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FACTORS INFLUENCING NON-LIFE INSURANCE DEMAND: CASE OF LITHUANIA

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Abstract
This paper studies factors affecting non-life insurance demand in Lithuania. The study identified variables that are important in analyzing the demand for non-life insurance and were applied in estimating multivariate VAR, Classical Granger, and Toda-Yamamoto causalities. Lithuania's case showed three significant causal relationships: positive - between non-life insurance demand and inflation and loss probability, negative - between density and short-term interest rate. Loss probability and short-term interest rate have been shown to be significant across all models. Inflation was deemed to be the effect of shift in demand rather than the cause.

Keywords: *non-life insurance demand, VAR, Granger Causality.*
JEL Codes: *O43, G22.*

Introduction

Understanding insurance business is important due to the benefits it brings to economic growth and the well-being of individuals. Demand estimation, in particular, is a crucial part of insurance company businesses, as it does not only help to sustain earnings, but also plays a major role in risk pooling process and pricing strategies. Lithuania and other Baltic countries have one of the least densely penetrated insurance markets in the European Union (Abele, Urban, 2013; Hodula, 2021; Eurostat, 2022). Such markets are perceived as having high potential to be more densely insured, especially knowing that living conditions are improving. The insurance business itself helps to remove uncertainty from either businesses or private consumers and transforms it into regular, pre-determined cash-flow. Moreover, this industry not only helps households and businesses, but it also contributes to the economy's development as a whole (Lee et al., 2021; Gupta et al., 2019; Chang, Lee, 2012; Outreville, 2014; Pradhan, et al., 2015). There are various ways identified, how it influences it, spanning from better trade and tax allocation to savings mobilization. According to Van der Veer (2015) insurance contributes to countries' trade balance through exporting companies, therefore private credit insurance has a positive impact on the exports. Pradhan et al. (2015) research, using Granger causality tests, showed, that insurance market development has long-run causal effect on country's economic growth. Consequently, countries, wishing to sustain long-run economic growth, should focus on their insurance market development and not just put the emphasis on the whole financial sector (Trinh et al., 2021; Pradhan et al., 2015). Understanding the demand of insurance and factors, having an effect on it, may be beneficial not only for the insurance companies, but also to financial industry and county's development.

The *purpose* of the paper is to find which factors are significant when trying to explain the demand for non-life insurance in Lithuania. This paper focuses on the macroeconomic and social determinants. Empirical part consists of the regression analysis on panel data, extracted from publicly available sources – Bank of Lithuania and Eurostat databases.

Literature Review

The majority of research papers examine insurance demand through practical approaches – looking to variations of one variable, when adding different factor variables (Trinh et al., 2021; Kozarevića et al., 2013; Lee et al., 2021; Ondruska, 2018; Kjosevski, Petkovski, 2015; Seneta, 2013). One of the most used variables included in regression analysis is the level of income (Beenstock et al., 1988; Esho et al., 2004, Dragos 2014). The research showed that income (measured as GDP per capita) in OECD countries was statistically significant, while education level (taken as a risk averseness proxy) is found to be significant at the 10% level and urbanization did not have any effect on the non-life insurance demand (Esho et al., 2004). The more income consumer has, the more affordable insurance becomes, or the more expensive goods one can acquire, the expected value of loss increases and becomes higher than the price for insurance.

Based on economic theories insurance should be highly associated with person's risk aversion: the more risk averse a consumer is, the more likely they are he to purchase insurance policy. However, the biggest issue is that this factor associated with consumer behavior is difficult to quantify. Therefore, authors look for proxy variables that best describes level of risk acceptance. The most popular proxy is the participation in tertiary education ratio. Studies show that it has a statistically significant positive effect on the consumption of non-life insurance products. Other studies tested for correlations between demand for insurance and participation in tertiary education ratio, which was taken as a proxy for risk aversion (Esho et al., 2004; Thinh et al., 2021; Abraham, 2015; Dragos, 2014). Results showed that the more educated people get, the more they become aware of the potential losses involved in possession of their belongings, therefore they are more eager to purchase insurance products.

