	2012–2025 Q1	Czech Insurance Association (2022) and personal communication with a staff member on 31-05-2021, 07-09-2022, and 13-06-2025.
Denmark	Non-life 2008–2025 Q1	Insurance and Pension Denmark (2023) and personal communication with a staff member on 04-12-2023.
Greece	2007–2025 Q1	Hellenic Association of Insurance Companies.
Italy	Life 2007–2025 Q1; Non-life 2012–2025 Q1	Associazione Nazionale fra le Imprese Assicuratrici.
Latvia	2008–2024 Q3	Latvian Insurers Association and personal communication with a staff member on 19-05-2021, 14-09-2022, and 16-09-2022.
Norway	Life 2001 Q3–2025 Q1; Non-life 1999 Q3–2025 Q1	Finance Norway.
Slovenia	2015–2024 Q2	Slovenian Insurance Association.
Spain	2000–2024	Personal communication with a staff member of UNESPA (Spanish Association of Insurers) on 21-05-2021, 24-05-2021, 07-09-2022, 08-09-2022, and 18-06-2025, forwarding ICEA survey results.

Notes: Personal communications were conducted via the university email account. All correspondence is available upon request for official inspection.

Currency conversions into euro were performed using the quarterly average of the official ECB exchange rate.

Table C.2: Explanatory variables' data sources

Description	Source
GDP at current prices, in million €	OECD
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, Federal Reserve Bank of St. Louis
Long-Term Interest rate	ECB, OECD
Business Confidence Index	OECD
Consumer Confidence Index	OECD, Finance Norway
World Uncertainty Index	World Uncertainty Index
Pandemic Index	World Uncertainty Index

Currency conversions into euro were conducted using the quarterly average of official exchange rate data, as provided by the ECB.

