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Comparative analysis of non-performing loans affecting factors in the Baltic States

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ABSTRACT
The deterioration of the economic situation during Covid-19 has raised the issue of the quality of banks' assets and in particular the growth of non-performing loans (NPL). This is a topical issue not only for banks that, in this context, incur additional costs for allowances and capital requirements but also for society as a whole, as credit availability is likely to be reduced. The Baltic States experienced a particularly severe financial crisis in 2008-2009, resulting in a rapid increase in NPLs. This study analyses the factors affecting NPLs in the Baltic States, using information available from WB, Eurostat, and econometrical modeling methods. The results of the study allow conclusions to be drawn on the necessary actions to mitigate credit risk.
Keywords*: non-performing loans, influencing factors, comparative analysis.*

1. INTRODUCTION

Over the last twenty years, the Baltic States have undergone significant structural changes in their economies and financial systems: in the first half of the first decade, with the approach of EU accession, there was a rapid inflow of foreign investments, real estate market development and a commercial bank credit boom. With the onset of the global financial crisis, the real estate price bubble burst, followed by bankruptcies of both companies and households. Although the dynamics of GDP in the Baltic States were relatively similar, the changes in non-performing loans, as shown in Figure # 1, differed significantly. The question, therefore, arises as to what factors may explain these differences.

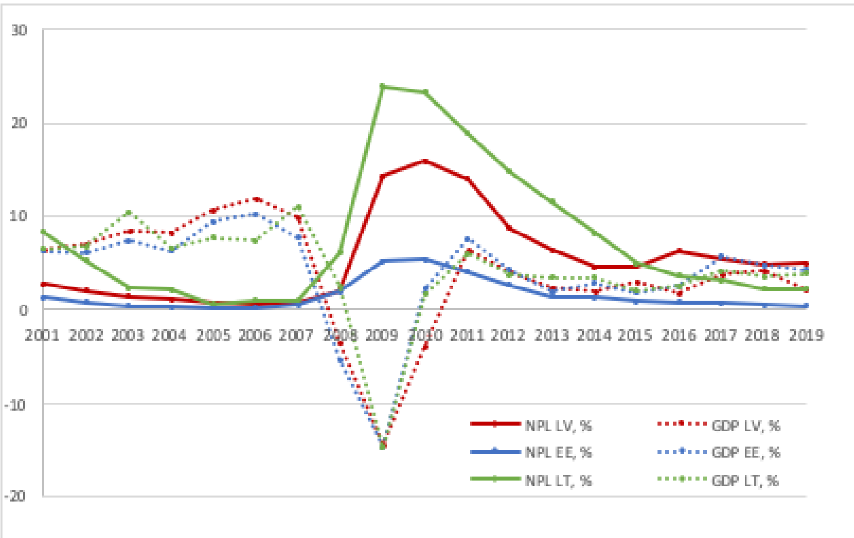

Figure 1. NPL and GDP growth dynamic in the Baltic States

2. LITERATURE REVIEW

Macroeconomic conditions form a link between the business cycle and lending, as environmental changes directly affect the borrower's ability to service debt. For example, research has often found that GDP growth shows a negative correlation with NPLs, indicating a countercyclical nature of NPLs (Louzis, 2012; Jakubik,

2013; Makri, 2014; Skarica, 2014; Beck, 2015; Cifter, 2015, Cucinelli, 2015; Tanaskovic, 2015; Dimitrios, 2016; Gila-Gourgoura, 2017; Kupcinskas, 2017; Peric, 2017; Koju, 2018; Ozili, 2019; Radivojevic, 2019).
With rising unemployment and falling wages, which are typically seen in times of economic downturns, borrowers face greater difficulties in repaying their debt, and, as a result, NPLs increase. Many researchers explicitly include unemployment in their models and find strong positive relationships between unemployment and NPLs (Louzis, 2012; Makri, 2014; Skarica, 2014; Cifter, 2015; Cucinelli, 2015; Dimitrios, 2016; Koju, 2018; Kupcinskas, 2017; Spilbergs, 2020). In addition to the above, the following are also considered to be important determinants of NPLs:
- inflation, since its growth reduces real wages and hence the ability to meet liabilities. This is particularly important in circumstances where inflation exceeds wage growth (Skarica, 2014; Filip, 2015; Koju, 2018);
- variable interest rates, which directly affect the ability of borrowers to pay interest, especially when the proportion of variable rate loans is significant (Louzis, 2012; Beck, 2015; Peric 2017);
- the house price index - falling house prices are tightly linked to higher default rates (Beck, 2015);
- foreign direct investment, the growth of which is usually conducive to economic growth and thus has a positive impact on NPLs (Cifter, 2015; Koju, 2018).