Like for any product or service, prices play a significant role in decision making process. However, the relation between inflation and insurance demand is not widely examined. Studies which included inflation level or any proxy, reflecting such variable, determined that this variable should have statistically significant negative effect on the insurance demand (Çelik, Kayali, 2009; Esho et al., 2004). As during high inflation times, consumers evaluate financial or more precisely insurance products as not a crucial good and reduce their consumption.

Another variable, that is rarely included into demand for insurance analysis, is interest rate. This variable usually reflects overall economic situation and therefore it should have an impact on the demand for insurance. Millo and Millossovich (2014) were able to confirm the hypothesis, that interest rates and insurance premiums have inverse relationship. Furthermore, for the industry level, after a change in the interest rates, they have observed negative response of insurance premiums. When looking at the data by insurance line, the effect of sudden change in interest rates is not realized immediately and insurance companies take some time to react.

Some authors have observed that the location of consumers is important when forecasting insurance demand (Simionescu, Ulbinaitė, 2021; Hwang, Gao 2003; Ondruska, 2018; Park, Lemaire, 2011). Urbanization was usually used as a proxy for loss probability. This

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was justified by previously done studies, that have shown that in urban areas loss frequency is higher, as urban areas are denser, there is higher probability of any interaction. Also, it was found that people, living in cities, receive higher income than those in rural areas. The factor was found to have statistically significantly positive effect on insurance density (Trinh et al., 2021; Hwang, Gao, 2003). The phenomena of families becoming smaller and economies switching from agricultural to industrialized was also found present and having significant effect on insurance demand (Park, Lemaire, 2011).

Research methodology

Data and assumptions. The research used publicly available data. Lithuania is favorable for any kind of analysis, due to the fact, that economy is quite small and sensitive to external shocks (Jadevičius, Goštautas, 2015). The data sample covers 10 year's quarterly data period. The variables included in the study are the following: *i)* non-life insurance density; *ii)* income (Esho et al., 2004, Dragos, 2014); *iii)* urbanization – a proxy for loss probability (Briys, Schlesinger, 1990; Trinh et al., 2021; Guiso, Paiella, 2008; Park, Lemaire, 2012); *iv)* - third level education – risk aversion proxy. (Dionne, Eeckhoudt, 1985; Trinh et al., 2021 Abraham, 2015). Yearly data was interpolated with linear trend and reconstructed into quarterly data. In this way, data has no drastic shocks, arising from seasonality of scholar year. *v)* - inflation – variable used to reflect the price level in the economy and as a proxy for insurance price (Outreville, 1992; Lee at al., 2021; Çelik, Kayali, 2009); *vi)* - interest rate - short-term – 3-month Euribor rate (monthly data was averaged into respective quarters) (Lee at al., 2021).

Variables used in this paper's empirical study and their abbreviations are summarized in Table 1.

Table 1. Selected variables and their sources

Abbreviation	Measure	Variable	Source
NL_den	Eur/capita	Non-life insurance density – ratio between non-life insurance premiums written to total population (15 years and more)	Bank of Lithuania, Eurostat
GDP_capita	Eur	GDP per capita	Eurostat, Statista
LP	%	Loss probability – ratio between people in urban areas to total population (15 years and more)	Eurostat
TE	%	Risk aversion – ratio of participation in tertiary education population to total population (15 years and more)	Eurostat
HICP	Index	Harmonised index of Consumer prices	Eurostat
STIR	%	Short-term interest rate - 3-month Euribor rate	ECB data warehouse

Note: *Summary of variables included into Vector Autoregression model of this paper.*

Research design and model specification. The main aim of this paper is to find which factors are significant when trying to explain the demand for insurance in Lithuania. The methodological approach and the sequence of the study will be based on the best practice of other authors as well as the literature reviewed.
The basic Vector Autoregression (VAR) formula that is applied in this paper is as follows:

$$Y_t = a + \sum_{i=1}^{n} A_i Y_{t-i} + \varepsilon_t$$

With

$$Y_t = \begin{bmatrix} Non-life\ insurance\ density \\ Income \\ Loss\ probability \\ Risk\ aversion \\ Inflation \\ Short-term\ interest\ rates \end{bmatrix} = \begin{bmatrix} NL\_ins\_den \\ GDP\_capita \\ TE \\ RA \\ HICP \\ STIR \end{bmatrix}$$

Where Y_t – Column vector of the variables under consideration; a – Vector of constants; A_i – Matrices of coefficients; n – Lag length; ε_t – Vector of random error terms.