D Data visualization

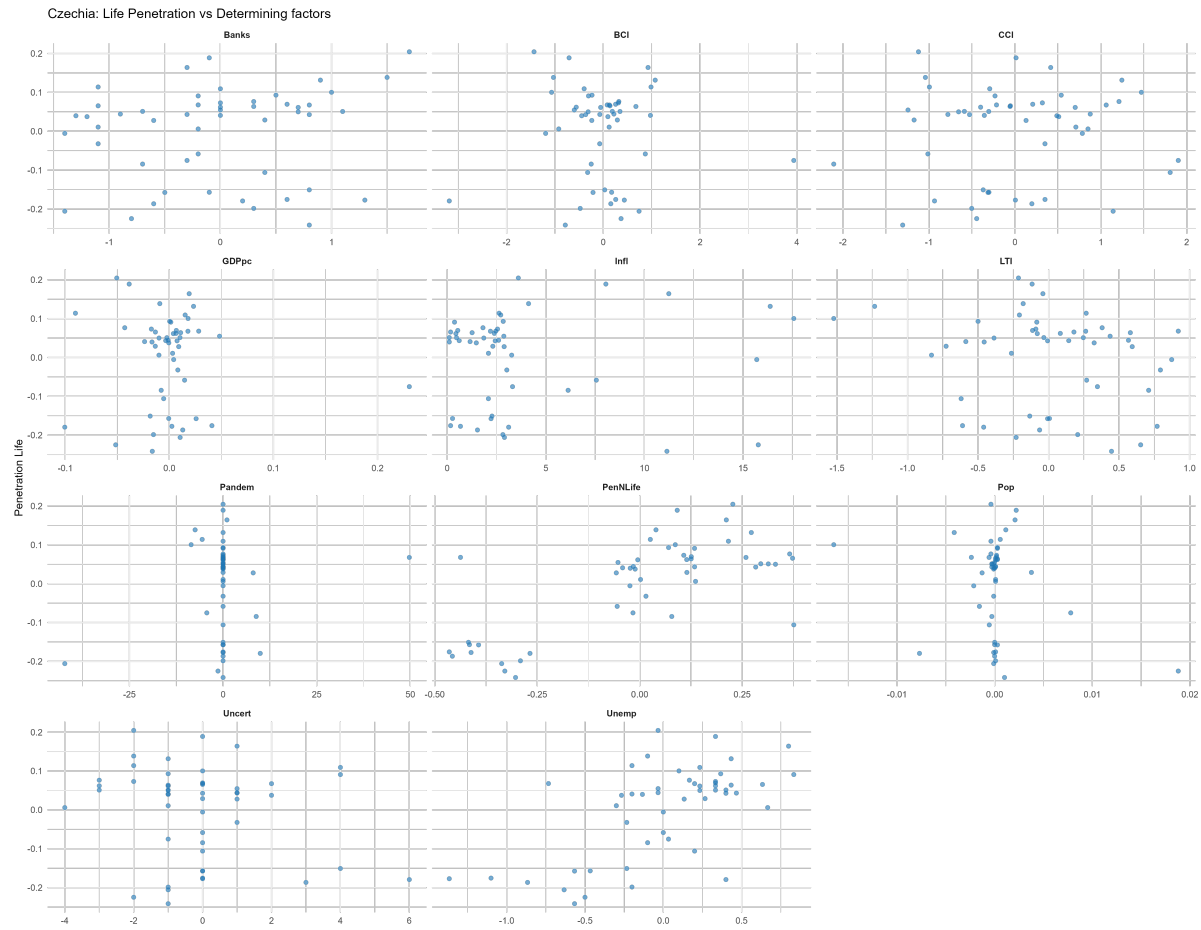


Figure D.1. Czechia – Life Insurance vs Regressors

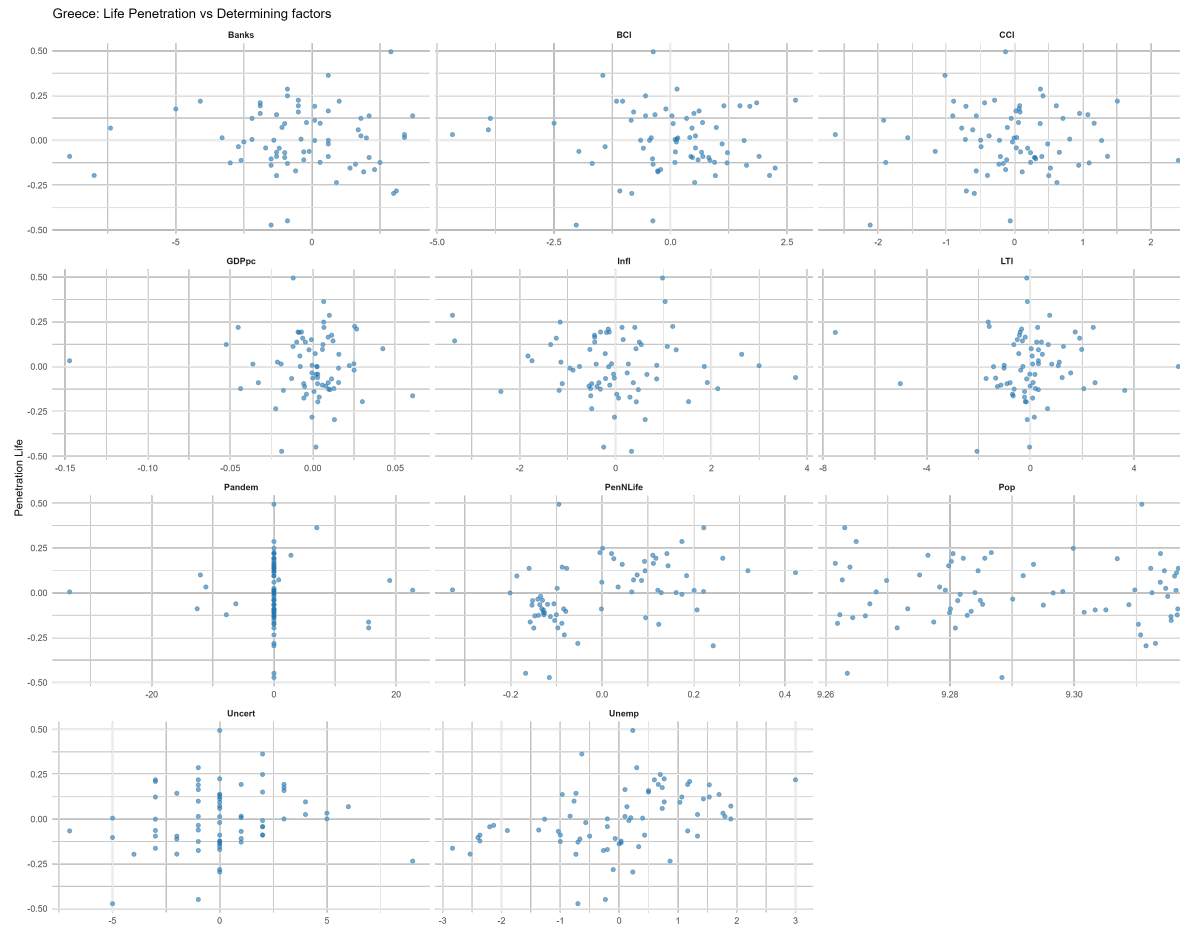


Figure D.2. Greece – Life Insurance vs Regressors

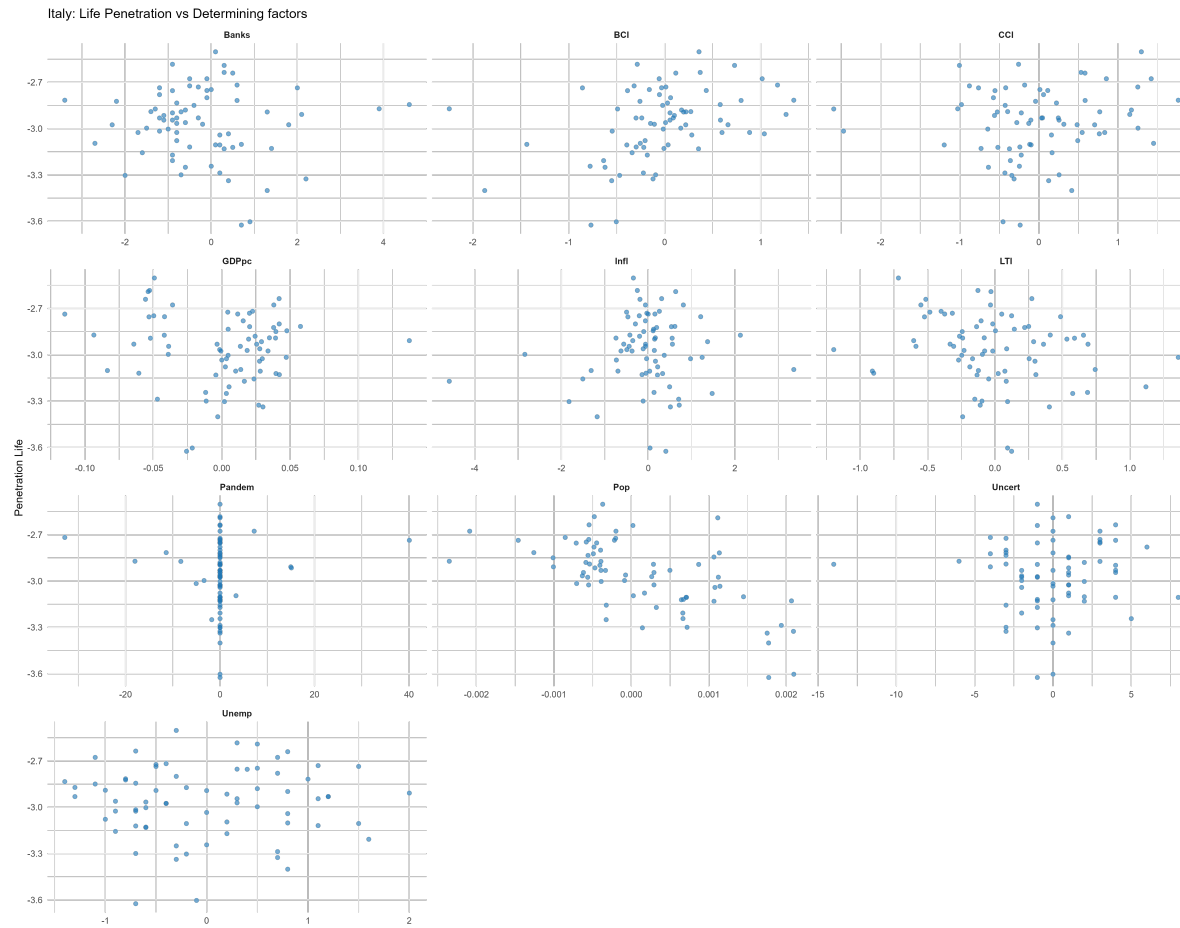


Figure D.3. Italy – Life Insurance vs Regressors

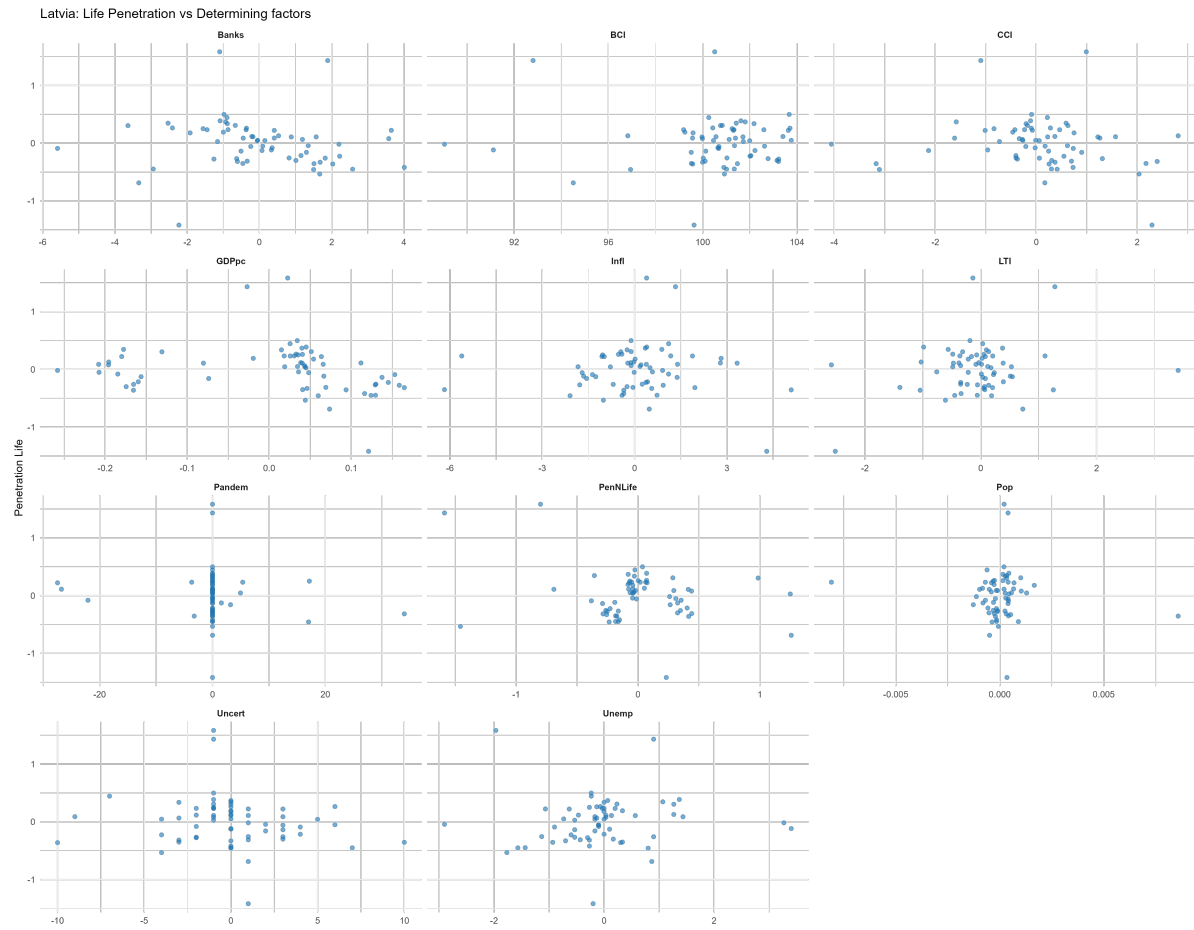


Figure D.4. Latvia – Life Insurance vs Regressors

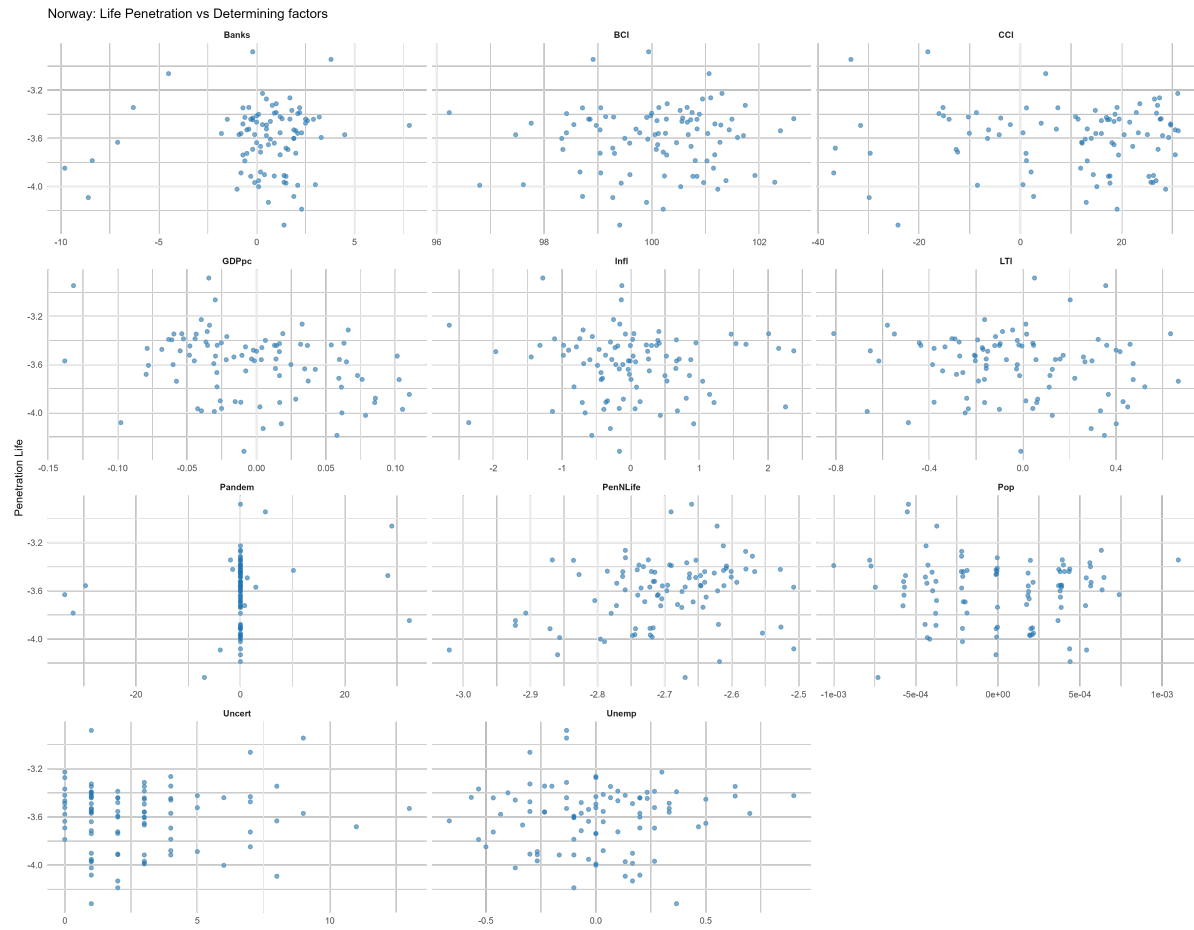


Figure D.5. Norway – Life Insurance vs Regressors

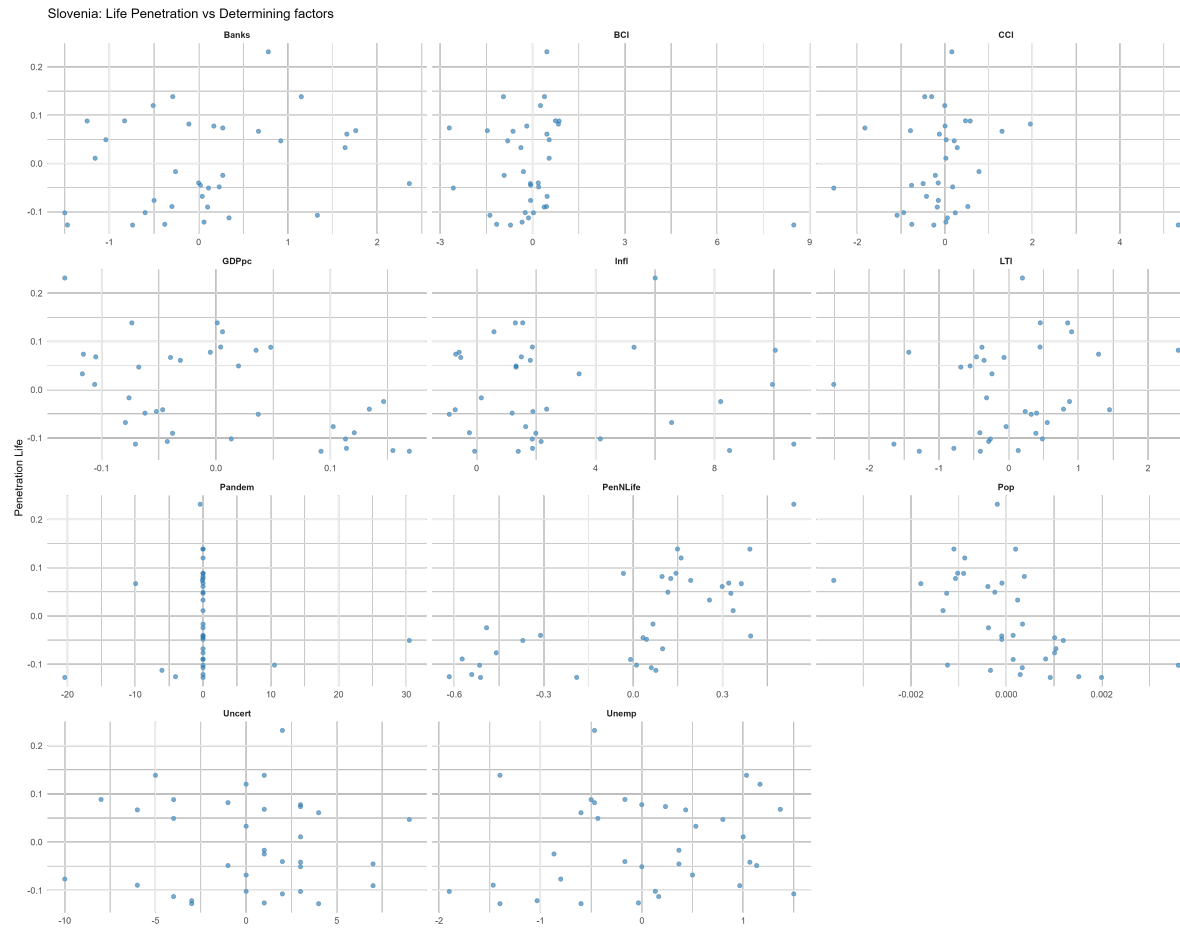


Figure D.6. Slovenia – Life Insurance vs Regressors

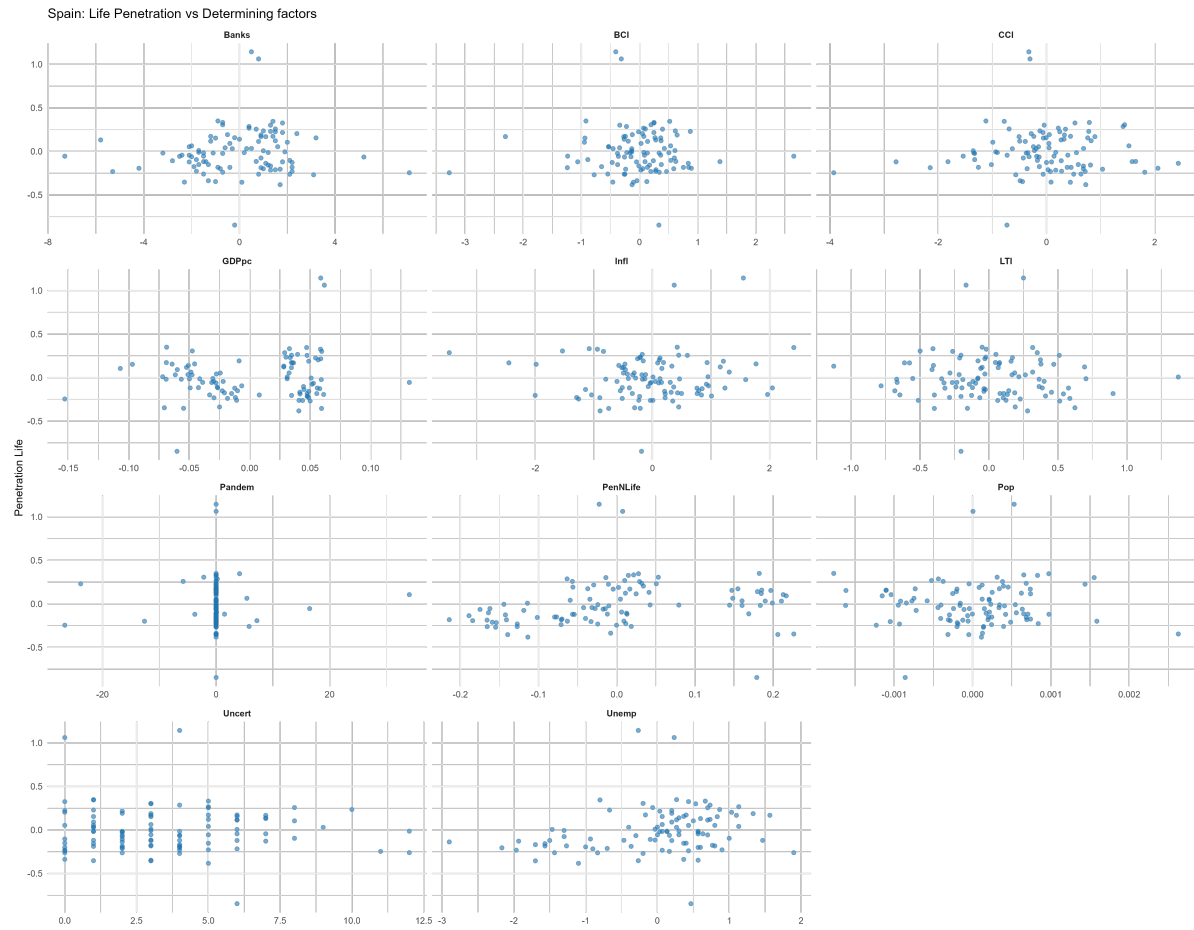


Figure D.7. Spain – Life Insurance vs Regressors

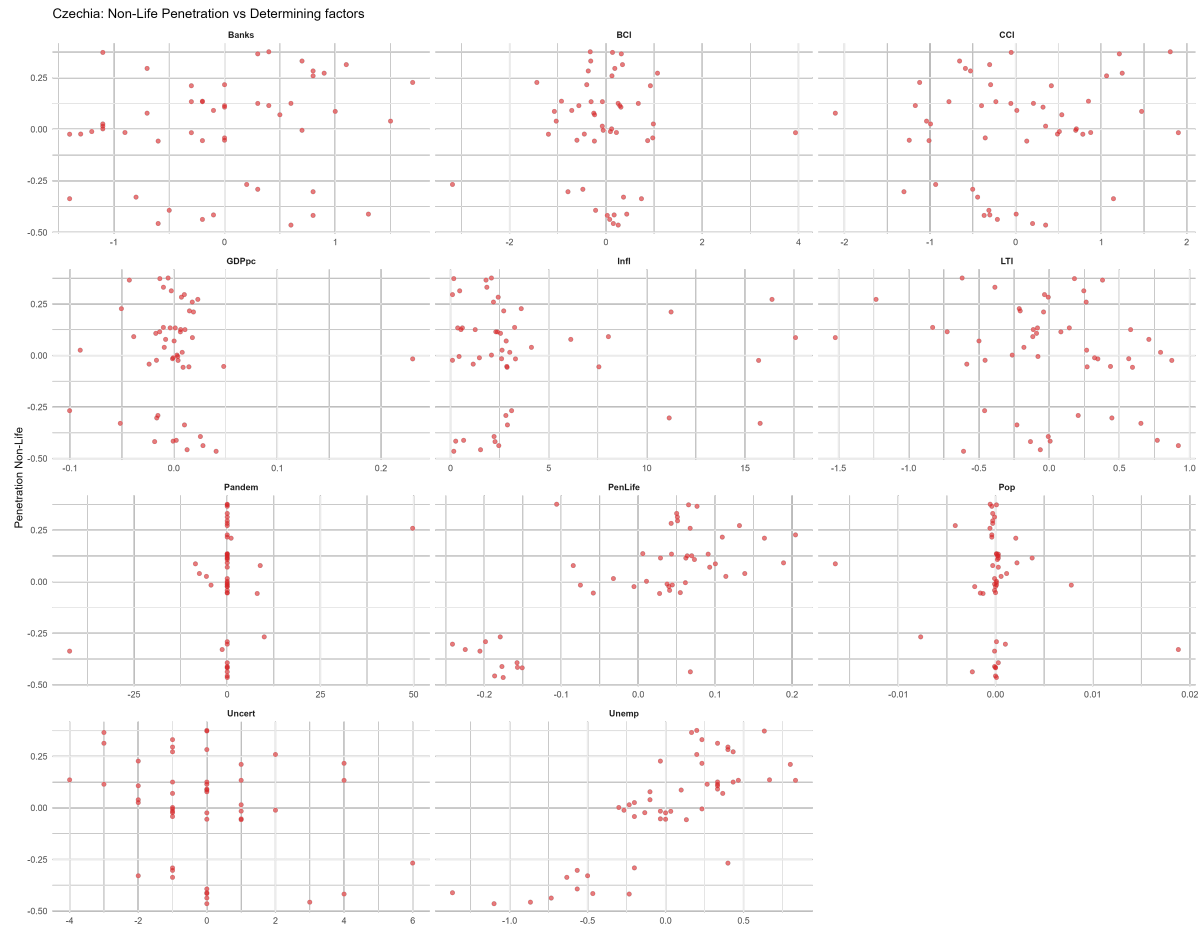


Figure D.8. Czechia – Nonlife Insurance vs Regressors

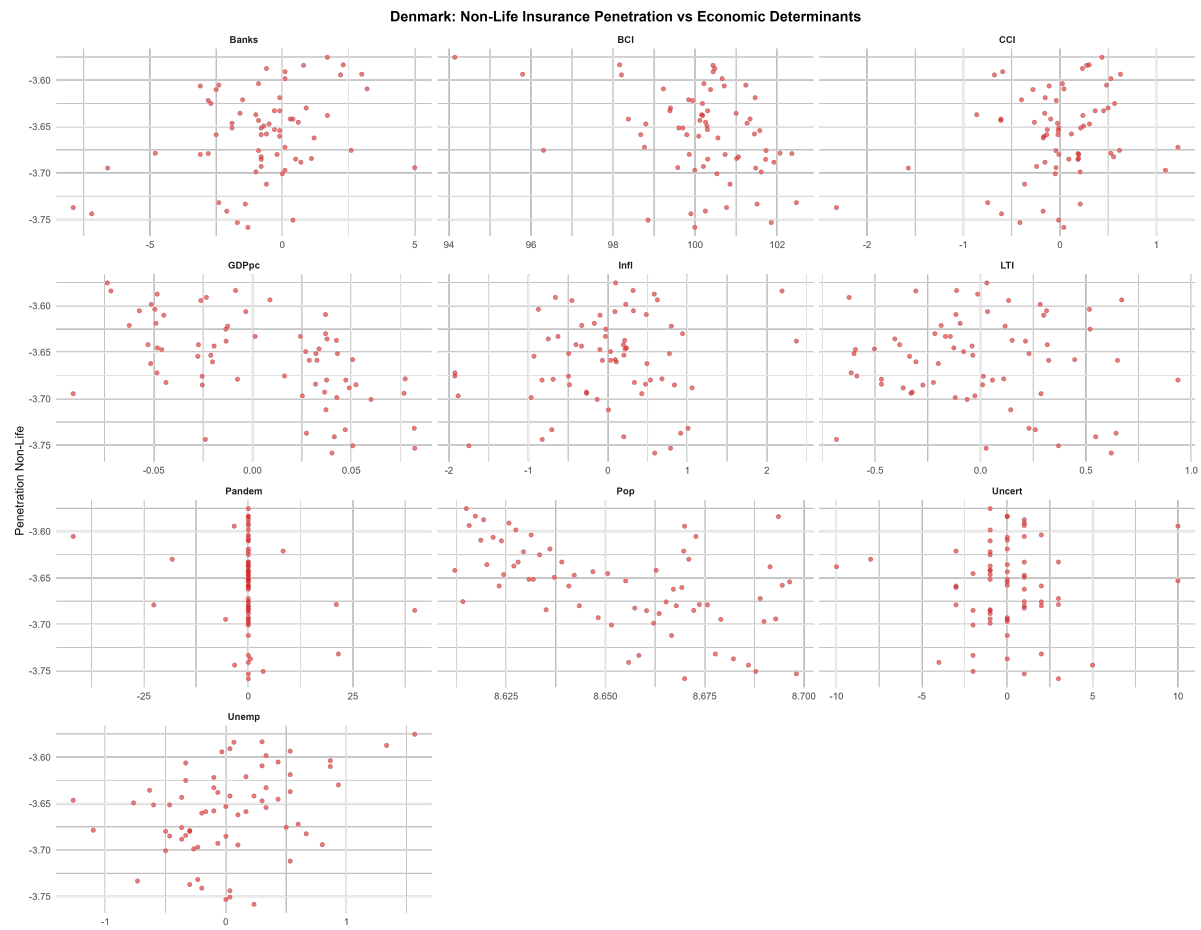


Figure D.9. Denmark – Nonlife Insurance vs Regressors

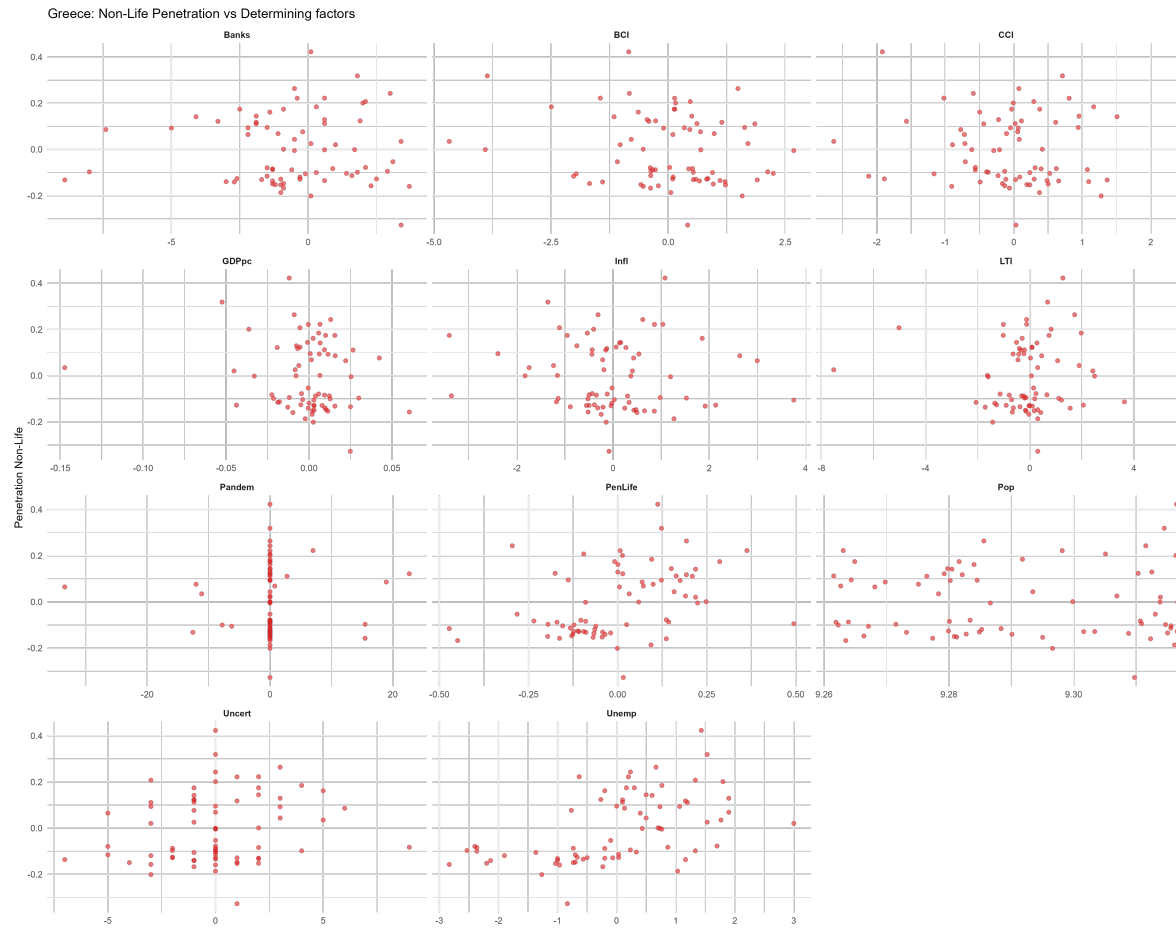


Figure D.10. Greece – Nonlife Insurance vs Regressors

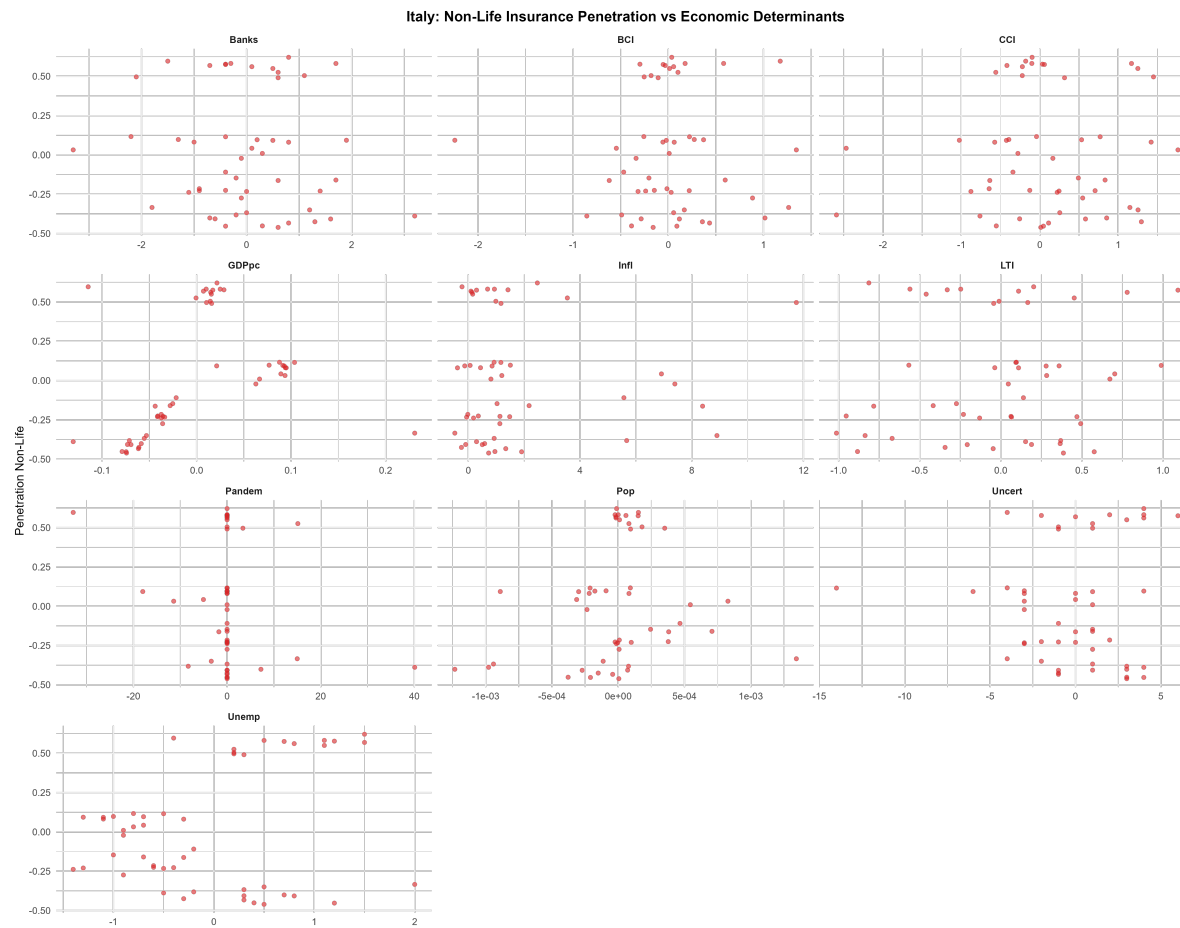


Figure D.11. Italy – Nonlife Insurance vs Regressors

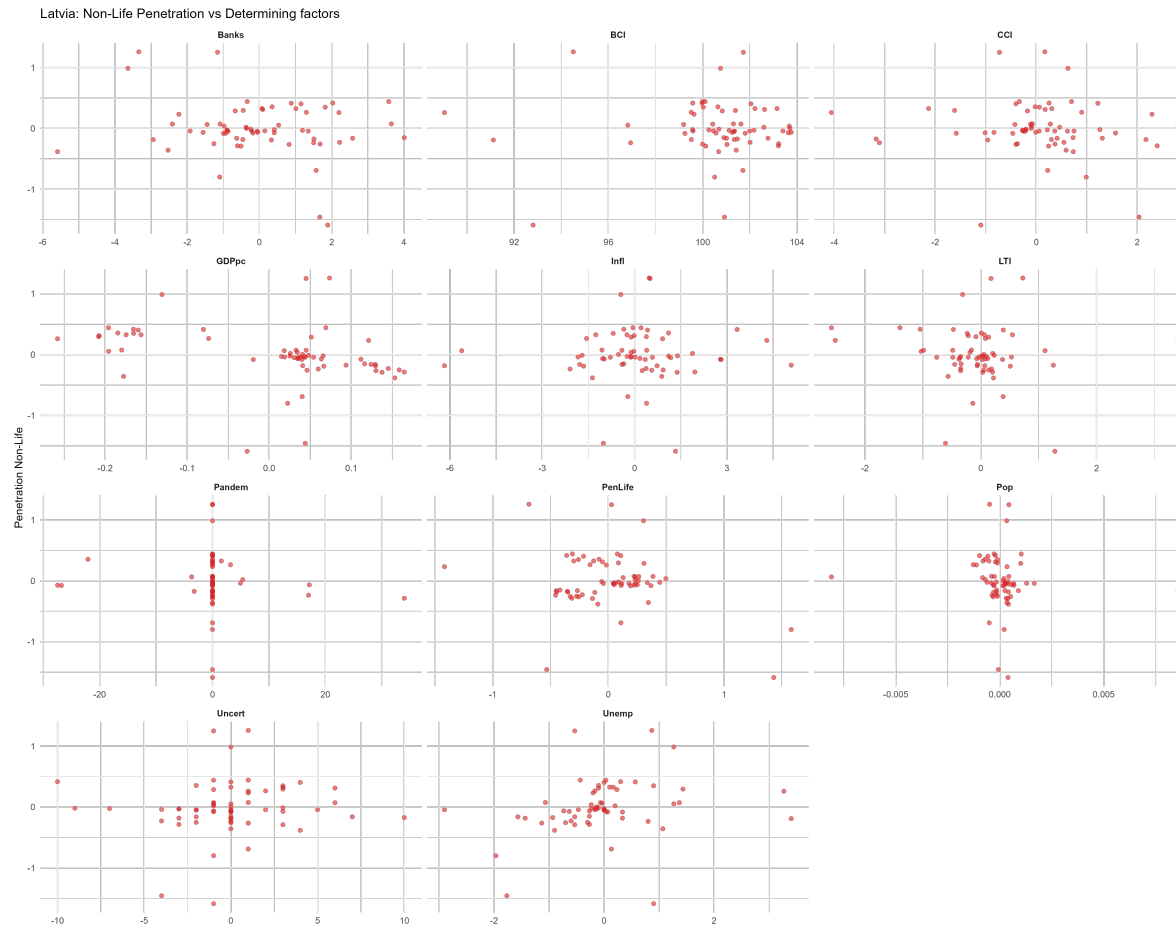


Figure D.12. Latvia – Nonlife Insurance vs Regressors

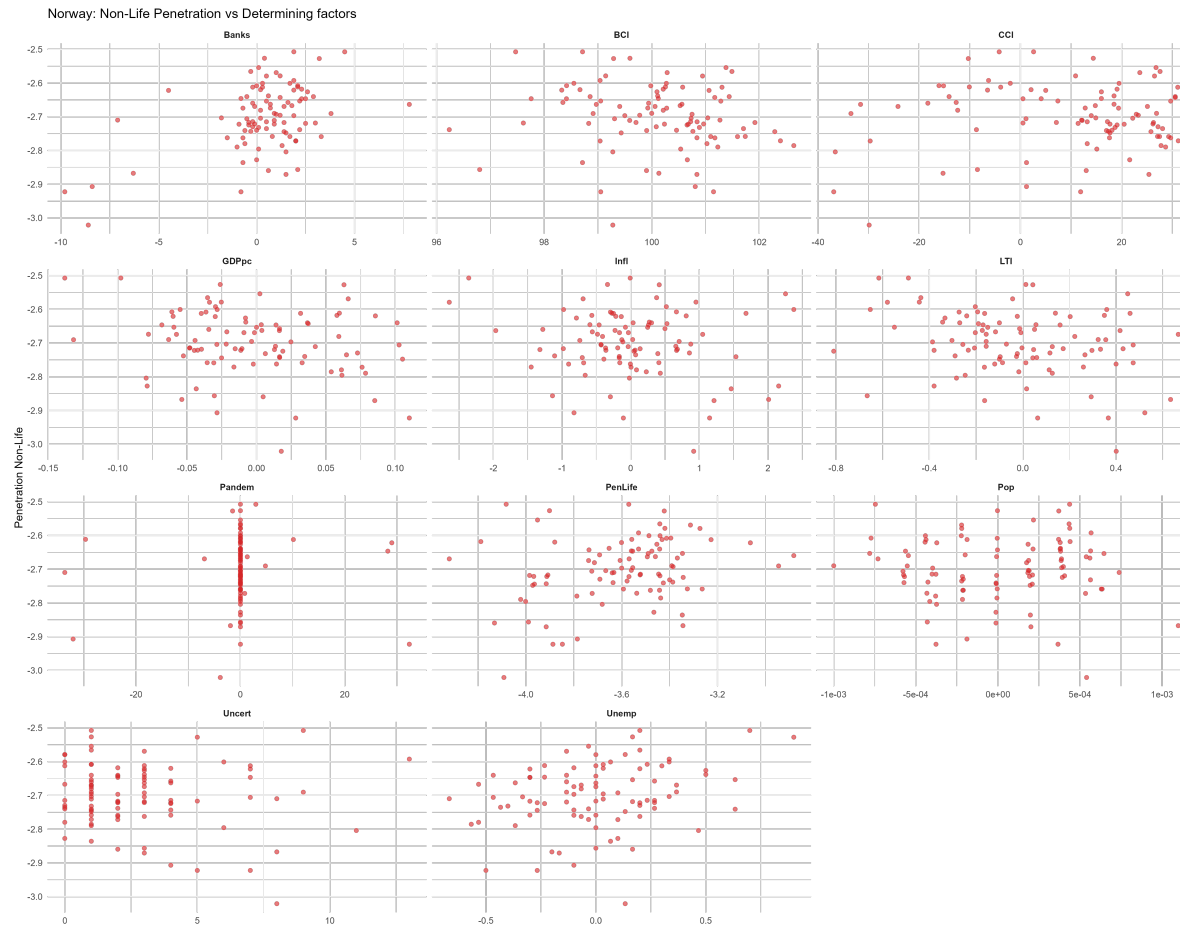


Figure D.13. Norway – Nonlife Insurance vs Regressors

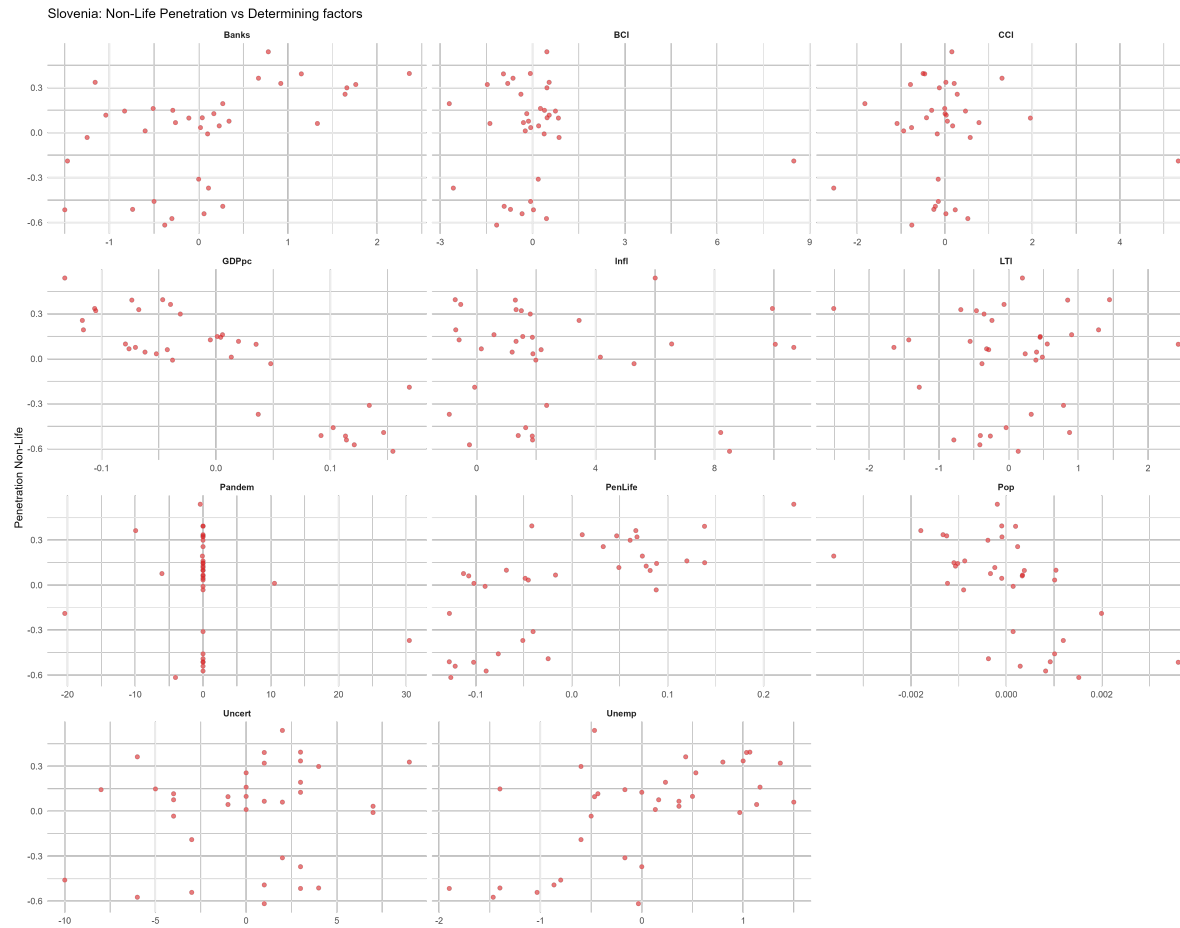


Figure D.14. Slovenia – Nonlife Insurance vs Regressors

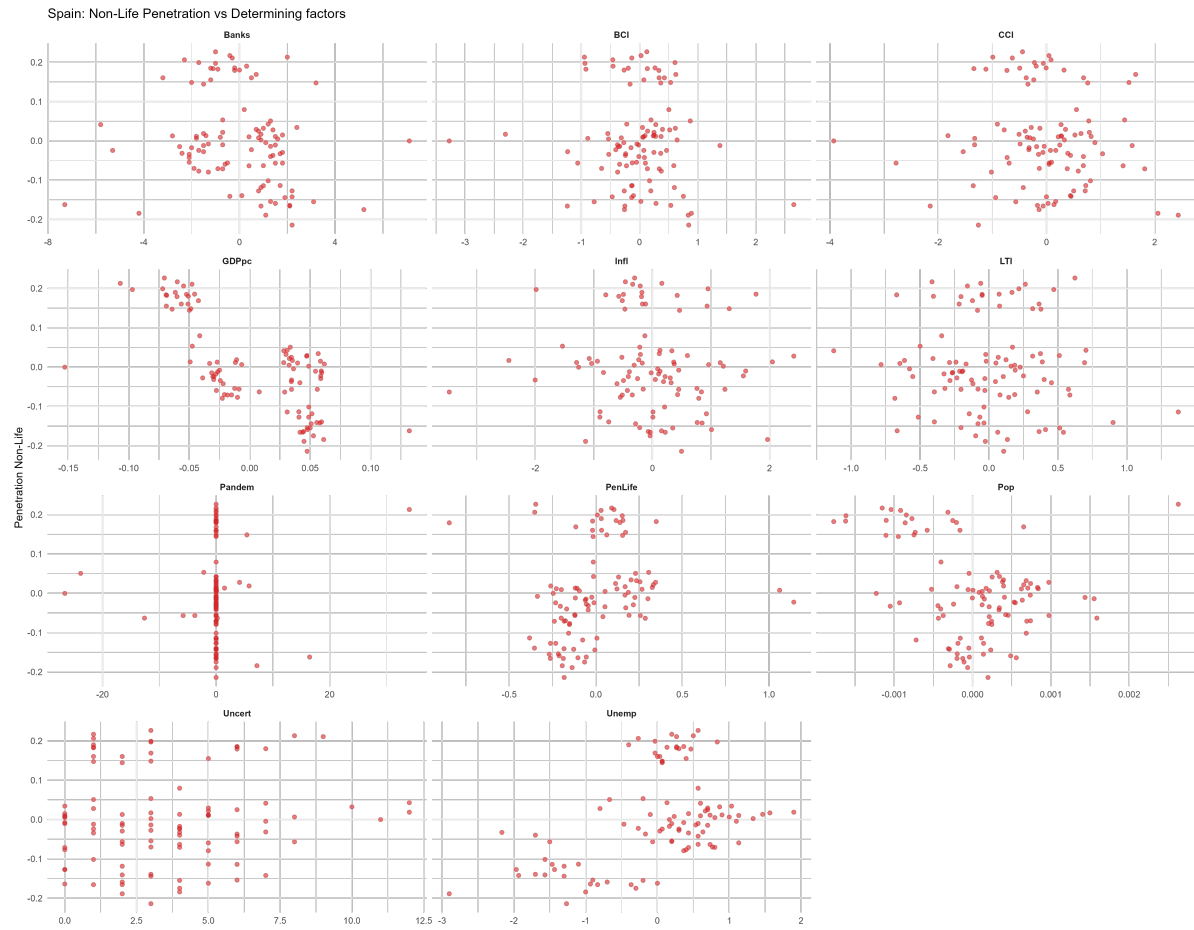


Figure D.15. Spain – Nonlife Insurance vs Regressors

E OLS - Complete models

Table E.1: OLS - Complete model - Life insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.001	0.009	0.146	0.884
Population	-9.385	3.391	-2.768	0.006
GDP per capita	-0.954	0.289	-3.299	0.001
Inflation	0.000	0.002	-0.286	0.775
Unemployment	0.110	0.033	3.346	0.001
Banking sector	-0.040	0.022	-1.840	0.066
LT Interest rate	0.065	0.026	2.469	0.014
Business Confidence	0.013	0.012	1.051	0.294
Consumer Confidence	-0.008	0.015	-0.531	0.596