3. **CORRELATION ANALYSIS OF NON-PERFORMING LOANS AN POTENTIAL INFLUENCING FACTORS**

Based on the literature analysis, 18 factors were selected that could potentially influence changes in NPLs. Using World Bank data on non-performing loan ratios from 2001 to 2019 and Eurostat data on selected factors, a list of the top 10 by correlation was created, see Table # 1, to which the coefficient of variation (CV) of the studied indicator is added in the last column. As can be seen, the values of the correlation coefficients of several factors are quite similar for all analyzed countries, such as unemployment (UPL), GDP, and net wage growth (NWG), while for others, such as the long-term interest rate (LTR), coefficients of correlations vary very significantly. Consequently, the question arises as to whether the Baltic States can be considered homogeneous from the point of view of the factors influencing NPLs.
To answer this question, NPL regression models were developed for each of the Baltic States separately and then the possibilities to improve them by developing unified models were explored.

Factor	**Estonia**	**Latvia**	**Lithuania**	**CV**
Household disposable income growth, %	-0,8112	-0,8857	-0,6934	12%
Unemployment rate – annual, %	0,7250	0,7640	0,7287	3%
Private sector debt: loans, % of GDP	0,6785	0,7066	0,4686	21%
Net wages growth rate, %	-0,6534	-0,7567	-0,7465	8%
Construction costs growth, %	-0,6334	-0,5199	-0,7042	15%
GDP growth rate, %	-0,5898	-0,6705	-0,6412	6%
Household debt, % of GDP	0,5720	0,5382	0,4585	11%
House price index, % annual	-0,5369	-0,5891	-0,8005	22%
Investments to GDP, %	-0,4937	-0,6510	-0,6796	16%
Loans growth to GDP growth	-0,3612	-0,6285	-0,5040	27%
Long-term interest rate, %	0,1709	0,4543	0,6079	54%

Table 1. Correlation coefficients of selected factors and NPLs by countries

4. **THE MODEL AND RESULTS**

Let NPL_t be the dependent variable non-performing ratio' in year t. Further, let $x_{1t},\ldots,x_{kt}$ denote independent variables and $b_{1t},\ldots,b_{kt}$ denote regression coefficients of independent variables, then the model can be expressed as in equation:

$$NPL_t' = f(x_{1t\,,}\ldots,x_{kt}) + \varepsilon_t$$

where ε_t – the error term.

During the research, combining the selected factors, more than a hundred linear and non-linear regression models were calibrated for each country and Baltics. To select the best fit from the compiled models, three tests were performed:
1) F-test to assess the statistical stability of models at a confidence level of 0,95 (α = 0,05);
2) Durbin-Watson test to detect the presence of autoregression at a confidence level 0,95 (α = 0,05);
3) t-test for estimation of statistical stability of regression parameters at a confidence level 0,95 (α = 0,05).

4.1 REGRESSION MODELS AND RESULTS FOR ESTONIA

For Estonia, three linear and two polynomial models provide the best fit to the selected data. The most common factors in created regression models are household disposable income growth, % (HDI), private sector debt, loans % of GDP (PSD), unemployment rate, % annual (UPL) and net wages growth rate, % (NWG), which corresponds to the previous correlation analysis. The following figure shows the relationships between HDI, UPL, and NPLs. As can be seen, the relationships are nonlinear in both cases. As HDI increases, NPLs decrease, and for negative HDI values, NPLs increase faster than for positive ones. On the other hand, with the increase in the UPL, the NPL also increases, and for higher unemployment rates, the increase in the NPL is faster.
The factors and statistics of the five best-fit regression models are summarized in Table 2. As can be seen, the best of the developed regression models allows explaining the absolute