Results

Correlation tests. Spearman (rank) and Pearson (classical) tests were implemented, in order to test the data for autocorrelations. Variables tend to move at the same direction (except for short-term interest rate) in all the cases. Strongest connection was between loss aversion, participation in tertiary education and GDP per capita pairs.

Stationarity. In order to avoid spurious regression results or not recovering from data shocks, all the time series, used in the model were tested for stationarity, using Augmented Dickey-Fuller test (Dickey, Fuller, 1979). It was checked for three instances - including time trend, including constant and including both time and constant. The outcome of the test provided p-values, that were tested using 5% significance level. The results of ADF test are summarized in Table 2.

Table 2. Augmented Dickey-Fuller test results

Variable	Notation	Without constant	With constant	With constant and trend
Non-life insurance density	LT_NL_den	0.9998	0.9958	0.5464
Inflation index	LT_HICP	0.9992	0.008518	0.7555
GDP per capita	LT_GDP_capita	0.9493	0.8023	7.36E-05
Loss probability	LT_LP	0.8712	0.6699	0.6961
Participation in tertiary education	LT_TE	1	0.9994	0.9994
Short-term interest rate	STIR	2.88E-05	0.001088	3.10E-07

The results show, that at the first difference all the variables became stationary and therefore can be used in modeling the relationship. Additionally, KPSS test was conducted for the variables to check for stationarity. The test revealed the values to be lower than critical values, therefore this implies, that the data is actually stationary (Table 3). However, the time series on inflation had to be differenced by 1 (integrated at level 1 (I (1)), to become stationary.

Table 3. KPSS test results

	With Trend			Without Trend		
Notation	10% 0.122	5% 0.149	1% 0.211	10% 0.353	5% 0.462	1% 0.716
d_LT_NL_den	0.090	0.090	0.090	0.360	0.360	0.360
d_LT_HICP	0.057	0.057	0.057	0.481	0.481	0.481
LT_GDP_capita	0.103	0.103	0.103	0.727	0.727	0.727
d_LT_LP	0.099	0.099	0.099	0.109	0.109	0.109
d_LT_TE	0.069	0.069	0.069	0.147	0.147	0.147
STIR	0.121	0.121	0.121	0.604	0.604	0.604

Note: *The values shown in the table reflect p-values from KPSS test.*

VAR Model. Vector autoregression analysis was conducted, based on the studies by (Horng *et al.*, 2012; Olayungbo, 2011). Despite that, the data was also tested pairwise with

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causality tests, where the dataset is sufficient by existing theories.

Lag selection. Maximum lag order allowed was set on 4, due to the quarterly data used. This lag selection is based on three information criteria: Akaike (AIC), Bayesian (BIC) and Hannan–Quinn (HQC). The lags were selected according to the lowest criterion and if there were any differences among them, the decision was made according to the AIC criterion.

Table 4. Lag selection for VAR model

	AIC	BIC	HQC
With trend	3 (2.085)	3 (2.552)	3 (2.234)
With constant	3 (2.091)	3 (2.558)	3 (2.241)
With C&T	3 (2.138)	1 (2.625)	3 (2.302)

Note: *The values shown in the table reflect the number of lags suggested by VAR lag selection test.*