Uncertainty	-0.011	0.005	-2.088	0.037
Pandemic uncertainty	-0.001	0.001	-0.608	0.544
Insurance penetration lag 1	-0.539	0.141	-3.813	0.000
Insurance penetration lag 3	-0.040	0.162	-0.249	0.803
Insurance penetration lag 4	0.326	0.198	1.650	0.099

Std. Error: Standard Error, LT: Long-term, Business Confidence: Business Confidence Index, Consumer Confidence: Consumer Confidence Index, Uncertainty: World Uncertainty Index, Pandemic Uncertainty: World Pandemic Uncertainty Index

Table E.2: OLS - Complete model - Life insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	2.207	3.221	0.685	0.493
Population	-0.238	0.347	-0.685	0.493
GDP per capita	-0.416	0.613	-0.679	0.497
Inflation	-0.005	0.007	-0.754	0.451
Unemployment	0.014	0.018	0.811	0.418
Banking sector	-0.001	0.006	-0.190	0.850
LT Interest rate	0.017	0.006	2.722	0.007
Business Confidence	0.006	0.006	0.943	0.346
Consumer Confidence	0.014	0.011	1.196	0.232
Uncertainty	0.006	0.005	1.236	0.217
Pandemic uncertainty	-0.001	0.002	-0.333	0.739
Insurance penetration lag 1	-0.790	0.088	-9.030	0.000
Insurance penetration lag 2	-0.726	0.117	-6.228	0.000
Insurance penetration lag 3	-0.717	0.090	-7.949	0.000

Table E.3: OLS - Complete model - Life insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-2.965	0.060	-49.736	0.000
Population	-71.464	42.808	-1.669	0.095
GDP per capita	0.383	0.234	1.634	0.102
Inflation	0.004	0.010	0.382	0.702
Unemployment	-0.037	0.019	-1.948	0.051
Banking sector	0.006	0.009	0.638	0.524
LT Interest rate	0.002	0.026	0.086	0.931
Business Confidence	0.076	0.022	3.438	0.001
Consumer Confidence	-0.010	0.014	-0.724	0.469
Uncertainty	-0.001	0.003	-0.271	0.786
Pandemic uncertainty	-0.001	0.001	-0.711	0.477
Insurance penetration lag 1	0.851	0.069	12.356	0.000
Insurance penetration lag 2	-0.988	0.009	-109.602	0.000
Insurance penetration lag 3	0.861	0.069	12.525	0.000
Moving average lag 1	-0.096	0.072	-1.328	0.184
Moving average lag 2	0.944	0.141	6.675	0.000