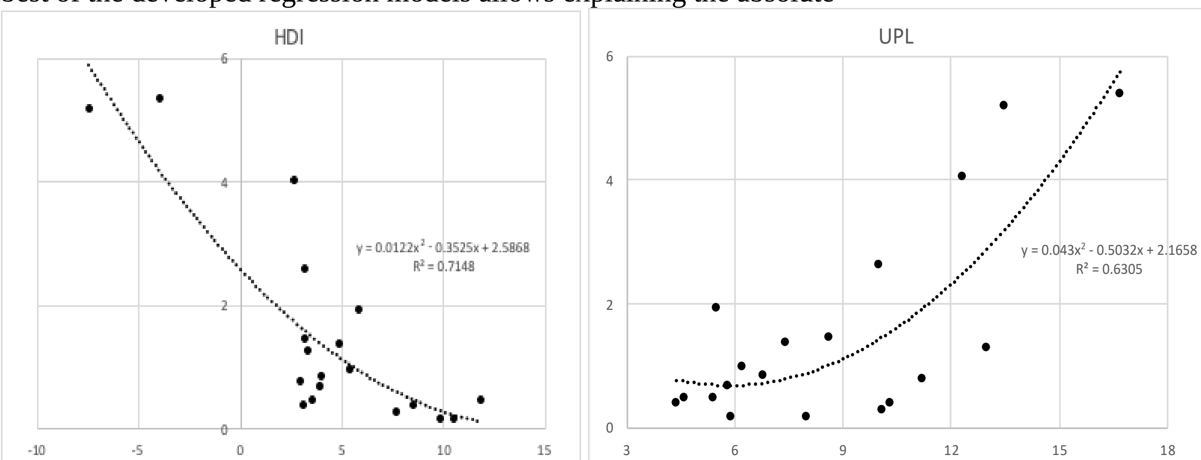

Figure 2. HDI, UPL, and NPL relationships for Estonia

majority of the changes in NPLs. Thus, for example, the linear model with three factors - HDI, UPL, and LtGDP - allows explaining ca. 94,5% of NPL changes in the case of Estonia.

Model type	**Factors**	***R*^{2}**	***F***	***p* - value**
Linear 1	HDI, UPL, LtGDP	0,9446	85,1874	<0,01
Linear 2	UPL, PSD	0,9249	98,5646	<0,01
Linear 3	PSD, HDI	0,8168	35,6656	<0,01
Polynomial 4	HDI	0,7148	20,0533	<0,01
Polynomial 5	NWG	0,6988	18,5637	<0,01

Table 2. Best five fitted regression model factors and statistics for Estonia

As shown in Table 2, the *F*-statistics are significantly higher than the *F*-critical values at a confidence level of 0,95 (α = 0,05) and the *p*-values are significantly lower than those traditionally used in such tests, indicating high statistical stability of all models.

The following table summarizes the results of the regression coefficient *t*-tests of the selected five models.

Model	Factors	Regression coefficient	*p* - value
Linear 1	HDI	-0,1149	0,0918%
	UPL	0,2219	0,0013%
	LtGDP	0,0799	0,0001%
Linear 2	UPL	0,3465	0,0000%
	PSD	0,0458	0,0000%
Linear 3	PSD	0,0764	0,0229%
	HDI	-0,2108	0,0076%
Polynomial 4	HDI	-0,3525	0,0024%
	HDI^2	0,0122	4,6686%
Polynomial 5	NWG	-0,7232	0,3556%
	NWG^2	0,0063	0,1307%

Table 3. Best five fitted model regression coefficients and statistics for Estonia

As one can see, the regression coefficients *t*-test *p*-values for all top 5 models do not exceed 5% and for 10 of total 11 are less than 0,5%, indicating a strong relationship between relevant macro indicators and NPLs for Estonia. Meanwhile, the regression coefficient signs are as expected and consistent with those reported in most published studies.

4.2 REGRESSION MODELS AND RESULTS FOR LATVIA

For Latvia linear and one polynomial models provide the best fit to the selected data. The most common factors in created regression models are net wages growth rate, % (NWG), household disposable income growth, % (HDI) and private sector debt, loans % of GDP (PSD), which corresponds to the previous correlation analysis. The following figure shows the relationships between HDI, UPL, and NPLs. As can be seen, the relationships are nonlinear in both cases and similar to Estonians.