Table 5. VAR model results

	d_LT_NL_den		d_LT_HICP		d_LT_TE		LT_GDP_capita		STIR	
	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value	Coef.	p-value
const	11.67	0.03	1.47	0.68	-0.03	0.27	544.65	0.07	0.00	0.79
d_LT_LP_1	15.76	0.04	-0.11	0.98	-0.06	0.17	362.82	0.36	-0.01	0.69
d_LT_LP_3	15.34	0.08	2.96	0.63	0.03	0.50	-13.10	0.98	-0.04	0.09
d_LT_TE_1	-8.36	0.81	10.28	0.70	-0.65	0.01	150.57	0.94	-0.01	0.93
d_LT_TE_2	-8.28	0.82	-32.16	0.26	-0.79	0.01	-1461.32	0.49	-0.05	0.66
d_LT_TE_3	5.22	0.89	-22.81	0.42	-0.41	0.10	-2316.69	0.29	0.02	0.85
d_LT_HICP_1	0.15	0.67	-0.78	0.01	0.00	0.96	5.56	0.78	0.00	0.03
d_LT_HICP_2	-0.20	0.61	-0.20	0.50	0.00	0.40	38.91	0.10	0.00	0.01
d_LT_HICP_3	-0.18	0.46	0.26	0.16	0.00	0.18	25.22	0.08	0.00	0.10
LT_GDP_c_1	-0.01	0.13	0.00	0.49	0.00	0.46	1.13	0.00	0.00	0.50
LT_GDP_c_2	0.00	0.64	0.00	0.27	0.00	0.34	-1.27	0.00	0.00	0.28
LT_GDP_c_3	0.00	0.32	0.00	0.72	0.00	0.15	0.90	0.00	0.00	0.47
STIR_1	95.08	0.24	50.43	0.40	-0.04	0.93	-4059.14	0.38	0.62	0.02
STIR_2	-195.10	0.08	86.75	0.28	0.74	0.28	12014.70	0.06	0.04	0.90
STIR_3	96.11	0.27	-12.83	0.84	-0.80	0.16	-13593.10	0.02	0.43	0.11
time	0.31	0.04	0.00	0.97	0.00	0.23	9.50	0.23	0.00	0.56

Note: *The values shown in the table reflect the coefficient values and p-values of each equation in VAR system of equations.*

With the selected 5% significance level, non-life insurance density can be estimated one quarter in advance by knowing the share of population in urban areas. With 10% significance level, third lag of loss probability and second lag of short-term interest rates can be included. Other variables were not proved to have any explanatory power of the dependent variable.

Causality tests. Due to the markets being not very well observed in Lithuania, and the lack observations, VAR model did not yield best results. Therefore, it was decided to check the connections pairwise, while using Classical

Granger Causality and Toda-Yamamoto causality tests, that are also based on VAR model framework. The lag selection was done two times, as Classical Granger Causality and Toda-Yamamoto models use different variables – for classical model the data has to be stationary, while Toda-Yamamoto causality uses only original data time series.

Lag selection. All the causality tests included both constant and trend, as the AIC has shown lowest value. For Classical Granger causality model, all pair's models had 4 possible lags, except the pair with short-term interest rate – the model included two lags. In Toda-Yamamoto models, all the pairs were lagged 4 times, except for the pair with inflation rate, which included 3 lags. Variables with same level of integration in the pair were tested for cointegration. In all three cases, the cointegration hypothesis was rejected (with inflation p-value = 0.259, with loss probability p-value = 0.5758 and with risk aversion p-value = 0.5265).

Causality Tests. The causality test results are summarized in the table below:

Table 6. Classical Granger and Toda-Yamamoto causality models results

Classical G-causality			**T-Y causality**		
d_LT_NL_den	**0.0001**	d_LT_HICP	LT_NL_den	0.2396	LT_HICP
d_LT_HICP	0.818	d_LT_NL_den	LT_HICP	0.3829	LT_NL_den
d_LT_NL_den	0.6118	LT_GDP_capita	LT_NL_den	0.4409	LT_GDP_capita
LT_GDP_capita	0.6545	d_LT_NL_den	LT_GDP_capita	0.6424	LT_NL_den
d_LT_NL_den	0.4205	d_LT_LP	LT_NL_den	0.567	LT_LP
d_LT_LP	**0.0328**	d_LT_NL_den	LT_LP	0.9918	LT_NL_den
d_LT_NL_den	0.2677	d_LT_TE	LT_NL_den	0.1537	LT_TE
d_LT_TE	0.1885	d_LT_NL_den	LT_TE	0.4729	LT_NL_den
d_LT_NL_den	0.1496	STIR	LT_NL_den	0.775	STIR
STIR	**0.0004**	d_LT_NL_den	STIR	**0.0305**	LT_NL_den