Table E.4: OLS - Complete model - Life insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.269	0.015	18.445	0.000
Population	-0.014	15.844	-0.001	0.999
GDP per capita	-0.186	0.476	-0.391	0.696
Inflation	0.009	0.011	0.868	0.386
Unemployment	0.006	0.033	0.189	0.850
Banking sector	-0.036	0.014	-2.611	0.009
LT Interest rate	-0.046	0.023	-1.969	0.049
Business Confidence	-0.003	0.000	-13.943	0.000
Consumer Confidence	-0.013	0.017	-0.766	0.444
Uncertainty	-0.002	0.007	-0.253	0.800
Pandemic uncertainty	-0.002	0.003	-0.943	0.346
Insurance penetration lag 1	-0.430	0.089	-4.811	0.000
Insurance penetration lag 2	-0.465	0.116	-4.010	0.000
Insurance penetration lag 3	-0.336	0.106	-3.159	0.002
Insurance penetration lag 4	0.440	0.110	4.016	0.000
Insurance penetration lag 5	0.072	0.068	1.057	0.291
Moving average lag 4	-0.382	0.119	-3.212	0.001

Table E.5: OLS - Complete model - Life insurance penetration - Norway

Parameter	Estimate	Std. Error	t-value	p-value
Intercept	0.187	1.540	0.121	0.903
GDP per capita	0.001	0.000	1.731	0.083
Unemployment	0.002	0.001	2.269	0.023
Banking sector	0.001	0.000	2.709	0.007
LT Interest rate	-0.003	0.001	-2.813	0.005
Consumer Confidence	0.000	0.000	0.756	0.450
Uncertainty	0.000	0.000	-1.327	0.184
Pandemic uncertainty	0.000	0.000	0.415	0.678
Insurance penetration lag 1	0.058	0.033	1.756	0.079
Insurance penetration lag 4	0.940	0.034	28.021	0.000
Moving average lag 4	-0.189	0.183	-1.033	0.301

Table E.6: OLS - Complete model - Life insurance penetration - Slovenia

	Estimate	Std. Error	t value	p value
Intercept	-0.006	0.007	-0.944	0.345
Population	-34.070	11.350	-3.002	0.003
GDP per capita	-0.367	0.179	-2.054	0.040
Inflation	0.000	0.002	0.200	0.842
Unemployment	-0.032	0.017	-1.906	0.057
Banking sector	0.023	0.015	1.482	0.138
LT Interest rate	0.030	0.012	2.485	0.013
Business Confidence	0.018	0.017	1.060	0.289
Consumer Confidence	-0.007	0.026	-0.260	0.795
Uncertainty	-0.002	0.002	-0.961	0.337
Pandemic uncertainty	0.001	0.003	0.221	0.825
Insurance penetration lag 1	-0.168	0.158	-1.062	0.288
Insurance penetration lag 2	-0.683	0.143	-4.761	0.000

Table E.7: OLS - Complete model - Life insurance penetration - Spain

	Estimate	Std. Error	t value	p value
Intercept	0.003	0.009	0.346	0.730
Population	-6.701	18.428	-0.364	0.716
GDP per capita	0.858	0.630	1.361	0.173
Inflation	-0.010	0.016	-0.605	0.545
Unemployment	-0.074	0.042	-1.751	0.080
Banking sector	0.003	0.011	0.308	0.758
LT Interest rate	-0.018	0.048	-0.365	0.715
Business Confidence	-0.062	0.029	-2.125	0.034
Consumer Confidence	0.007	0.017	0.425	0.671
Uncertainty	-0.003	0.003	-1.016	0.310
Pandemic uncertainty	-0.001	0.003	-0.177	0.859
Insurance penetration lag1	-0.147	0.153	-0.958	0.338
Insurance penetration lag2	-0.263	0.135	-1.950	0.051
Insurance penetration lag3	-0.180	0.145	-1.245	0.213
Insurance penetration lag8	0.700	0.151	4.627	0.000
Moving average lag 1	-0.512	0.193	-2.654	0.008
Moving average lag 8	-0.374	0.247	-1.514	0.130

Table E.8: OLS - Complete model - Non-life insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.000	0.001	-0.345	0.730
Population	-1.622	1.097	-1.478	0.139
GDP per capita	-0.182	0.101	-1.812	0.070
Inflation	0.000	0.001	0.650	0.516
Unemployment	0.003	0.015	0.192	0.848
Banking sector	0.005	0.006	0.867	0.386
External trade	0.021	0.077	0.274	0.785
Business Confidence	-0.002	0.005	-0.337	0.736
Consumer Confidence	-0.009	0.004	-2.068	0.039
Uncertainty	-0.005	0.002	-2.356	0.019
Pandemic uncertainty	0.001	0.001	1.341	0.180
Insurance penetration lag 1	-1.460	0.131	-11.137	0.000
Insurance penetration lag 2	-1.458	0.132	-11.025	0.000
Insurance penetration lag 3	-1.455	0.131	-11.082	0.000
Insurance penetration lag 4	-0.462	0.132	-3.502	0.000

Table E.9: OLS - Complete model - Non-life insurance penetration - Denmark

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-3.452	0.253	-13.625	0.000
GDP per capita	-0.737	0.036	-20.575	0.000
Inflation	-0.001	0.002	-0.334	0.738
Unemployment	-0.000	0.004	-0.022	0.982
Banking sector	0.005	0.001	4.126	0.000
External trade	-0.612	0.099	-6.205	0.000
Business Confidence	0.002	0.003	0.779	0.436
Consumer Confidence	-0.008	0.004	-2.171	0.030
Uncertainty	-0.001	0.000	-1.935	0.053
Pandemic uncertainty	0.000	0.000	0.395	0.693
Insurance penetration lag 1	0.881	0.127	6.947	0.000
Insurance penetration lag 2	-0.335	0.140	-2.389	0.017
Insurance penetration lag 3	0.282	0.136	2.069	0.039
Insurance penetration lag 4	0.301	0.126	2.383	0.017
Insurance penetration lag 5	0.193	0.121	1.590	0.112
Insurance penetration lag 6	-0.557	0.114	-4.885	0.000
Insurance penetration lag 7	0.676	0.148	4.567	0.000
Insurance penetration lag 8	-0.470	0.135	-3.480	0.001

Table E.10: OLS - Complete model - Non-life insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	11.230	0.194	57.767	0.000
Population	-1.201	0.022	-55.131	0.000
GDP per capita	-0.454	0.606	-0.749	0.454
Inflation	-0.004	0.009	-0.479	0.632
Unemployment	0.000	0.016	0.008	0.994
Banking sector	0.002	0.006	0.365	0.715
External trade	-0.144	0.065	-2.236	0.025
Business Confidence	0.003	0.008	0.339	0.734
Consumer Confidence	0.021	0.013	1.638	0.101
Uncertainty	0.008	0.005	1.619	0.105
Pandemic uncertainty	-0.002	0.002	-0.879	0.379
Insurance penetration lag 1	-0.684	0.087	-7.843	0.000
Insurance penetration lag 2	-0.725	0.098	-7.400	0.000
Insurance penetration lag 3	-0.568	0.096	-5.937	0.000

Table E.11: OLS - Complete model - Non-life insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.000	4.670	0.000
Population	12.441	4.797	2.593	0.010
GDP per capita	-0.784	0.063	-12.429	0.000
Inflation	0.000	0.000	0.773	0.440
Unemployment	0.010	0.001	6.476	0.000
Banking sector	0.007	0.003	2.603	0.009
External trade	0.238	0.035	6.816	0.000
Business Confidence	-0.002	0.001	-1.053	0.293
Consumer Confidence	0.002	0.002	1.508	0.131
Uncertainty	0.001	0.001	1.262	0.207
Pandemic uncertainty	-0.001	0.000	-8.803	0.000
Insurance penetration lag 1	-0.998	0.011	-91.625	0.000
Insurance penetration lag 2	-0.995	0.011	-89.318	0.000
Insurance penetration lag 3	-0.997	0.003	-349.982	0.000
Moving average lag 1	-0.935	0.523	-1.788	0.074

Table E.12: OLS - Complete model - Non-life insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.339	0.011	-29.621	0.000
Population	-0.004	13.586	0.000	1.000
GDP per capita	-1.643	0.203	-8.088	0.000
Inflation	-0.004	0.009	-0.452	0.651
Unemployment	-0.016	0.027	-0.595	0.552
External trade	0.175	0.183	0.958	0.338
Business Confidence	0.004	0.000	23.404	0.000
Consumer Confidence	0.009	0.014	0.612	0.540
Uncertainty	-0.004	0.006	-0.677	0.499
Pandemic uncertainty	-0.001	0.002	-0.536	0.592
Insurance penetration lag 1	-0.402	0.071	-5.645	0.000
Insurance penetration lag 2	-0.529	0.066	-8.000	0.000
Insurance penetration lag 3	-0.295	0.099	-2.974	0.003
Insurance penetration lag 4	-0.179	0.066	-2.692	0.007
Insurance penetration lag 5	-0.092	0.057	-1.629	0.103
Insurance penetration lag 6	-0.024	0.052	-0.466	0.641
Insurance penetration lag 8	-0.154	0.068	-2.269	0.023

Table E.13: OLS – Complete model – Non-life insurance penetration – Norway

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-2.554	0.663	-3.850	0.000
Population	26.633	6.342	4.199	0.000
GDP per capita	-0.364	0.051	-7.134	0.000
Inflation	0.002	0.003	0.631	0.528
Unemployment	0.058	0.013	4.575	0.000
Banking sector	0.012	0.003	5.000	0.000
External trade	0.074	0.039	1.885	0.060
Business Confidence	-0.004	0.007	-0.599	0.549
Consumer Confidence	0.003	0.001	3.407	0.001
Uncertainty	0.001	0.002	0.609	0.543
Pandemic uncertainty	0.000	0.000	-0.032	0.974
Insurance penetration lag 1	0.719	0.102	7.051	0.000
Insurance penetration lag 2	0.160	0.106	1.516	0.130

Table E.14: OLS - Complete model - Non-life insurance penetration - Slovenia

Variable	Estimate	Std. Error	t-value	p-value
intercept	0.002	0.001	1.894	0.058
Population	14.931	6.927	2.156	0.031
GDP per capita	-0.876	0.256	-3.421	0.001
Inflation	-0.001	0.000	-3.621	0.000
Unemployment	0.012	0.015	0.808	0.419
Banking sector	-0.001	0.010	-0.134	0.893
External trade	-0.153	0.051	-2.994	0.003
Business Confidence	-0.008	0.009	-0.865	0.387
Consumer Confidence	0.009	0.011	0.756	0.450
Uncertainty	0.000	0.001	0.087	0.931
Pandemic uncertainty	-0.001	0.002	-0.363	0.717
Insurance penetration lag 1	-0.968	0.038	-25.453	0.000
Insurance penetration lag 2	-0.980	0.029	-34.259	0.000
Insurance penetration lag 3	-0.958	0.032	-30.112	0.000
Moving average lag 1	-1.000	0.109	-9.161	0.000

Table E.15: OLS - Complete model - Non-life insurance penetration - Spain

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.007	0.010	-0.713	0.476
Population	4.507	1.782	2.529	0.011
GDP per capita	-0.843	0.058	-14.505	0.000
Inflation	-0.002	0.001	-1.566	0.117
Unemployment	-0.005	0.004	-1.064	0.287
Banking sector	-0.002	0.001	-1.938	0.053
External trade	0.014	0.016	0.901	0.368
Business Confidence	0.006	0.002	2.582	0.010
Consumer Confidence	-0.008	0.001	-6.466	0.000
Pandemic uncertainty	0.000	0.000	-0.525	0.599
Insurance penetration lag 1	-0.546	0.049	-11.147	0.000
Insurance penetration lag 2	-0.522	0.053	-9.907	0.000
Insurance penetration lag 3	-0.518	0.050	-10.378	0.000
Insurance penetration lag 4	0.454	0.048	9.504	0.000
Moving average lag 3	0.539	0.069	7.768	0.000

F OLS - Variable selection models

Table F.1: OLS - Variable Selection Model - Life insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.001	0.007	-0.108	0.914
Population	-7.761	2.679	-2.897	0.004
GDP per capita	-0.804	0.236	-3.404	0.001
Unemployment	0.101	0.032	3.142	0.002
Banking sector	-0.039	0.017	-2.309	0.021
LT Interest rate	0.062	0.026	2.409	0.016
Uncertainty	-0.012	0.005	-2.492	0.013
Insurance penetration lag 1	-0.540	0.120	-4.483	0.000
Insurance penetration lag 4	0.363	0.121	3.004	0.003

Table F.2: OLS - Variable Selection Model - Life insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.015	0.118	0.906
Unemployment	0.023	0.015	1.591	0.112
LT Interest rate	0.016	0.007	2.442	0.015
Consumer Confidence	0.019	0.008	2.253	0.024
Insurance penetration lag 1	-0.772	0.088	-8.751	0.000
Insurance penetration lag 2	-0.676	0.110	-6.137	0.000
Insurance penetration lag 3	-0.691	0.091	-7.555	0.000

Table F.3: OLS - Variable Selection Model - Life insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-2.967	0.060	-49.402	0.000
Population	-67.378	41.162	-1.637	0.102
GDP per capita	0.440	0.215	2.044	0.041
Unemployment	-0.046	0.017	-2.710	0.007
Business Confidence	0.065	0.020	3.297	0.001
Insurance penetration lag 1	0.850	0.068	12.491	0.000
Insurance penetration lag 2	-0.988	0.008	-125.208	0.000
Insurance penetration lag 3	0.860	0.068	12.615	0.000
Moving average lag 1	-0.097	0.064	-1.509	0.131
Moving average lag 2	0.974	0.215	4.541	0.000

Table F.4: OLS - Variable Selection Model - Life insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.228	0.010	22.999	0.000
Inflation	0.010	0.008	1.273	0.203
Banking sector	-0.032	0.014	-2.357	0.018
LT Interest rate	-0.031	0.019	-1.653	0.098
Business Confidence	-0.002	0.000	-15.102	0.000
Pandemic uncertainty	-0.002	0.002	-0.974	0.330
Insurance penetration lag 1	-0.454	0.084	-5.373	0.000
Insurance penetration lag 2	-0.524	0.117	-4.500	0.000
Insurance penetration lag 3	-0.390	0.109	-3.561	0.000
Insurance penetration lag 4	0.397	0.102	3.877	0.000
Insurance penetration lag 5	0.036	0.065	0.555	0.579
Moving average lag 4	-0.400	0.120	-3.333	0.001

Table F.5: OLS - Variable Selection Model - Life insurance penetration - Norway

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.028	0.008	3.629	0.000
GDP per capita	0.001	0.000	1.575	0.115
Unemployment	0.002	0.001	1.998	0.046
Banking sector	0.001	0.000	2.650	0.008
LT Interest rate	-0.003	0.001	-2.640	0.008
Consumer Confidence	0.000	0.000	0.976	0.329
Uncertainty	0.000	0.000	-1.167	0.243
Pandemic uncertainty	0.000	0.000	0.388	0.698
Insurance penetration lag 4	0.916	0.086	10.603	0.000
Moving average lag 4	-0.199	0.178	-1.119	0.263

Table F.6: OLS - Variable Selection Model - Life insurance penetration - Slovenia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.004	0.006	-0.762	0.446
Population	-36.526	11.426	-3.197	0.001
GDP per capita	-0.523	0.139	-3.750	0.000
Unemployment	-0.036	0.013	-2.744	0.006
LT Interest rate	0.038	0.010	3.651	0.000
Business Confidence	0.016	0.007	2.439	0.015
Insurance penetration lag 2	-0.615	0.137	-4.494	0.000

Table F.7: OLS - Variable Selection Model - Life insurance penetration - Spain

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.006	0.004	-1.316	0.188
Unemployment	-0.091	0.039	-2.310	0.021
Business Confidence	-0.053	0.018	-2.865	0.004
Insurance penetration lag 1	-0.262	0.138	-1.900	0.057
Insurance penetration lag 2	-0.345	0.120	-2.868	0.004
Insurance penetration lag 3	-0.287	0.125	-2.298	0.022
Insurance penetration lag 8	0.619	0.129	4.797	0.000
Moving average lag 1	-0.356	0.157	-2.262	0.024
Moving average lag 8	-0.291	0.153	-1.908	0.056

Table F.8: OLS - Variable Selection model - Non-life insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.000	0.001	0.635	0.526
Population	-1.378	0.945	-1.458	0.145
GDP per capita	-0.232	0.093	-2.496	0.013
Banking sector	0.008	0.006	1.405	0.160
External trade	0.014	0.047	0.302	0.763
Consumer Confidence	-0.006	0.004	-1.446	0.148
Uncertainty	-0.004	0.002	-2.293	0.022
Insurance penetration lag 1	-1.482	0.126	-11.764	0.000
Insurance penetration lag 2	-1.479	0.127	-11.622	0.000
Insurance penetration lag 3	-1.476	0.126	-11.708	0.000
Insurance penetration lag 4	-0.483	0.127	-3.816	0.000

Table F.9: OLS - Variable Selection model - Non-life insurance penetration - Denmark

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-3.461	0.256	-13.537	0.000
GDP per capita	-0.727	0.029	-25.246	0.000
Banking sector	0.005	0.001	4.221	0.000
External trade	-0.605	0.099	-6.126	0.000
Business Confidence	0.002	0.003	0.786	0.432
Consumer Confidence	-0.009	0.004	-2.478	0.013
Uncertainty	-0.001	0.000	-1.957	0.050
Insurance penetration lag 1	0.859	0.127	6.790	0.000
Insurance penetration lag 2	-0.309	0.140	-2.215	0.027
Insurance penetration lag 3	0.279	0.122	2.278	0.023
Insurance penetration lag 4	0.303	0.122	2.489	0.013
Insurance penetration lag 5	0.184	0.121	1.514	0.130
Insurance penetration lag 6	-0.547	0.114	-4.789	0.000
Insurance penetration lag 7	0.647	0.137	4.735	0.000
Insurance penetration lag 8	-0.446	0.132	-3.372	0.001

Table F.10: OLS - Variable Selection model - Non-life insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	5.081	0.355	14.330	0.000
Population	-0.543	0.038	-14.199	0.000
Inflation	-0.012	0.005	-2.234	0.025
External trade	-0.068	0.039	-1.729	0.084
Uncertainty	0.008	0.005	1.806	0.071
Insurance penetration lag 1	-0.690	0.079	-8.731	0.000
Insurance penetration lag 2	-0.693	0.083	-8.356	0.000
Insurance penetration lag 3	-0.570	0.085	-6.711	0.000

Table F.11: OLS - Variable Selection model - Non-life insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.001	0.001	2.442	0.015
Population	12.503	4.309	2.901	0.004
GDP per capita	-0.705	0.077	-9.163	0.000
Unemployment	0.005	0.003	1.505	0.132
Banking sector	0.004	0.001	2.867	0.004
External trade	0.152	0.066	2.302	0.021
Insurance penetration lag 1	-1.000	0.010	-104.302	0.000
Insurance penetration lag 2	-0.998	0.010	-102.008	0.000
Insurance penetration lag 3	-0.997	0.002	-455.581	0.000
Moving average lag 1	-0.493	0.113	-4.355	0.000

Table F.12: OLS - Variable Selection model - Non-life insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.009	0.003	2.807	0.005
GDP per capita	-1.644	0.123	-13.407	0.000
Inflation	-0.007	0.004	-1.616	0.106
Unemployment	-0.051	0.013	-3.857	0.000
External trade	0.428	0.125	3.416	0.001
Uncertainty	-0.007	0.003	-2.703	0.007
Insurance penetration lag 1	-0.477	0.030	-15.844	0.000
Insurance penetration lag 2	-0.557	0.026	-21.834	0.000
Insurance penetration lag 3	-0.479	0.037	-13.079	0.000
Insurance penetration lag 4	-0.159	0.042	-3.742	0.000
Insurance penetration lag 5	-0.133	0.030	-4.390	0.000
Insurance penetration lag 6	-0.087	0.034	-2.581	0.010
Insurance penetration lag 8	-0.278	0.035	-7.957	0.000