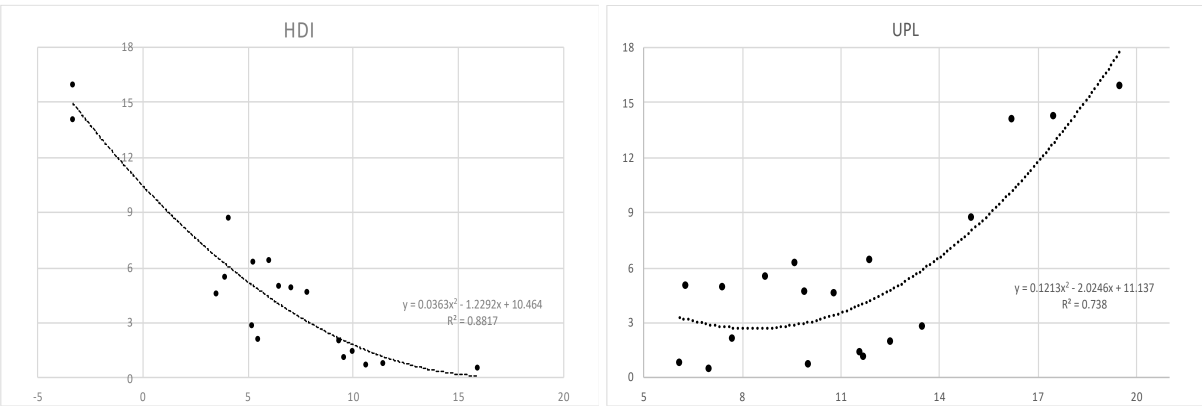

Figure 3. HDI, UPL and NPL relationships for Latvia

The factors and statistics of the five best-fit regression models are summarized in Table 4.

Model type	**Factors**	R^2	***F***	***p* - value**
Linear 1	NWG, HDtI	0,9288	104,3294	<0,01
Linear 2	NWG, HDtGDP	0,9116	82,5246	<0,01
Linear 3	NWG, PSD	0,9101	80,9617	<0,01
Polynomial 4	HDI	0,8817	55,9184	<0,01
Linear 5	HDI, PSD	0,8563	44,6982	<0,01

Table 4. Best five fitted regression model factors and statistics for Latvia

As can be seen, the best of the developed regression models allows explaining the absolute majority of the changes in NPLs. Thus, for example, the linear model with two factors – NWG and household debt to income, % (HDtI) - allows explaining ca. 92,9% of NPL changes in the case of Latvia. Unlike in Estonia, the coefficients of determination of the following regression models are also high, which gives a wider choice in case of necessity. As shown in Table 4, the *F*-statistics are significantly higher than the *F*-critical values at a confidence level of 0,95 (α = 0,05) and the *p*-values are significantly lower than those traditionally used in such tests, indicating high statistical stability of all models. The following table summarizes the results of the regression coefficient *t*-tests of the selected five models.

Model	Factors	Regression coefficient	*p* - value
Linear 1	NWG	-0,4338	0,0000%
	HDtI	0,1402	0,0000%
Linear 2	NWG	-0,4168	0,0000%
	HDtGDP	0,2105	0,0000%
Linear 3	NWG	-0,3437	0,0000%
	PSD	0,2126	0,0000%
Polynomial 4	HDI	-1,2292	0,0000%
	HDI^2	0,0363	0,4056%
Linear 4	HDI	-0,7221	0,0002%
	PSD	0,0924	2,0480%

Table 5. Best five fitted model regression coefficients and statistics for Latvia

As one can see, the regression coefficients *t*-test *p*-values for all top 5 models do not exceed 2,1% and for 9 of total 10 are less than 0,5%, indicating a strong relationship between NPLs and relevant macro indicators for Latvia. Meanwhile, the regression coefficient signs are as expected and consistent with those reported in most published studies.

4.3 REGRESSION MODELS AND RESULTS FOR LITHUANIA

For Lithuania, five linear models provide the best fit to the selected data. The most common factors in created regression models are unemployment rate, % annual (UPL), net wages growth rate, % (NWG), household disposable income growth, % (HDI) and private sector debt, loans % of GDP (PSD), which corresponds to the previous correlation analysis. The following figure shows the relationships between HDI, UPL, and NPLs. As can be seen, the relationships are nonlinear in both cases and similar to Estonians and Latvians, however, the nonlinearity is less noticeable in the case of Lithuania and the disturbances are more visible.