Note: *The values shown in the table reflect p-values gathered from both Classical Granger and Toda-Yamamota causality tests.*

The Classical Granger causality model was able to detect three relationships. Non-life insurance spendings per person has a positive causal effect on inflation and that loss probability, granger causes the changes in non-life insurance density. However, this relationship did not hold through the more sensitive Toda-Yamamoto causality test, which showed no significance. Both tests found short-term interest rate to have a causal effect on non-life insurance demand, meaning it has an effect on customer spending on the insurance.

IRF and FEVD. The tests showed the nature of the relationships and how much one can explain the other's dynamic.

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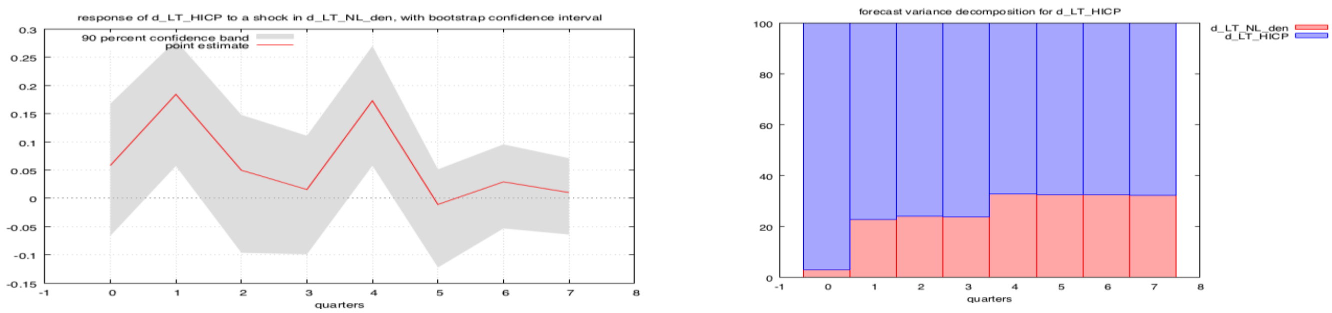

Figure 1. IRF and FEVD graphs between NL insurance density and inflation in Lithuania. On the left – IRF graph showing inflation response to shock in NL insurance density, on the right – FEVD graph showing how much information it explains

The first significant relationship implied that non-life insurance spendings per person has a causal effect on inflation. From the impulse response graph, it can be seen, that the relationship is mostly positive, but not consistent. First quarter it increases very fast and begins to dissolve in the second and third quarter. The cycle continues again from the fourth quarter. Around 30 % of inflation dynamics can be explained by non-life insurance density dynamics. Even though, the relationship is quite significant it is inconsistent.

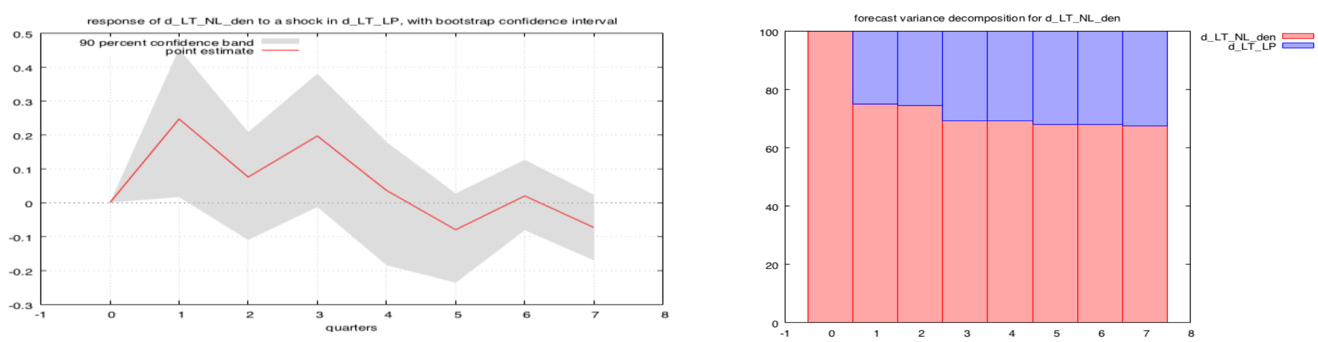

Figure 2. IRF and FEVD graphs between NL ins. density and loss probability in Lithuania. On the left – IRF graph showing NL insurance density response to shock in LP, on the right – FEVD graph showing how much information it explains