Table F.13: OLS - Variable Selection model - Non-life insurance penetration - Norway

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-2.951	0.058	-51.013	0.000
Population	26.483	6.251	4.237	0.000
GDP per capita	-0.371	0.051	-7.320	0.000
Unemployment	0.059	0.012	4.768	0.000
Banking sector	0.012	0.002	5.427	0.000
External trade	0.075	0.039	1.917	0.055
Consumer Confidence	0.003	0.001	3.564	0.000
Insurance penetration lag 1	0.711	0.101	7.036	0.000
Insurance penetration lag 2	0.163	0.106	1.544	0.123

Table F.14: OLS - Variable Selection model - Non-life insurance penetration - Slovenia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.001	1.894	0.058
Population	14.931	6.927	2.156	0.031
GDP per capita	-0.876	0.256	-3.421	0.001
Inflation	-0.001	0.000	-3.621	0.000
Unemployment	0.012	0.015	0.808	0.419
Banking sector	-0.001	0.010	-0.134	0.893
External trade	-0.153	0.051	-2.994	0.003
Business Confidence	-0.008	0.009	-0.865	0.387
Consumer Confidence	0.009	0.011	0.756	0.450
Uncertainty	0.000	0.001	0.087	0.931
Pandemic uncertainty	-0.001	0.002	-0.363	0.717
Insurance penetration lag 1	-0.968	0.038	-25.453	0.000
Insurance penetration lag 2	-0.980	0.029	-34.259	0.000
Insurance penetration lag 3	-0.958	0.032	-30.112	0.000
Moving average lag 1	-1.000	0.109	-9.161	0.000

Table F.15: OLS - Variable Selection model - Non-life insurance penetration - Spain

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.001	2.151	0.032
Population	4.141	1.600	2.589	0.010
GDP per capita	-0.848	0.056	-15.143	0.000
Banking sector	-0.001	0.001	-1.548	0.122
Business Confidence	0.007	0.002	3.540	0.000
Consumer Confidence	-0.006	0.001	-6.714	0.000
Insurance penetration lag 1	-0.583	0.043	-13.515	0.000
Insurance penetration lag 2	-0.566	0.046	-12.342	0.000
Insurance penetration lag 3	-0.553	0.044	-12.710	0.000
Insurance penetration lag 4	0.414	0.040	10.322	0.000
Moving average lag 3	0.529	0.057	9.338	0.000

G Test statistics

Table G.1: Life insurance penetration - complete models, Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.103	0.183	0.172
Greece	0.178	0.251	0.437
Italy	0.424	0.266	0.363
Latvia	0.848	0.262	0.497
Norway	0.143	0.451	0.125
Slovenia	0.327	0.439	0.306
Spain	0.974	0.974	0.963

Table G.2: Life insurance penetration - complete models, Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.436	0.719	0.918
Greece	0.669	0.950	0.954
Italy	0.113	0.299	0.359
Latvia	0.994	0.060	0.237
Norway	0.462	0.597	0.306
Slovenia	0.930	0.940	0.922
Spain	0.246	0.050	0.052

Table G.3: Life insurance penetration - complete models, Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.190	—
Greece	0.604	—
Italy	0.866	—
Latvia	—	6.9
Norway	—	2.0
Slovenia	0.690	—
Spain	0.095	—

Table G.4: Nonlife insurance penetration - complete models, Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.353	0.558	0.834
Denmark	0.369	0.303	0.458
Greece	0.835	0.680	0.862
Italy	0.354	0.457	0.771
Latvia	0.934	0.228	0.448
Norway	0.179	0.351	0.329
Slovenia	0.681	0.701	0.829
Spain	0.957	0.566	0.820

Table G.5: Nonlife insurance penetration - complete models, Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.864	0.753	0.884
Denmark	0.623	0.937	0.866
Greece	0.744	0.892	0.955
Italy	0.480	0.448	0.206
Latvia	0.996	0.642	0.904
Norway	0.915	0.706	0.861
Slovenia	0.258	0.514	0.835
Spain	0.994	1.000	1.000

Table G.6: Nonlife insurance penetration - complete models, Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.120	—
Denmark	0.984	—
Greece	—	3.2
Italy	0.824	—
Latvia	—	6.6
Norway	0.708	—
Slovenia	0.734	—
Spain	—	2.0

Table G.7: Life insurance penetration - variable selection models, Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.066	0.204	0.120
Greece	0.282	0.368	0.578
Italy	0.307	0.176	0.286
Latvia	0.928	0.265	0.517
Norway	0.303	0.596	0.183
Slovenia	0.156	0.109	0.050
Spain	0.815	0.920	0.864

Table G.8: Life insurance penetration - variable selection models, Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.655	0.864	0.975
Greece	0.318	0.742	0.824
Italy	0.077	0.272	0.419
Latvia	0.996	0.050	0.209
Norway	0.632	0.566	0.271
Slovenia	0.395	0.816	0.801
Spain	0.363	0.151	0.050

Table G.9: Life insurance penetration - variable selection models, Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.262	–
Greece	0.543	–
Italy	0.703	–
Latvia	–	6.9
Norway	–	3.0
Slovenia	0.901	–
Spain	0.247	–

Table G.10: Nonlife insurance penetration - variable selection models, Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.179	0.158	0.318
Denmark	0.448	0.436	0.553
Greece	0.600	0.413	0.625
Italy	0.301	0.563	0.750
Latvia	0.915	0.539	0.651
Norway	0.112	0.231	0.240
Slovenia	0.681	0.701	0.829
Spain	0.907	0.566	0.820

Table G.11: Nonlife insurance penetration - variable selection models, Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.881	0.793	0.892
Denmark	0.569	0.845	0.852
Greece	0.833	0.938	0.979
Italy	0.404	0.559	0.434
Latvia	0.997	0.961	0.995
Norway	0.902	0.536	0.797
Slovenia	0.258	0.514	0.835
Spain	0.994	0.999	1.000

Table G.12: Nonlife insurance penetration - variable selection models, Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.094	–
Denmark	0.998	–
Greece	–	5.3
Italy	0.650	–
Latvia	–	2.0
Norway	0.935	–
Slovenia	0.734	–
Spain	–	2.0

Table G.13: Life insurance penetration - variable selection models (method 2), Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.226	0.371	0.445
Greece	0.988	0.982	0.980
Italy	0.165	0.183	0.173
Latvia	0.416	0.804	0.658
Norway	0.629	0.814	0.593
Slovenia	0.125	0.304	0.135
Spain	0.372	0.778	0.792

Table G.14: Life insurance penetration - variable selection models (method 2), Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.533	0.799	0.517
Greece	0.991	0.996	0.999
Italy	0.618	0.830	0.915
Latvia	0.206	0.133	0.218
Norway	0.088	0.283	0.209
Slovenia	0.124	0.326	0.570
Spain	0.061	0.262	0.525

Table G.15: Life insurance penetration - variable selection models (method 2), Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.505	—
Greece	—	4.4
Italy	0.799	—
Latvia	0.838	—
Norway	0.981	—
Slovenia	0.822	—
Spain	—	2.2

Table G.16: Nonlife insurance penetration - variable selection models (method 2), Ljung-Box p value for residuals' lags

Up to lag	4	8	12
Czechia	0.319	0.435	0.556
Denmark	0.989	0.726	0.336
Greece	0.668	0.298	0.493
Italy	0.393	0.436	0.496
Latvia	0.552	0.102	0.225
Norway	0.227	0.274	0.530
Slovenia	0.347	0.332	0.448
Spain	0.092	0.092	0.137

Table G.17: Nonlife insurance penetration - variable selection models (method 2), Ljung-Box p value for squared residuals' lags

Up to lag	4	8	12
Czechia	0.855	0.902	0.853
Denmark	0.731	0.613	0.091
Greece	0.087	0.085	0.232
Italy	0.253	0.683	0.628
Latvia	0.445	0.132	0.367
Norway	0.582	0.701	0.850
Slovenia	0.932	0.852	0.902
Spain	0.877	0.971	0.986

Table G.18: Nonlife insurance penetration - variable selection models (method 2), Residuals' distribution

Country	Jarque-Bera residuals normality test statistics / p-values	Student's distribution degrees of freedom
Czechia	0.532	—
Denmark	0.484	—
Greece	0.689	—
Italy	0.722	—
Latvia	—	3.1
Norway	0.111	—
Slovenia	0.719	—
Spain	0.621	—

H Signs' frequencies

Table H.1: Signs frequencies – Variable selection models - Life insurance

Parameter / Sign	Positive	Negative
Population	0	2
GDP per capita	1	2
Inflation	0	0
Unemployment	2	3
Banking sector	1	2
LT Interest rate	3	2
Business Confidence	2	2
Consumer Confidence	1	0
Uncertainty	0	1
Pandemic Uncertainty	0	0

Note: The counts reported above reflect the number of instances in which the variables were statistically significant at the 10% level (i.e., p-value < 0.10).

LT: Long-term, Business Confidence: Business Confidence Index, Consumer Confidence: Consumer Confidence Index, Uncertainty: World Uncertainty Index, Pandemic Uncertainty: World Pandemic Uncertainty Index

Table H.2: Signs frequencies – Variable selection models - Nonlife insurance

Parameter / Sign	Positive	Negative
Population	4	1
GDP per capita	0	7
Inflation	0	2
Unemployment	1	1
Banking sector	3	0
External trade	3	3
Business Confidence	1	0
Consumer Confidence	1	2
Uncertainty	1	3
Pandemic Uncertainty	0	0

Note: The counts reported above reflect the number of instances in which the variables were statistically significant at the 10% level (i.e., p-value < 0.10).

I Quantile regression reports

Table I.1: Life insurance penetration – Quantile regression models, Czechia

Variable / Quantile	Czechia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.070***	−0.043***	0.004	0.043**	0.087***
S.E.	0.026	0.016	0.015	0.017	0.016
Population	0.638	−2.552	−4.440	−6.737	−4.521
S.E.	9.182	7.896	6.980	7.129	10.949
GDP per capita	−0.534	−0.721	−0.808	−0.792	−0.456
S.E.	1.016	0.698	0.560	0.522	0.675
Unemployment	0.018	0.005	0.026	0.057	−0.040
S.E.	0.088	0.058	0.053	0.055	0.056
Banking sector	0.004	−0.011	−0.009	−0.006	−10 ^{−4}
S.E.	0.030	0.022	0.019	0.017	0.017
LT Interest rate	−0.015	0.043	0.018	0.012	0.063
S.E.	0.061	0.049	0.038	0.041	0.040
Uncertainty	0.002	0.003	−0.006	0.003	0.005
S.E.	0.011	0.009	0.010	0.012	0.010
Insurance penetration lag 1	−0.421*	−0.408**	−0.320**	−0.389**	−0.839***
S.E.	0.244	0.182	0.147	0.193	0.244
Insurance penetration lag 4	0.486	0.708***	0.738***	0.461	0.800**
S.E.	0.307	0.233	0.243	0.287	0.323

S.E. = Standard Error; LT = Long-term; Business Confidence = Business Confidence Index; Consumer Confidence = Consumer Confidence Index; Uncertainty = World Uncertainty Index; Pandemic Uncertainty = World Pandemic Uncertainty Index.

Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I.2: Life insurance penetration – Quantile regression models, Greece

Variable	Greece				
	Q0.1	Q0.25	Q0.5	Q0.75	Q0.9
Intercept	−0.135***	−0.059**	0.008	0.077***	0.126***
S.E.	0.023	0.025	0.019	0.021	0.018
Unemployment	−0.026	0.012	0.023	0.028**	0.024
S.E.	0.025	0.021	0.015	0.013	0.019
LT Interest rate	0.002	0.002	0.004	0.004	0.015
S.E.	0.012	0.013	0.011	0.012	0.015
Consumer Confidence	0.059	0.050	0.016	0.013	0.011
S.E.	0.040	0.031	0.022	0.019	0.018
Insurance penetration lag 1	−0.789***	−0.670***	−0.610***	−0.532***	−0.535***
S.E.	0.228	0.222	0.162	0.160	0.153
Insurance penetration lag 2	−0.951***	−0.779***	−0.698***	−0.440***	−0.503***
S.E.	0.270	0.201	0.140	0.147	0.158
Insurance penetration lag 3	−0.645***	−0.681***	−0.577***	−0.540***	−0.738***
S.E.	0.189	0.180	0.146	0.170	0.204

Table I.3: Life insurance penetration - Quantile regression models, Italy

Variable / Quantile	Italy				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.531	−0.643	−1.009**	−0.498	−0.211
S.E.	0.455	0.455	0.464	0.434	0.465
Population	−41.994	−49.372	−32.730	−3.081	60.145
S.E.	30.698	34.616	30.364	41.516	46.036
GDP per capita	−0.655	−0.896	−0.676	−0.870	−1.736**
S.E.	0.746	0.570	0.545	0.635	0.787
Unemployment	0.079**	0.076**	0.069*	0.109**	0.015
S.E.	0.036	0.037	0.041	0.045	0.051
Business Confidence	0.006	0.045	0.035	0.053	0.084*
S.E.	0.042	0.040	0.038	0.050	0.048
Insurance penetration lag 1	0.954***	1.013***	0.845***	0.931***	0.825***
S.E.	0.165	0.191	0.189	0.173	0.184
Insurance penetration lag 2	−0.262	−0.349**	−0.461***	−0.192	−0.291
S.E.	0.200	0.189	0.168	0.217	0.258
Insurance penetration lag 3	0.169	0.145	0.271*	0.063	0.346*
S.E.	0.253	0.222	0.160	0.196	0.180

Table I.4: Life insurance penetration - Quantile regression models, Latvia

Variable / Quantile	Latvia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−4.422	−5.883*	−1.579	−2.224	−0.841
S.E.	3.060	3.504	3.345	2.498	3.470
Inflation	0.012	−0.001	0.014	0.012	0.012
S.E.	0.022	0.022	0.024	0.027	0.034
Banking sector	−0.055*	−0.025	−0.036	−0.049	−0.084**
S.E.	0.031	0.027	0.031	0.035	0.042
LT Interest rate	0.108	0.057	−0.029	−0.085	−0.154
S.E.	0.110	0.115	0.095	0.096	0.119
Business Confidence	0.041	0.057*	0.016	0.023	0.010
S.E.	0.030	0.034	0.033	0.025	0.034
Pandemic Uncertainty	−0.003	−0.003	−0.001	−0.001	−0.003
S.E.	0.007	0.005	0.004	0.004	0.010
Insurance penetration lag 1	−0.805***	−1.037***	−0.714**	−0.668**	−0.574*
S.E.	0.241	0.273	0.320	0.271	0.302
Insurance penetration lag 2	−0.984***	−1.192***	−0.704*	−0.506	−0.256
S.E.	0.270	0.346	0.400	0.355	0.418
Insurance penetration lag 3	−1.144***	−1.155***	−0.709	−0.462	−0.187
S.E.	0.363	0.439	0.458	0.375	0.474
Insurance penetration lag 4	−0.380	−0.435	0.092	0.187	0.329
S.E.	0.309	0.364	0.429	0.390	0.428
Insurance penetration lag 5	−0.094	−0.153	−0.040	0.152	0.317
S.E.	0.212	0.203	0.230	0.218	0.291

Table I.5: Life insurance penetration – Quantile regression models, Norway

Variable / Quantile	Norway				
	0.1	0.25	0.5	0.75	0.9
Intercept	−1.746**	−0.744*	−0.970**	−1.226*	−1.235
S.E.	0.817	0.402	0.458	0.679	0.918
GDP per capita	−1.515	−0.014	−0.039	−0.504	−0.071
S.E.	1.195	0.585	0.548	0.667	1.179
Unemployment	−0.211	0.050	−0.006	−0.080	−0.254**
S.E.	0.290	0.127	0.065	0.070	0.123
Banking sector	−0.003	0.020	0.027*	0.032*	0.033
S.E.	0.029	0.017	0.014	0.019	0.022
LT Interest rate	−0.174	−0.080	−0.106	−0.035	−0.032
S.E.	0.209	0.124	0.093	0.092	0.110
Consumer Confidence	0.003	−0.001	0.001	0.000	0.002
S.E.	0.004	0.003	0.001	0.002	0.004
Uncertainty	0.007	0.005	−0.000	0.003	0.025
S.E.	0.032	0.015	0.008	0.013	0.023
Pandemic Uncertainty	0.002	0.001	0.000	0.002	0.009
S.E.	0.009	0.006	0.005	0.006	0.005
Insurance penetration lag 4	0.606***	0.820***	0.728***	0.638***	0.614**
S.E.	0.217	0.107	0.128	0.189	0.254

Table I.6: Life insurance penetration - Quantile regression models, Slovenia

Variable / Quantile	Slovenia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.069***	−0.050***	−0.008	0.032*	0.053***
S.E.	0.026	0.018	0.014	0.017	0.017
Population	−1.422	−8.750	−25.973	−17.117	−22.325
S.E.	24.564	20.217	18.017	17.487	21.765
GDP per capita	−0.550	−0.716**	−0.445	−0.597**	−0.841***
S.E.	0.499	0.359	0.356	0.282	0.320
Unemployment	−0.027	−0.053*	−0.046	−0.021	−0.031
S.E.	0.040	0.028	0.031	0.022	0.027
LT Interest rate	−0.002	0.016	0.026	0.055**	0.067**
S.E.	0.031	0.017	0.020	0.023	0.028
Business Confidence	0.005	0.010	0.005	0.007	0.011
S.E.	0.022	0.016	0.016	0.015	0.017
Insurance penetration lag 2	−0.349	−0.542**	−0.404**	−0.423**	−0.285
S.E.	0.281	0.212	0.182	0.195	0.246

Table I.7: Life insurance penetration - Quantile regression models, Spain

Variable / Quantile	Spain				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.179***	−0.094***	−0.021	0.072***	0.167***
S.E.	0.026	0.022	0.018	0.024	0.036
Unemployment	−0.013	0.021	0.030	−0.016	−0.017
S.E.	0.041	0.037	0.037	0.033	0.038
Business Confidence	0.005	−0.005	−0.026	−0.042	−0.077
S.E.	0.035	0.037	0.032	0.028	0.054
Insurance penetration lag 1	−0.226	−0.392*	−0.512**	−0.424**	−0.410
S.E.	0.234	0.235	0.207	0.208	0.251
Insurance penetration lag 2	−0.322	−0.422**	−0.535***	−0.768***	−0.764***
S.E.	0.215	0.210	0.197	0.182	0.173
Insurance penetration lag 3	−0.203	−0.419**	−0.482***	−0.470**	−0.355
S.E.	0.231	0.195	0.179	0.229	0.291
Insurance penetration lag 8	0.301**	0.210	0.229	0.188	0.245
S.E.	0.155	0.133	0.162	0.200	0.193

Table I.8: Non-life insurance penetration – Quantile regression models, Czechia

Variable / Quantile	Czechia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.037***	−0.013*	0.004	0.018***	0.028**
S.E.	0.009	0.007	0.006	0.007	0.013
Population	−1.138	2.024	−0.558	−1.369	0.032
S.E.	4.279	2.935	3.015	2.512	3.298
GDP per capita	−0.318	−0.014	−0.083	−0.213	−0.488
S.E.	0.379	0.365	0.344	0.307	0.479
Banking sector	0.026*	0.022**	0.004	0.009	0.010
S.E.	0.014	0.011	0.010	0.011	0.018
External trade	0.197	−0.158	−0.023	0.058	0.198
S.E.	0.267	0.250	0.259	0.227	0.332
Consumer Confidence	0.008	−0.001	−0.005	−0.002	0.003
S.E.	0.017	0.015	0.012	0.015	0.016
Uncertainty	0.001	0.001	−0.001	0.000	0.003
S.E.	0.007	0.006	0.004	0.004	0.006
Insurance penetration lag 1	−0.853***	−1.008***	−1.084***	−1.149***	−1.144***
S.E.	0.262	0.226	0.201	0.209	0.334
Insurance penetration lag 2	−0.794***	−1.022***	−1.092***	−1.156***	−1.151***
S.E.	0.264	0.234	0.207	0.214	0.348
Insurance penetration lag 3	−0.740***	−0.971***	−1.089***	−1.122***	−1.099***
S.E.	0.281	0.232	0.203	0.213	0.350
Insurance penetration lag 4	0.141	0.011	−0.089	−0.153	−0.118
S.E.	0.267	0.225	0.200	0.202	0.331