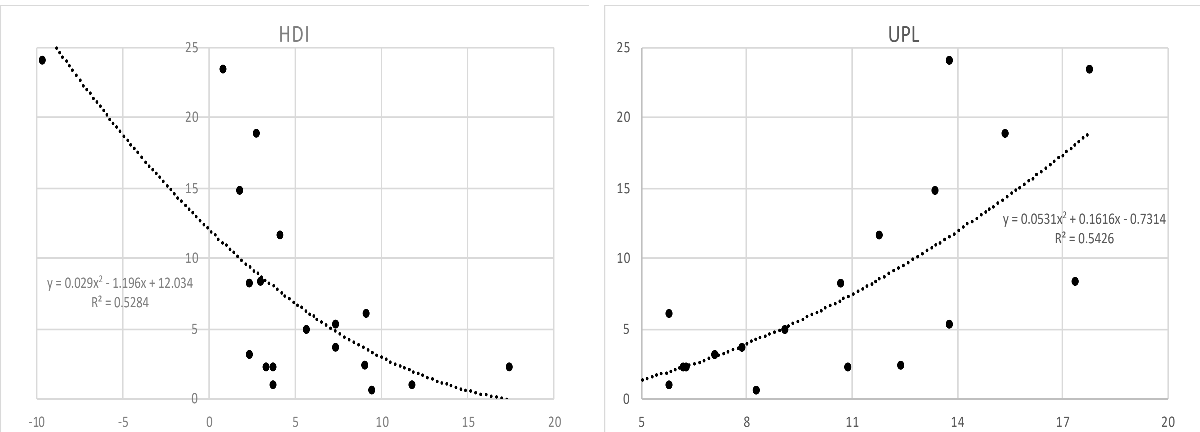

Figure 4. HDI, UPL and NPL relationships for Lithuania

The factors and statistics of the five best-fit regression models are summarized in Table 6.

Model type	**Factors**	R^2	F	***p* - value**
Linear 1	UPL, HDtGDP	0,9722	279,5968	<0,01
Linear 2	UPL, HDtI	0,9542	166,5027	<0,01
Linear 3	UPL, NWG, PSD	0,9306	67,0218	<0,01
Linear 4	HDI, UPL, PSD	0,9174	55,5121	<0,01
Linear 5	Loans, PSD, INV	0,9018	45,9410	<0,01

Table 6. Best five fitted regression model factors and statistics for Lithuania

As can be seen, the best of the developed regression models allows explaining the absolute majority of the changes in NPLs. Thus, for example, the linear model with two factors – UPL and household debt to GDP, % (HDtGDP) - allows explaining ca. 97,2% of NPL changes in the case of Lithuania. Like in Latvia, the coefficients of determination of the following regression models are also high, which gives a wider choice in case of necessity.
As shown in Table 6, the *F*-statistics are significantly higher than the *F*-critical values at a confidence level of 0,95 ($\alpha = 0,05$) and the *p*-values are significantly lower than those traditionally used in such tests, indicating high statistical stability of all models.
The following table summarizes the results of the regression coefficient *t*-tests of the selected five models.

Model	Factors	Regression coefficient	*p* - value
Linear 1	UPL	1,6428	0,0000%
	HDtGDP	0,5727	0,0000%
Linear 2	UPL	1,7408	0,0000%
	HDtI	0,3739	0,0000%
Linear 3	UPL	1,0550	0,0002%
	NWG	-0,4932	0,0200%
	PSD	0,4867	0,0002%
Linear 4	HDI	-0,4518	0,0786%
	UPL	1,2171	0,0000%
	PSD	0,4297	0,0045%
Linear 5	Loans	-0,0449	2,5445%
	PSD	0,6626	0,0000%
	INV	-1,7307	0,0001%

Table 7. Best five fitted model regression coefficients and statistics for Lithuania

As one can see, the regression coefficients *t*-test *p*-values for all top 5 models do not exceed 2,6% and for 12 of total 13 are less than 0,1%, indicating a strong relationship between NPLs and relevant macro indicators for Lithuania. Meanwhile, the regression coefficient signs are as expected and consistent with those reported in most published studies.

4.4 COMMON BALTIC REGRESSION MODELS AND RESULTS

For Baltics fore, linear models and one polynomial model provide the best fit to the selected data. The most common factors in created regression models are investments, % of GDP (INV), unemployment rate, % annual (UPL), and household disposable income growth, % (HDI)). The following figure shows the relationships between INV, UPL, and NPLs. As can be seen, the relationships are nonlinear in both cases and similar to those for each country, however, the disturbances are more visible.