Second pair was between loss probability and non-life insurance density. From impulse response graph it can be seen that after shocking loss probability data by one standard deviation size shock, non-life insurance density tends to increase and dissolve after one year. However, the relationship is not very consistent, as in the second year after the shock the effect becomes inverse, which can be the reason for the renewal of insurance policies. Almost 30% of non-life insurance density dynamics can be explained by loss probability dynamics. Therefore, this variable bears quite a significant effect.

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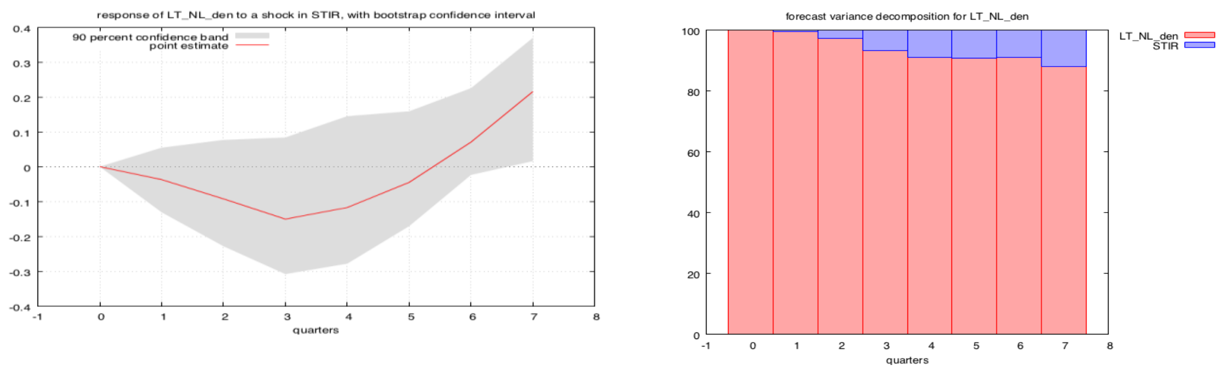

Figure 3. IRF and FEVD graphs between NL insurance density and STIR in Lithuania. On the left – IRF graph showing NL insurance density response to shock in STIR, on the right – FEVD graph showing how much information it explains

Finally, relationship between short-term interest rate and non-life insurance density was shown to be inverse. Even though in the last quarter of two years the effect moved into positive side, overall negative relationship was observed. This goes along with the theory that increasing interest rates increases borrowing costs and this at the end results in the decreasing spending on non-life insurance premiums. Even though, that the relationship was present and is perfectly explained by the existing theories, it only is able to explain up to 10% of overall non-life insurance demand dynamics, and therefore is not very significant.

Conclusions

According to the reviewed literature, six variables, possibly influencing insurance demand were selected. Causal relationships were attempted to find by running VAR analysis on every one of them simultaneously and by Causality tests pairwise. VAR model appeared to have spurious results; therefore, more emphasis was put on causality test results. For causality analysis, Classical Granger and Toda-Yamamoto tests, were carried out. Doing the test with both methods, allowed to check for consistency of the relationship.

Lithuania's case showed three significant causal relationships: positive between non-life insurance demand and inflation and loss probability, negative - between density and short-term interest rate. Both loss probability and short-term interest rate, have been shown to be significant in VAR model as well. Inflation was not the cause but the effect of causal relationship – the changes in non-life insurance demand Granger caused changes in inflation. Gathered results imply, that in Lithuania insurance companies should design their products for urban population, because urbanization factor was found to be significant. Finally, the unsustainability of results in insurance market signal about renewability issues, as the first year's effect goes in line with theory, while in the second year the results flip around.

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