Table I.9: Non-life insurance penetration – Quantile regression models, Denmark

Variable / Quantile	Denmark				
	0.1	0.25	0.5	0.75	0.9
Intercept	0.157	−0.375	−0.396	−1.707*	−2.138*
S.E.	1.848	1.186	0.931	1.031	1.145
GDP per capita	−0.432	−0.599**	−0.683***	−0.658***	−0.884***
S.E.	0.371	0.290	0.232	0.257	0.285
Banking sector	0.012**	0.006	0.005	0.005	0.005
S.E.	0.006	0.005	0.004	0.005	0.005
External trade	0.087	−0.045	−0.061	−0.090	−0.074
S.E.	0.144	0.088	0.079	0.093	0.102
Business Confidence	0.010	−0.002	−0.004	−0.001	0.003
S.E.	0.010	0.007	0.005	0.006	0.006
Consumer Confidence	−0.008	0.000	−0.002	−0.001	−0.011
S.E.	0.016	0.012	0.011	0.011	0.011
Uncertainty	0.003	0.001	0.000	−0.001	−0.002
S.E.	0.003	0.003	0.002	0.002	0.002
Insurance penetration lag 1	0.959***	0.575**	0.589***	0.407*	0.464*
S.E.	0.319	0.230	0.187	0.231	0.250
Insurance penetration lag 2	−0.232	0.213	0.081	−0.100	−0.001
S.E.	0.373	0.229	0.177	0.200	0.226
Insurance penetration lag 3	−0.392	−0.203	−0.015	0.141	−0.088
S.E.	0.353	0.239	0.202	0.217	0.268
Insurance penetration lag 4	0.525	0.096	0.111	0.259	0.288
S.E.	0.422	0.285	0.204	0.269	0.285
Insurance penetration lag 5	0.061	0.153	−0.005	−0.014	0.041
S.E.	0.439	0.327	0.289	0.279	0.302
Insurance penetration lag 6	0.094	−0.193	−0.135	0.025	−0.065
S.E.	0.345	0.259	0.224	0.229	0.206

Table I.10: Non-life insurance penetration – Quantile regression models, Greece

Variable / Quantile	Greece				
	0.1	0.25	0.5	0.75	0.9
Intercept	21.920	12.732	22.178*	10.314	−3.589
S.E.	14.277	10.782	11.077	13.656	15.427
Population	−2.358	−1.369	−2.370*	−1.090	0.398
S.E.	1.528	1.152	1.184	1.459	1.649
Inflation	−0.015	−0.011	−0.010	−0.006	−0.032**
S.E.	0.010	0.007	0.008	0.012	0.014
External trade	−0.202	−0.108	−0.367*	−0.309	−0.016
S.E.	0.214	0.202	0.189	0.255	0.276
Uncertainty	−0.006	0.000	−0.002	−0.002	0.005
S.E.	0.006	0.004	0.004	0.006	0.007
Insurance penetration lag 1	−0.757***	−0.757***	−0.852***	−0.766***	−0.934***
S.E.	0.186	0.153	0.117	0.095	0.118
Insurance penetration lag 2	−0.929***	−0.926***	−1.012***	−0.900***	−0.849***
S.E.	0.125	0.115	0.100	0.110	0.108
Insurance penetration lag 3	−0.847***	−0.817***	−0.911***	−0.730***	−0.741***
S.E.	0.181	0.181	0.145	0.126	0.125

Table I.11: Non-life insurance penetration – Quantile regression models, Italy

Variable / Quantile	Italy				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.024***	−0.011*	0.006	0.018***	0.022***
S.E.	0.006	0.006	0.005	0.004	0.004
Population	3.612	−14.568	7.783	10.863	10.088
S.E.	24.779	25.407	24.039	17.032	16.047
GDP per capita	−0.343	−0.145	−0.133	−0.258	−0.318
S.E.	0.378	0.374	0.292	0.300	0.329
Unemployment	0.022	0.013	0.013	0.002	0.004
S.E.	0.014	0.011	0.013	0.013	0.012
Banking sector	0.018**	0.018**	0.013**	0.011**	0.011**
S.E.	0.009	0.008	0.006	0.005	0.006
External trade	0.053	−0.065	−0.388	−0.036	0.022
S.E.	0.443	0.411	0.357	0.272	0.321
Insurance penetration lag 1	−1.055***	−1.044***	−0.986***	−1.018***	−1.038***
S.E.	0.079	0.078	0.067	0.054	0.057
Insurance penetration lag 2	−0.947***	−0.990***	−0.968***	−0.951***	−0.944***
S.E.	0.059	0.061	0.055	0.045	0.042
Insurance penetration lag 3	−0.910***	−0.943***	−0.966***	−0.976***	−0.968***
S.E.	0.052	0.045	0.042	0.036	0.032

Table I.12: Non-life insurance penetration – Quantile regression models, Latvia

Variable / Quantile	Latvia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.168	−0.029	0.011	0.120**	0.157*
S.E.	0.119	0.052	0.025	0.050	0.087
GDP per capita	−1.138	−1.443**	−1.395***	−1.008*	−0.755
S.E.	1.142	0.695	0.528	0.638	0.909
Inflation	0.002	−0.011	−0.001	−0.003	−0.002
S.E.	0.045	0.028	0.015	0.020	0.029
Insurance penetration lag 1	−0.101	−0.335	−0.379	−0.104	−0.084
S.E.	0.350	0.343	0.328	0.320	0.396
Insurance penetration lag 2	−0.587*	−0.532**	−0.525***	−0.572***	−0.554*
S.E.	0.315	0.238	0.207	0.206	0.271
Insurance penetration lag 3	−0.275	−0.393	−0.413*	−0.140	−0.093
S.E.	0.344	0.286	0.241	0.267	0.373
Insurance penetration lag 4	−0.135	−0.231	−0.209	−0.113	−0.025
S.E.	0.417	0.327	0.239	0.261	0.324
Insurance penetration lag 5	−0.112	−0.180	−0.159	−0.140	−0.089
S.E.	0.351	0.197	0.156	0.191	0.242
Insurance penetration lag 6	−0.061	−0.017	−0.043	0.077	0.130
S.E.	0.279	0.184	0.141	0.208	0.271
Insurance penetration lag 8	0.198	−0.113	−0.180	−0.083	−0.107
S.E.	0.347	0.341	0.253	0.284	0.331

Table I.13: Non-life insurance penetration – Quantile regression models, Norway

Variable / Quantile	Norway				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.422	−0.730**	−0.940***	−0.457**	−0.389*
S.E.	0.405	0.348	0.358	0.307	0.288
Population	6.715	1.706	11.739	14.857	7.175
S.E.	15.769	9.438	13.825	17.306	18.851
GDP per capita	−0.813***	−0.748***	−0.660***	−0.694***	−0.551***
S.E.	0.127	0.098	0.114	0.137	0.144
Unemployment	0.016	0.025*	0.022	−0.002	−0.005
S.E.	0.016	0.014	0.016	0.015	0.017
Banking sector	0.009***	0.010***	0.006**	0.009***	0.011***
S.E.	0.003	0.003	0.003	0.003	0.004
External trade	−0.015**	−0.010**	−0.005	0.010	0.008
S.E.	0.017	0.016	0.016	0.017	0.019
Consumer Confidence	0.002	0.002	0.001	0.001	0.000
S.E.	0.001	0.001	0.002	0.001	0.001
Insurance penetration lag 1	0.757***	0.729***	0.655***	0.714***	0.649***
S.E.	0.157	0.126	0.175	0.154	0.169
Insurance penetration lag 2	0.114	0.032	0.018	0.110	0.191
S.E.	0.137	0.133	0.149	0.127	0.154

Table I.14: Non-life insurance penetration – Quantile regression models, Slovenia

Variable / Quantile	Slovenia				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.051	−0.030	−0.001	0.026	0.040
S.E.	0.039	0.032	0.025	0.029	0.026
Population	−29.574	1.359	−0.511	5.584	−3.233
S.E.	46.468	37.666	32.247	32.319	33.727
GDP per capita	0.679	−0.640	−1.331	−1.053	−1.285
S.E.	1.515	1.398	1.154	1.369	1.101
Inflation	−0.004	0.002	0.000	−0.001	−0.002
S.E.	0.012	0.008	0.007	0.008	0.009
Unemployment	0.032	0.014	0.008	0.014	0.008
S.E.	0.045	0.047	0.038	0.035	0.031
Banking sector	−0.007	0.064	0.068	0.069	0.099
S.E.	0.071	0.058	0.051	0.061	0.055
External trade	−0.435	−0.440	−0.400	−0.068	−0.223
S.E.	0.644	0.568	0.593	0.606	0.625
Business Confidence	0.016	0.027	0.036	0.017	0.049
S.E.	0.069	0.057	0.045	0.047	0.045
Consumer Confidence	−0.032	0.012	0.007	0.009	0.010
S.E.	0.079	0.065	0.048	0.057	0.054
Uncertainty	−0.006	−0.002	−0.003	−0.001	−0.001
S.E.	0.009	0.008	0.006	0.006	0.006
Pandemic Uncertainty	0.000	0.000	0.000	0.000	0.000
S.E.	0.010	0.009	0.008	0.009	0.082
Insurance penetration lag 1	−1.102**	−0.841**	−0.667*	−0.650	−0.600*
S.E.	0.484	0.411	0.374	0.427	0.349
Insurance penetration lag 2	−0.922***	−0.943***	−0.785***	−0.808***	−0.768***
S.E.	0.313	0.280	0.253	0.271	0.237
Insurance penetration lag 3	−0.958**	−0.759**	−0.585**	−0.648*	−0.593**

Table I.15: Non-life insurance penetration – Quantile regression models, Spain

Variable / Quantile	Spain				
	0.1	0.25	0.5	0.75	0.9
Intercept	−0.035***	−0.013***	0.003	0.018***	0.029***
S.E.	0.010	0.005	0.003	0.004	0.006
Population	−16.340	−8.319	5.738	0.544	2.047
S.E.	17.904	9.327	6.326	5.924	7.833
GDP per capita	−1.120***	−0.836***	−0.790***	−0.654***	−0.688*
S.E.	0.423	0.324	0.229	0.222	0.365
Banking sector	0.001	0.003	0.001	0.001	0.001
S.E.	0.005	0.004	0.004	0.003	0.004
Business Confidence	0.006	0.003	0.001	0.007	0.014
S.E.	0.014	0.011	0.007	0.007	0.011
Consumer Confidence	−0.001	−0.005	−0.008	−0.010	−0.011
S.E.	0.008	0.008	0.005	0.007	0.009
Insurance penetration lag 1	−0.475**	−0.466***	−0.400***	−0.289**	−0.342***
S.E.	0.219	0.175	0.151	0.119	0.127
Insurance penetration lag 2	−0.604**	−0.570***	−0.550***	−0.401***	−0.481***
S.E.	0.251	0.186	0.139	0.116	0.146
Insurance penetration lag 3	−0.178	−0.329	−0.322**	−0.208*	−0.265**
S.E.	0.294	0.209	0.156	0.123	0.128
Insurance penetration lag 4	0.205	0.295**	0.362***	0.450***	0.364**
S.E.	0.230	0.167	0.126	0.108	0.158

J Elastic net

Table J.1: OLS - Elastic Net Screening Model - Life insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.002	0.007	-0.276	0.785
Inflation lag 2	0.005	0.002	2.266	0.030
Inflation lag 4	-0.005	0.002	-2.448	0.020
GDP per capita lag 4	0.253	0.150	1.691	0.100
Banking sector lag 2	0.022	0.010	2.333	0.026
Population lag 2	-2.335	1.508	-1.548	0.131
Population lag 4	-3.420	1.570	-2.179	0.037
LT Interest rate lag 4	0.036	0.015	2.364	0.024
Consumer Confidence	-0.020	0.009	-2.268	0.030
Business Confidence	-0.021	0.007	-2.876	0.007
Insurance penetration lag 1	-1.006	0.070	-14.326	0.000
Insurance penetration lag 2	-0.927	0.084	-11.080	0.000
Insurance penetration lag 3	-0.837	0.069	-12.069	0.000

Table J.2: OLS - Elastic Net Screening Model - Life insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.021	0.011	1.816	0.069
Unemployment	0.038	0.011	3.376	0.001
Unemployment lag 2	-0.039	0.011	-3.674	0.000
Unemployment lag 3	-0.026	0.011	-2.424	0.015
Banking sector lag 2	0.015	0.005	2.708	0.007
LT Interest rate lag 4	-0.014	0.005	-2.529	0.011
Insurance penetration lag 1	-0.555	0.106	-5.256	0.000
Insurance penetration lag 2	-0.286	0.117	-2.449	0.014
Insurance penetration lag 3	-0.400	0.090	-4.465	0.000

Table J.3: ARMA-GARCH - Elastic Net Screening Model - Life insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-1.187	0.300	-3.959	0.000
GDP per capita lag 4	-0.715	0.145	-4.914	0.000
Unemployment lag 4	0.021	0.006	3.215	0.001
LT Interest rate lag 1	-0.099	0.019	-5.223	0.000
LT Interest rate lag 3	-0.038	0.013	-2.959	0.003
Insurance penetration lag 4	0.596	0.106	5.636	0.000
MA(1)	0.942	0.112	8.390	0.000
MA(2)	0.535	0.114	4.705	0.000
ω	0.000000	0.000025	0.000	1.000
β_1	0.987	0.004	253.043	0.000

Table J.4: OLS - Elastic Net Screening Model - Life insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.029	0.026	-1.114	0.271
Banking sector	-0.059	0.018	-3.216	0.002
GDP per capita lag 1	0.797	0.299	2.660	0.010
Unemployment lag 2	-0.055	0.035	-1.585	0.119
Banking sector lag 2	0.038	0.017	2.169	0.035
Insurance penetration lag 1	-0.902	0.119	-7.577	0.000
Insurance penetration lag 2	-0.670	0.119	-5.616	0.000
Insurance penetration lag 3	-0.829	0.110	-7.514	0.000
Insurance penetration lag 4	-0.383	0.107	-3.563	0.001

Table J.5: OLS - Elastic Net Screening Model - Life insurance penetration - Norway

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-7.011	1.993	-3.518	0.001
Banking sector	0.020	0.009	2.093	0.040
LT Interest rate	-0.102	0.067	-1.517	0.134
Population lag 1	-98.100	49.810	-1.970	0.053
Population lag 2	-107.500	61.650	-1.744	0.085
Population lag 4	-217.300	66.720	-3.257	0.002
GDP per capita lag 3	0.648	0.473	1.369	0.175
Inflation lag 2	-0.033	0.023	-1.413	0.162
Unemployment lag 1	0.156	0.073	2.133	0.036
LT Interest rate lag 1	0.129	0.069	1.877	0.065
LT Interest rate lag 2	-0.087	0.068	-1.285	0.203
LT Interest rate lag 4	0.093	0.066	1.400	0.166
Business Confidence	0.045	0.019	2.389	0.020
Uncertainty	0.019	0.008	2.241	0.028
Pandemic Uncertainty	0.004	0.002	1.543	0.127
Insurance penetration lag 3	-0.259	0.085	-3.047	0.003
Insurance penetration lag 4	0.569	0.092	6.207	0.000

Table J.6: OLS - Elastic Net Screening Model - Life insurance penetration - Slovenia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.010	0.005	-2.022	0.060
GDP per capita	-1.380	0.111	-12.485	0.000
GDP per capita lag 2	0.510	0.098	5.211	0.000
GDP per capita lag 4	0.701	0.096	7.266	0.000
Inflation	0.002	0.001	1.670	0.114
Unemployment	-0.030	0.006	-4.733	0.000
Unemployment lag 1	0.012	0.008	1.581	0.133
Unemployment lag 4	0.018	0.006	2.858	0.011
LT Interest rate	0.067	0.006	11.476	0.000
Banking sector lag 2	0.033	0.007	4.640	0.000
Business Confidence	0.035	0.004	8.308	0.000
Uncertainty	-0.002	0.001	-2.066	0.055
Insurance penetration lag 1	0.429	0.066	6.460	0.000
Insurance penetration lag 3	-0.349	0.079	-4.429	0.000
Insurance penetration lag 4	0.416	0.080	5.165	0.000

Table J.7: OLS - Elastic Net Screening Model - Life insurance penetration - Spain

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.020	0.019	1.068	0.286
Inflation	0.042	0.020	2.084	0.037
Inflation lag 1	-0.027	0.018	-1.504	0.133
Unemployment lag 1	0.068	0.016	4.138	0.000
Unemployment lag 4	0.056	0.019	2.994	0.003
LT Interest rate lag 3	0.118	0.027	4.369	0.000
LT Interest rate lag 4	0.074	0.032	2.281	0.023
Business Confidence	-0.107	0.026	-4.050	0.000
Consumer Confidence	0.049	0.014	3.428	0.001
Uncertainty	-0.011	0.005	-2.233	0.026
Insurance penetration lag 1	-0.667	0.110	-6.043	0.000
Insurance penetration lag 2	-0.690	0.097	-7.123	0.000
Insurance penetration lag 3	-0.414	0.075	-5.485	0.000

Table J.8: OLS - Elastic Net Screening Model - Nonlife insurance penetration - Czechia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.000	0.005	0.096	0.924
GDP per capita	-0.408	0.128	-3.194	0.003
Banking sector	0.019	0.007	2.527	0.017
Population lag 1	2.394	0.963	2.485	0.018
Inflation lag 4	0.001	0.001	1.758	0.088
Banking sector lag 1	0.020	0.007	2.631	0.013
External trade lag 1	-0.254	0.095	-2.667	0.012
External trade lag 2	-0.148	0.082	-1.799	0.081
Consumer Confidence	0.017	0.006	2.980	0.005
Uncertainty	-0.005	0.002	-2.185	0.036
Pandemic Uncertainty	0.001	0.000	2.846	0.008
Insurance penetration lag 1	-0.987	0.023	-43.511	0.000
Insurance penetration lag 2	-1.006	0.032	-31.543	0.000
Insurance penetration lag 3	-1.009	0.024	-41.910	0.000

Table J.9: ARMA - Elastic Net Screening Model - Nonlife insurance penetration - Denmark

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.499	0.200	-2.498	0.012
GDP per capita	-0.841	0.080	-10.550	0.000
Banking sector	0.007	0.001	5.525	0.000
Insurance penetration lag 1	0.671	0.078	8.592	0.000
Insurance penetration lag 4	0.191	0.076	2.516	0.012
AR(1)	-1.115	0.127	-8.767	0.000
AR(2)	-0.360	0.123	-2.922	0.003
MA(1)	1.000	0.048	20.928	0.000

Table J.10: ARMA - Elastic Net Screening Model - Nonlife insurance penetration - Greece

Variable	Estimate	Std. Error	t-value	p-value
Intercept	43.452	11.337	3.833	0.000
Inflation	-0.008	0.005	-1.384	0.166
Banking sector	0.017	0.003	6.617	0.000
Population lag 4	-4.642	1.216	-3.819	0.000
GDP per capita lag 2	-0.556	0.107	-5.199	0.000
Unemployment lag 3	-0.015	0.004	-3.758	0.000
External trade lag 1	-0.658	0.147	-4.464	0.000
Uncertainty	-0.004	0.001	-3.210	0.001
Insurance penetration lag 1	-1.214	0.082	-14.743	0.000
Insurance penetration lag 2	-1.238	0.081	-15.198	0.000
Insurance penetration lag 3	-1.172	0.088	-13.275	0.000
Insurance penetration lag 4	-0.338	0.078	-4.316	0.000
MA(1)	1.047	0.070	14.869	0.000
MA(2)	1.047	0.085	12.371	0.000
MA(3)	1.000	0.077	12.911	0.000