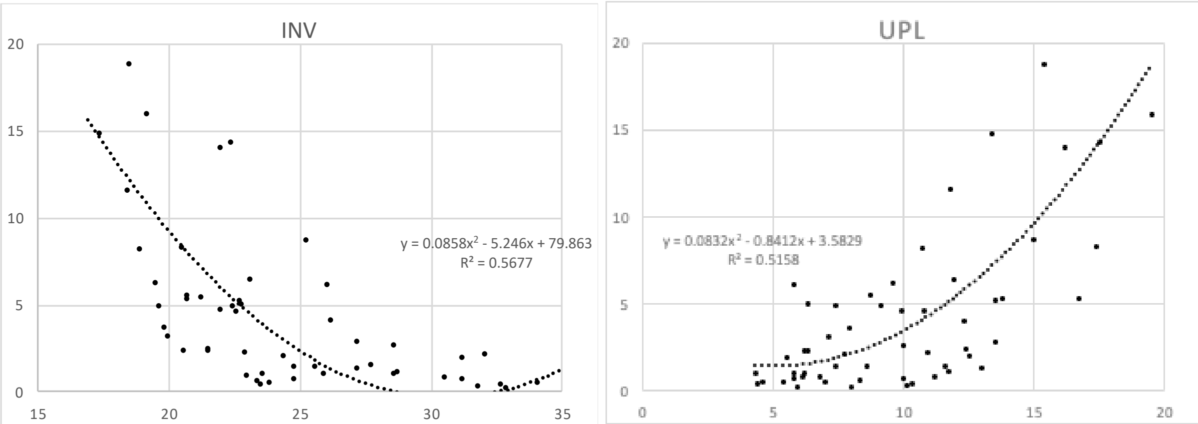

Figure 5. INV, UPL, and NPL relationships for Baltics

The factors and statistics of the five best-fit regression models are summarized in Table 8.

Model type	**Factors**	R^2	F	***p* - value**
Linear 1	INV, LTR	0,6704	54,9283	<0,01
Linear 2	HDI, UPL, INV	0,6300	30,0864	<0,01
Polynomial 3	INV	0,6201	41,6228	<0,01
Linear 4	UPL, INV	0,5920	39,1821	<0,01
Linear 5	INV, HDI	0,5534	33,4567	<0,01

Table 8. Best five fitted regression model factors and statistics for Baltics

As can be seen, the best of the developed regression models allows to explain up to two-thirds of the changes in NPLs in the Baltics, which is significantly less than the country-calibrated models. Another problem for the calibration of a statistically stable unified Baltic model is the autocorrelation of factors that appeared in the Durbin-Watson tests. This is not surprising, given that the macroeconomic indicators of the Baltic States in the study period are quite similar. As shown in Table 8, the *F*-statistics are significantly higher than the *F*-critical values at a confidence level of 0,95 ($\alpha = 0,05$) and the *p*-values are significantly lower than those traditionally used in such tests, indicating high statistical stability of all models. The following table summarizes the results of the regression coefficient *t*-tests of the selected five models. As one can see, the regression coefficients *t*-test *p*-values for all top 5 models do not exceed 1,2% and for 10 of total 11 are less than 0,1%, indicating a strong relationship between NPLs and relevant macro indicators for Baltics. Meanwhile, the regression coefficient signs are as expected and consistent with those reported in most published studies.

Model	Factors	Regression coefficient	*p* - value
Linear 1	INV	-0,6758	0,0000%
	LTR	0,9919	0,0000%
Linear 2	HDI	-0,2497	1,1726%
	UPL	0,6112	0,0061%
	INV	-0,3576	0,0926%
Polynomial 3	INV	-5,4363	0,0000%
	INV^2	0,0884	0,0003%
Linear 4	UPL	0,7414	0,0001%
	INV	-0,4435	0,0059%
Linear 5	INV	-0,4243	0,0298%
	HDI	-0,5256	0,0022%

Table 9. Best five fitted Baltic model's regression coefficients and statistics

5. CONCLUSION

The economies of the Baltic States have shown relatively similar development trends over the last twenty years, and thus the list of factors influencing non-performing loans is comparable. As a result of the study, five statistically stable regression models have been compiled, with a confidence level of over 95%, for each of the

Baltic States, whose ability to determine changes in NPLs depending on such macroeconomic factors as HDI, UPL, PSD, and GDP is higher than 90%. Therefore, a basis has been prepared to provide an analysis-based assessment of credit risk management performance and to develop forecasts of expected credit quality changes based on a qualitative comparison of the results of several models. The development of uniform NPL regression models for the Baltic States is a certain challenge, as the volatility of the factors included in the models is quite different. This explains, why the coefficients of determinants for uniform Baltic regression models are significantly lower than country-specific models. Simultaneous research also shows that the developed regression models need to be regularly validated and, if necessary, recalibrated to capture changes in the impact of microeconomic indicators on NPLs, as the Baltic States, as small economies, are more sensitive to changes in the external environment.

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