Table J.11: OLS - Elastic Net Screening Model - Nonlife insurance penetration - Italy

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.003	0.626	0.535
Banking sector	0.009	0.003	3.013	0.005
Population lag 4	21.911	8.618	2.542	0.015
Business Confidence	-0.023	0.006	-4.157	0.000
Insurance penetration lag 1	-0.992	0.015	-67.662	0.000
Insurance penetration lag 2	-0.994	0.016	-61.089	0.000
Insurance penetration lag 3	-0.993	0.012	-85.687	0.000

Table J.12: ARMA-GARCH - Elastic Net Screening Model - Nonlife insurance penetration - Latvia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.011	0.000	1626.683	0.000
GDP per capita	-0.829	0.106	-7.790	0.000
External trade	0.103	0.066	1.564	0.118
Insurance penetration lag 1	-0.108	0.000	-1542.356	0.000
Insurance penetration lag 2	0.066	0.000	944.811	0.000
Insurance penetration lag 3	-0.004	0.001	-3.113	0.002
Insurance penetration lag 4	0.365	0.000	1033.921	0.000
MA(1)	-0.536	0.003	-201.927	0.000
MA(2)	-0.656	0.002	-329.102	0.000
ω	0.000367	0.000348	1.057	0.290
α_1	0.000000	0.006669	0.000	1.000
β_1	0.928483	0.039522	23.493	0.000

Table J.13: OLS - Elastic Net Screening Model - Nonlife insurance penetration - Norway

Variable	Estimate	Std. Error	t-value	p-value
Intercept	-0.327	0.111	-2.955	0.004
GDP per capita	-0.608	0.086	-7.044	0.000
Banking sector	0.009	0.002	4.488	0.000
GDP per capita lag 4	-0.169	0.073	-2.320	0.023
External trade lag 3	0.097	0.039	2.501	0.014
Insurance penetration lag 1	0.736	0.073	10.093	0.000
Insurance penetration lag 2	0.042	0.066	0.637	0.526
Insurance penetration lag 4	0.104	0.064	1.632	0.107

Table J.14: OLS - Elastic Net Screening Model - Nonlife insurance penetration - Slovenia

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.006	0.013	0.500	0.622
Banking sector	0.039	0.014	2.766	0.011
Inflation lag 4	-0.006	0.003	-1.808	0.083
External trade lag 3	-0.288	0.129	-2.238	0.035
Insurance penetration lag 1	-0.935	0.040	-23.278	0.000
Insurance penetration lag 2	-0.892	0.046	-19.370	0.000
Insurance penetration lag 3	-0.794	0.052	-15.308	0.000

Table J.15: OLS - Elastic Net Screening Model - Nonlife insurance penetration - Spain

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.002	0.002	0.809	0.421
GDP per capita	-0.865	0.090	-9.637	0.000
GDP per capita lag 2	-0.418	0.111	-3.780	0.000
Unemployment	-0.017	0.005	-3.684	0.000
Unemployment lag 1	0.009	0.004	2.062	0.042
Unemployment lag 3	-0.006	0.004	-1.484	0.142
Population lag 2	13.034	4.268	3.054	0.003
Population lag 4	6.870	4.262	1.612	0.111
Inflation lag 3	-0.008	0.003	-2.630	0.010
Banking sector lag 3	0.006	0.002	3.781	0.000
External trade lag 2	0.011	0.007	1.665	0.100
Consumer Confidence	-0.005	0.003	-1.575	0.119
Insurance penetration lag 1	-0.221	0.043	-5.108	0.000
Insurance penetration lag 2	-0.406	0.052	-7.809	0.000
Insurance penetration lag 4	0.428	0.051	8.373	0.000

Table J.16: FE - Elastic Net Screening Model - Life insurance penetration - Panel

Variable	Estimate	Std. Error	t-value	p-value
Banking sector	0.007	0.003	2.700	0.008
Banking sector lag 1	0.007	0.003	2.279	0.024
Banking sector lag 2	0.012	0.003	4.310	0.000
LT interest rate lag 1	−0.049	0.010	−5.088	0.000
LT interest rate lag 2	−0.049	0.019	−2.583	0.010
Insurance penetration lag 1	−0.121	0.107	−1.129	0.260
Insurance penetration lag 2	−0.220	0.104	−2.123	0.035
Insurance penetration lag 3	−0.209	0.124	−1.691	0.092
Insurance penetration lag 4	0.637	0.107	5.968	0.000

Table J.17: RE - Elastic Net Screening Model - Nonlife insurance penetration - Panel

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.000	0.003	0.119	0.905
GDP per capita	−0.389	0.077	−5.031	0.000
GDP per capita lag 4	0.438	0.073	5.962	0.000
Banking sector	0.018	0.002	9.556	0.000
Banking sector lag 1	0.005	0.002	2.837	0.005
Banking sector lag 2	0.004	0.002	2.081	0.039
Banking sector lag 3	0.004	0.002	2.016	0.045
Consumer Confidence	−0.002	0.000	−5.162	0.000
Uncertainty	−0.002	0.001	−2.115	0.036
Insurance penetration lag 4	0.992	0.002	512.364	0.000

AR(1) error parameter: $\rho = -0.305$

Table J.18: Life insurance penetration – Fixed Effects robustness model (backward elimination)

Variable	Estimate	Std. Error	t-value	p-value
Banking sector	0.007	0.004	2.063	0.040
Banking sector lag 2	0.012	0.003	3.956	0.000
Banking sector lag 3	0.008	0.004	1.905	0.058
LT Interest rate lag 1	−0.045	0.010	−4.628	0.000
LT Interest rate lag 2	−0.060	0.022	−2.768	0.006
LT Interest rate lag 3	−0.025	0.010	−2.427	0.016
Insurance penetration lag 1	−0.161	0.130	−1.237	0.217
Insurance penetration lag 2	−0.244	0.121	−2.012	0.046
Insurance penetration lag 3	−0.237	0.146	−1.627	0.105
Insurance penetration lag 4	0.587	0.130	4.501	0.000

Table J.19: Non-life insurance penetration – Random Effects robustness model

Variable	Estimate	Std. Error	t-value	p-value
Intercept	−0.002	0.003	−0.498	0.619
Population lag 2	−0.002	0.001	−1.633	0.104
GDPpc	−0.414	0.077	−5.370	0.000
GDPpc lag 4	0.469	0.073	6.410	0.000
Unemployment lag 4	0.007	0.004	1.714	0.088
Banking sector	0.018	0.002	9.551	0.000
Banking sector lag 1	0.005	0.002	2.417	0.016
Banking sector lag 2	0.004	0.002	2.289	0.023
Banking sector lag 3	0.003	0.002	1.933	0.055
External trade lag 2	0.033	0.012	2.646	0.009
Consumer Confidence	−0.002	0.000	−5.692	0.000
Uncertainty	−0.003	0.001	−3.205	0.002
Pandemic uncertainty	0.001	0.000	2.006	0.046
Insurance penetration lag 4	0.992	0.002	483.101	0.000

AR(1) error parameter: $\rho = -0.311$

Table J.20: FE - Elastic Net Screening Model with Interaction Terms - Life insurance penetration - Panel

Variable	Estimate	Std. Error	t-value	p-value
Intercept	0.001	0.001	1.190	0.235
Banking sector	0.006	0.003	2.203	0.029
Banking sector lag 1	0.006	0.004	1.580	0.116
Banking sector lag 2	0.010	0.003	2.732	0.007
LT Interest rate lag 1	−0.047	0.013	−3.790	0.000
LT Interest rate lag 2	−0.047	0.020	−2.371	0.019
Consumer Confidence	0.002	0.001	1.630	0.105
Banking sector × Consumer Confidence	−0.001	0.000	−7.135	0.000
Insurance penetration lag 1	−0.151	0.145	−1.042	0.299
Insurance penetration lag 2	−0.239	0.138	−1.732	0.085
Insurance penetration lag 3	−0.226	0.161	−1.409	0.161
Insurance penetration lag 4	0.639	0.137	4.662	0.000

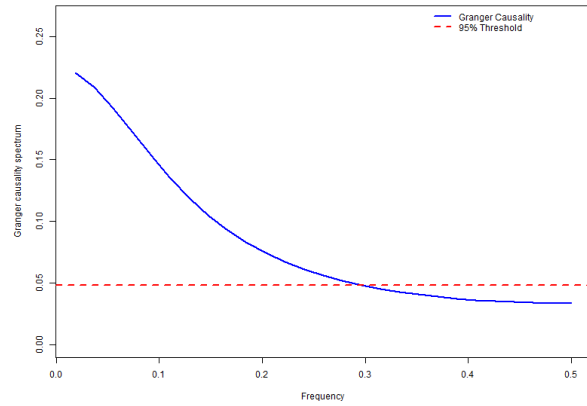
Table J.21: RE - Elastic Net Screening Model with Interaction Terms - Nonlife insurance penetration - Panel

Variable	Estimate	Std. Error	t-value	p-value
Intercept	−0.003	0.003	−1.018	0.310
GDP per capita	−0.340	0.078	−4.351	0.000
GDP per capita lag 3	−0.170	0.058	−2.910	0.004
GDP per capita lag 4	0.319	0.076	4.174	0.000
Unemployment lag 4	0.012	0.004	2.828	0.005
Banking sector	0.019	0.002	10.588	0.000
Banking sector lag 1	0.004	0.002	1.998	0.047
Banking sector lag 2	0.005	0.002	2.876	0.004
External trade	0.020	0.008	2.405	0.017
Consumer Confidence Index	−0.002	0.000	−4.417	0.000
Uncertainty	−0.002	0.001	−2.416	0.017
GDP per capita × External trade	−1.274	0.369	−3.450	0.001
External trade × Banking sector	−0.038	0.012	−3.161	0.002
Insurance penetration lag 2	0.032	0.013	2.433	0.016
Insurance penetration lag 4	0.963	0.013	73.913	0.000

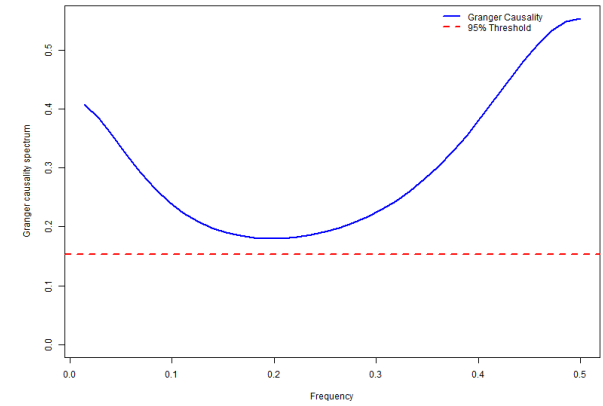
AR(1) error parameter: $\rho = -0.367$

K Granger causality in the frequency domain, Life insurance

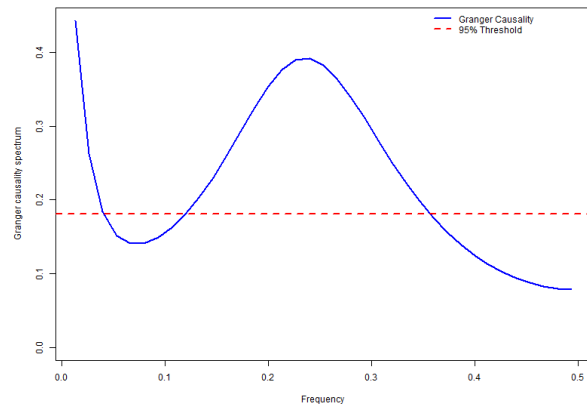
Figure K.1. Granger Causality in the time domain: GDP pc to Life insurance penetration



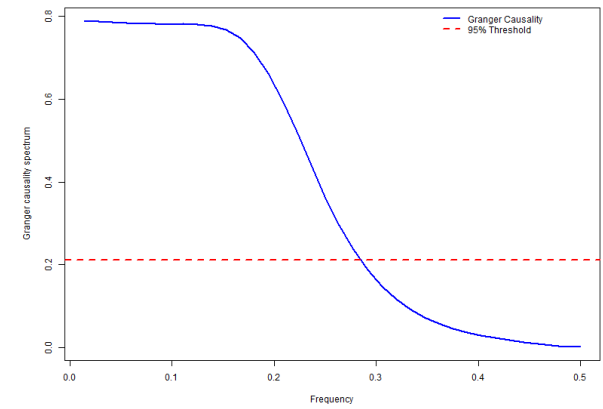
(a) Czechia



(b) Greece

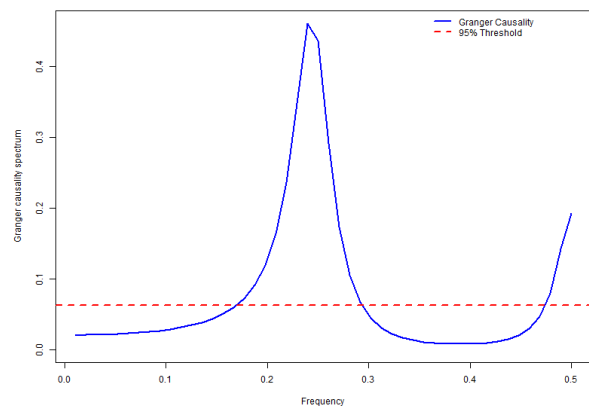


(c) Italy

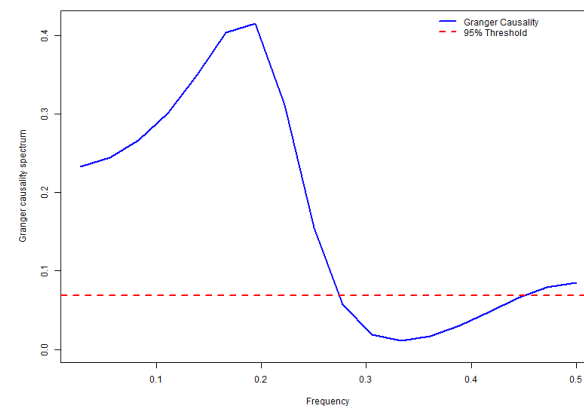


(d) Latvia

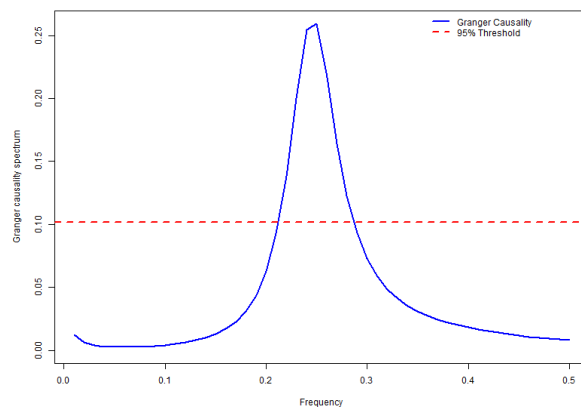
Figure K.2. Granger Causality in the time domain: GDP pc to Life insurance penetration (continued)



(a) Norway

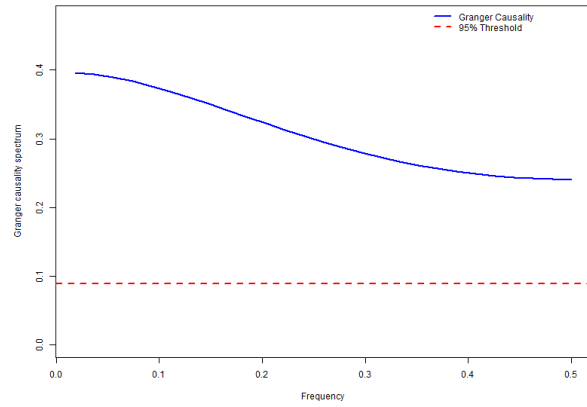


(b) Slovenia

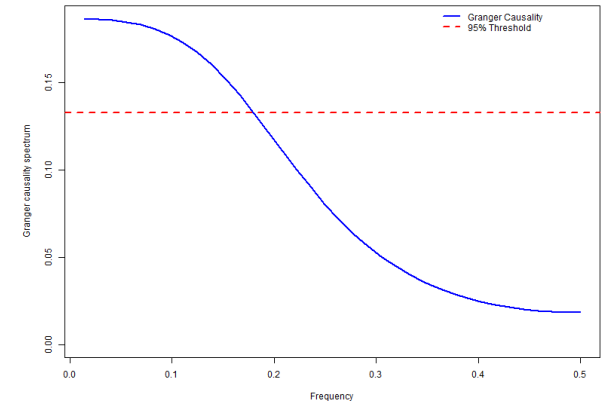


(c) Spain

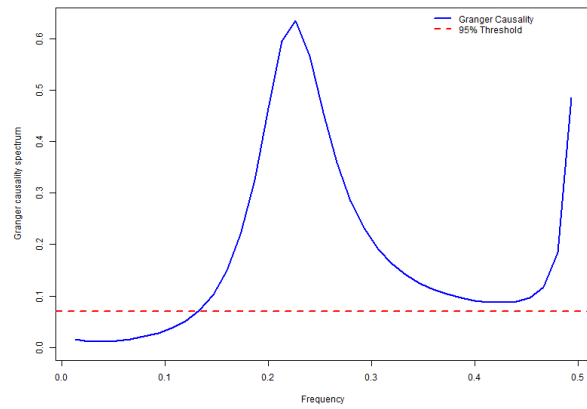
Figure K.3. Granger Causality in the time domain: Life insurance penetration to GDP pc



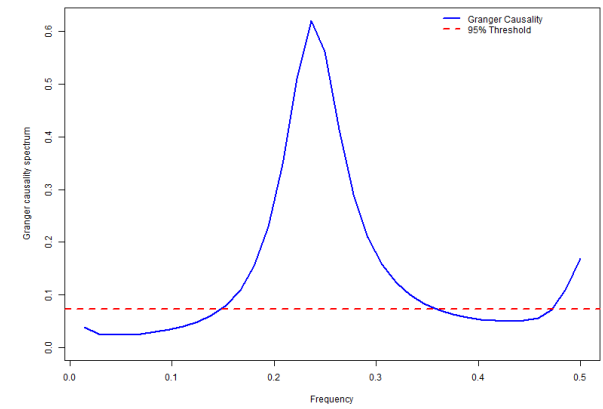
(a) Czechia



(b) Greece

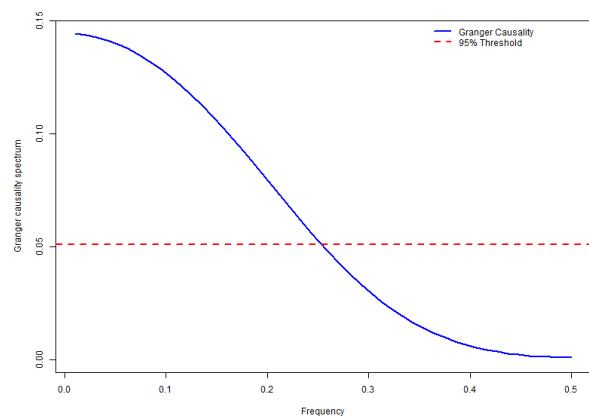


(c) Italy

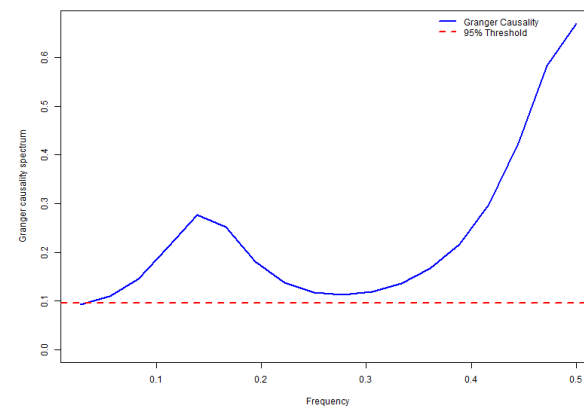


(d) Latvia

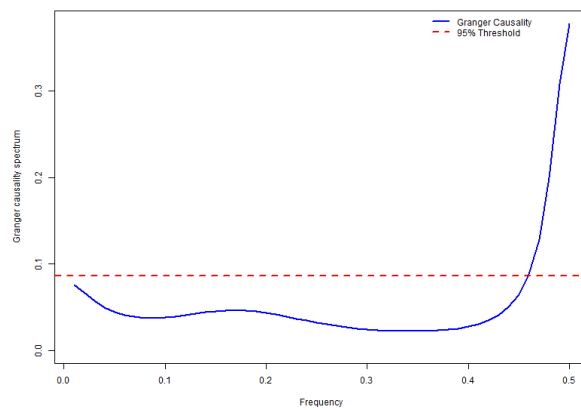
Figure K.4. Granger Causality in the time domain: Life insurance penetration to GDP pc (continued)



(a) Norway



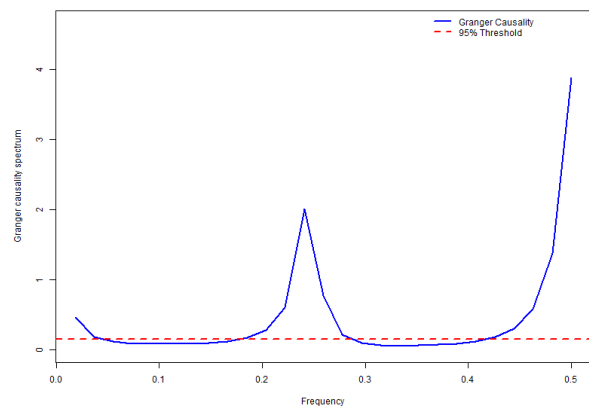
(b) Slovenia



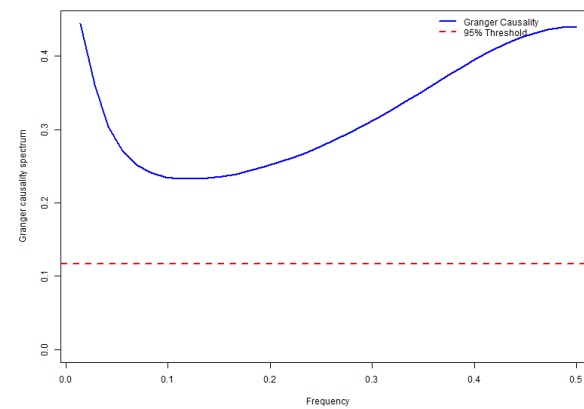
(c) Spain

L Granger causality in the frequency domain, Non-life insurance

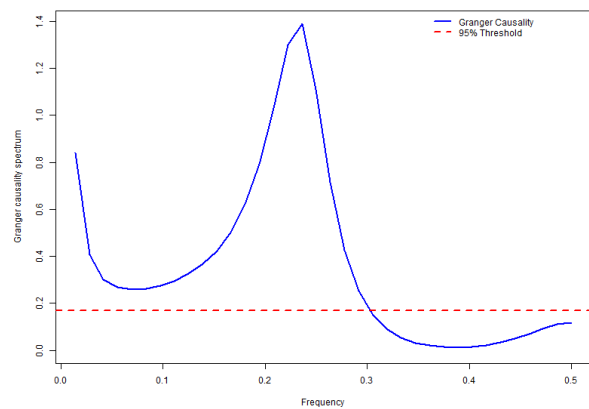
Figure L.1. Granger Causality in the time domain: GDP pc to Non-life insurance penetration



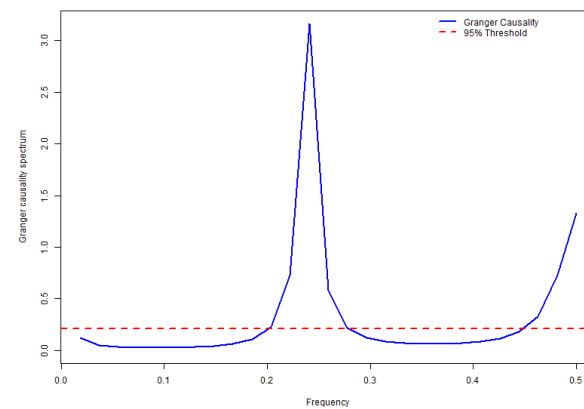
(a) Czechia



(b) Denmark

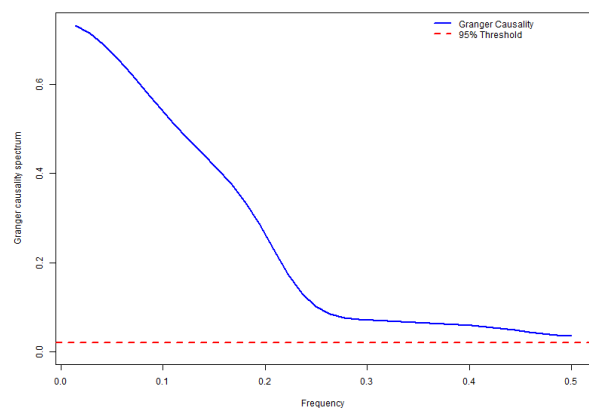


(c) Greece

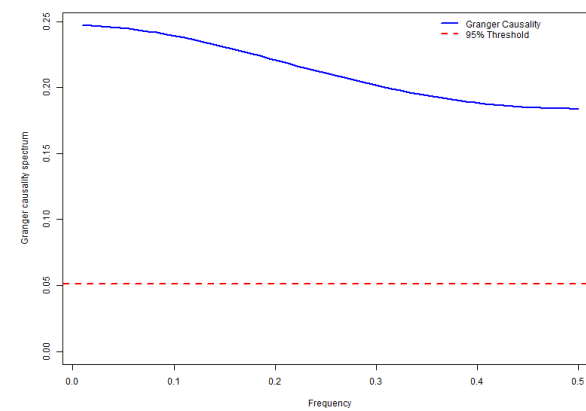


(d) Italy

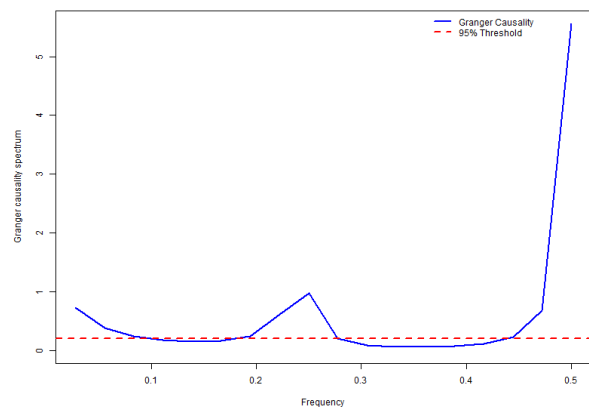
Figure L.2. Granger Causality in the time domain: GDP pc to Non-life insurance penetration (continued)



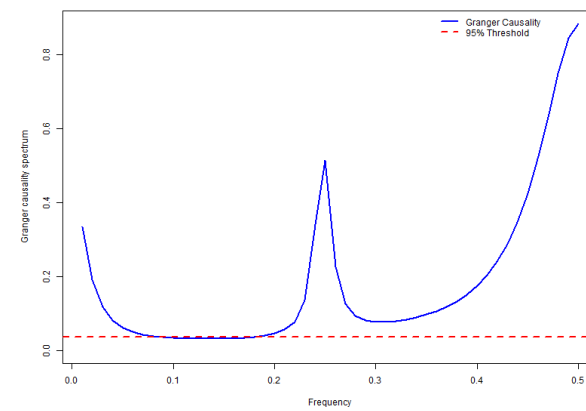
(a) Latvia



(b) Norway

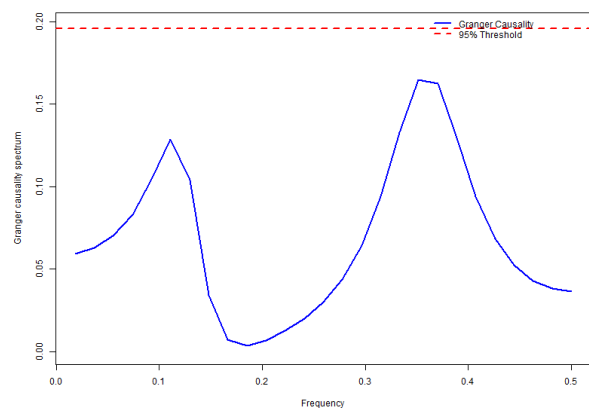


(c) Slovenia

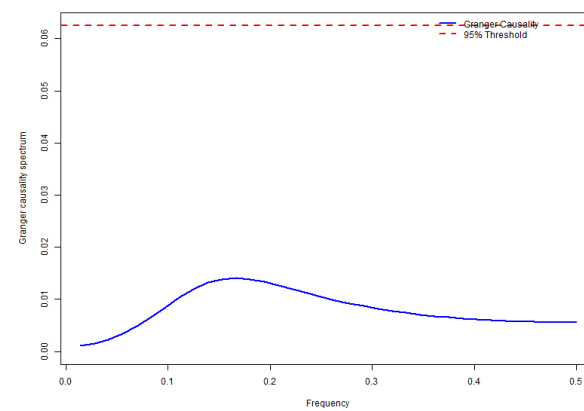


(d) Spain

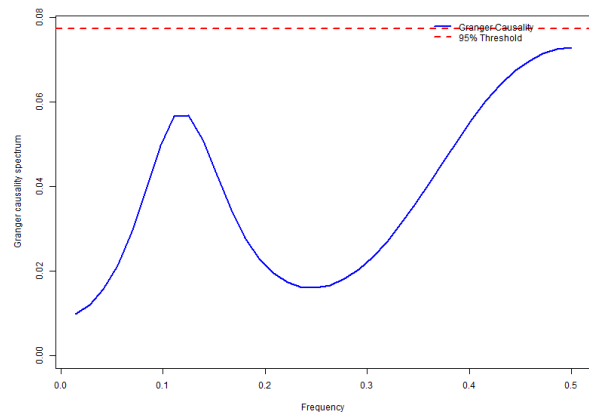
Figure L.3. Granger Causality in the time domain: Non-life insurance penetration to GDP pc



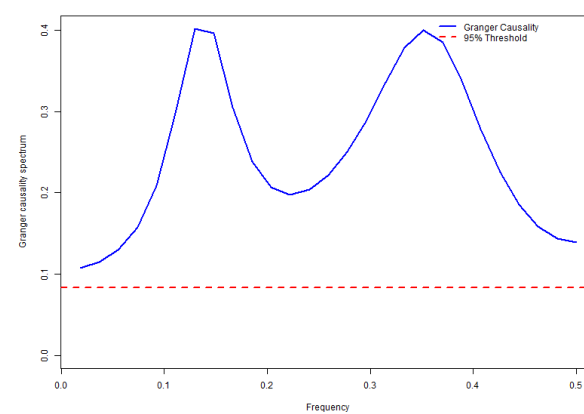
(a) Czechia



(b) Denmark

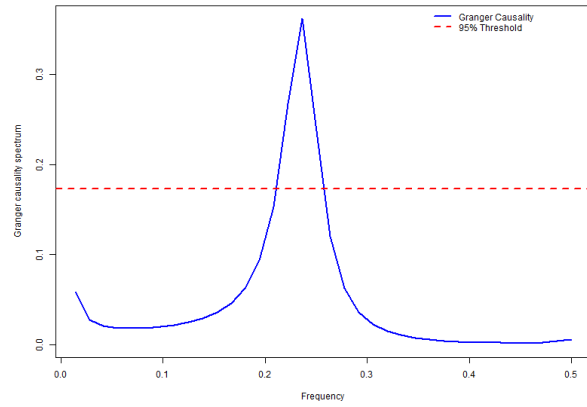


(c) Greece

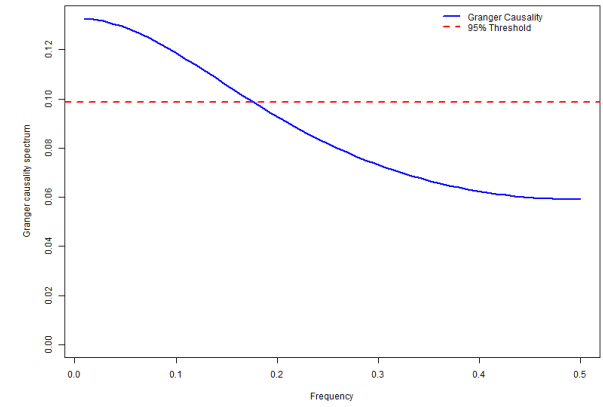


(d) Italy

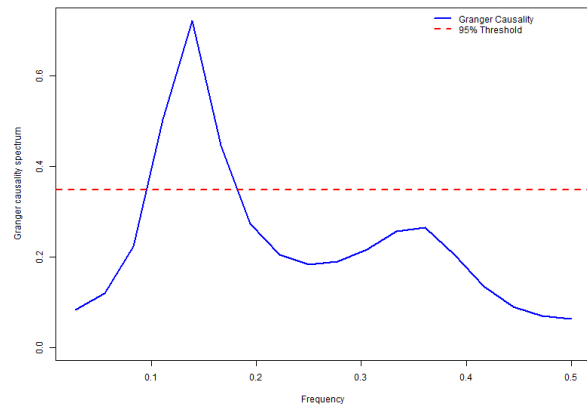
Figure L.4. Granger Causality in the time domain: Non-life insurance penetration to GDP pc (continued)



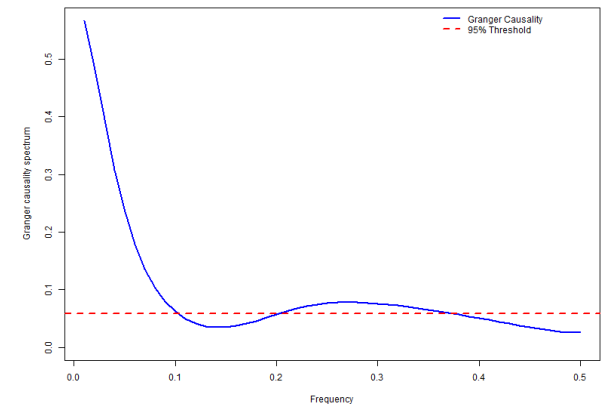
(a) Latvia



(b) Norway



(c) Slovenia



(d) Spain

M Robustness test

Table M.1: Robustness Test Results – Life insurance penetration

Country Parameter	Czechia	Greece	Italy	Latvia	Norway	Slovenia	Spain
Intercept	OLS - / QR +	OLS + / QR +	OLS - / QR -	OLS + / QR -	OLS + / QR -	OLS + / QR -	OLS - / QR -
Population	OLS - / QR -	–	OLS - / QR -	–	–	OLS - / QR -	–
GDP per capita	OLS - / QR -	–	OLS + / QR -	–	OLS + / QR -	OLS - / QR -	–
Inflation	–	–	–	OLS + / QR +	–	–	–
Unemployment	OLS + / QR +	OLS + / QR +	OLS - / QR +	–	OLS + / QR -	OLS - / QR -	OLS - / QR +
Banking sector	OLS - / QR -	–	–	OLS - / QR -	OLS + / QR +	–	–
LT Interest rate	OLS + / QR +	OLS + / QR +	–	OLS - / QR -	OLS - / QR -	OLS + / QR +	–
Business Confidence	–	–	OLS + / QR +	OLS - / QR +	–	OLS + / QR +	OLS - / QR -
Consumer Confidence	–	OLS + / QR +	–	–	OLS + / QR +	–	–
Uncertainty	OLS - / QR -	–	–	–	OLS + / QR -	–	–
Pandemic Uncertainty	–	–	–	OLS - / QR -	OLS + / QR +	–	–
Insurance penetration lag 1	OLS - / QR -	OLS - / QR -	OLS + / QR +	OLS - / QR -	–	–	OLS - / QR -
Insurance penetration lag 2	–	OLS - / QR -	OLS - / QR -	OLS - / QR -	–	OLS - / QR -	OLS - / QR -
Insurance penetration lag 3	–	OLS - / QR -	OLS + / QR +	OLS - / QR -	–	–	OLS - / QR -
Insurance penetration lag 4	OLS + / QR +	–	–	OLS + / QR +	OLS + / QR +	–	–
Insurance penetration lag 5	–	–	–	OLS + / QR -	–	–	–
Insurance penetration lag 8	–	–	–	–	–	–	OLS + / QR +

Table M.2: Robustness Test Results – Nonlife insurance penetration

Country Parameter	Czechia	Denmark	Greece	Italy	Latvia	Norway	Slovenia	Spain
Intercept	OLS + / QR +	OLS - / QR -	OLS + / QR -	OLS + / QR +	OLS + / QR +	OLS - / QR -	OLS + / QR -	OLS + / QR +
Population	OLS - / QR -	–	–	OLS + / QR +	–	OLS + / QR +	OLS + / QR -	OLS + / QR +
GDP per capita	OLS - / QR -	OLS - / QR -	–	OLS - / QR -	OLS - / QR -	OLS - / QR -	OLS - / QR -	OLS - / QR -
Inflation	–	–	OLS - / QR -	–	OLS - / QR -	OLS + / QR -	OLS + / QR +	–
Unemployment	–	–	–	OLS + / QR +	OLS - / QR -	OLS + / QR +	OLS + / QR +	–
Banking sector	OLS + / QR +	OLS + / QR +	–	OLS + / QR +	–	OLS + / QR +	OLS - / QR +	OLS - / QR +
External trade	OLS + / QR +	OLS - / QR -	–	OLS + / QR -	OLS + / QR +	OLS + / QR -	OLS - / QR -	–
Business Confidence	–	OLS + / QR -	–	–	–	–	OLS - / QR +	OLS + / QR +
Consumer Confidence	OLS - / QR -	OLS - / QR -	–	–	–	OLS + / QR +	OLS + / QR +	OLS - / QR -
Uncertainty	OLS - / QR -	OLS - / QR -	OLS + / QR -	–	OLS - / QR -	–	OLS + / QR -	–
Pandemic Uncertainty	–	–	–	–	–	–	OLS - / QR -	–
Insurance penetration lag 1	OLS - / QR -	OLS + / QR +	OLS - / QR -	OLS - / QR -	OLS - / QR -	OLS + / QR +	OLS - / QR -	OLS - / QR -
Insurance penetration lag 2	OLS - / QR -	OLS - / QR +	OLS - / QR -	OLS - / QR -	OLS - / QR -	OLS + / QR +	OLS - / QR -	OLS - / QR -
Insurance penetration lag 3	OLS - / QR -	OLS + / QR -	OLS - / QR -	OLS - / QR -	OLS - / QR -	–	OLS - / QR -	OLS - / QR -
Insurance penetration lag 4	OLS - / QR -	OLS + / QR +	–	–	OLS - / QR -	–	–	OLS + / QR +
Insurance penetration lag 5	–	OLS + / QR -	–	–	OLS + / QR -	–	–	–
Insurance penetration lag 6	–	OLS - / QR -	–	–	OLS - / QR -	–	–	–
Insurance penetration lag 7	–	OLS + / QR -	–	–	–	–	–	–
Insurance penetration lag 8	–	OLS - / QR +	–	–	OLS - / QR -	–	–	–

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