

# Residential Mortgage Loans Delinquencies Analysis and Risk Drivers Assessment

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## Abstract

Residential mortgage loans play an important role in improving living conditions in developed countries. In Latvia, however, residential mortgage volumes have declined throughout the post-crisis year's and were at the end of 2018 12% below the end 2008 level, while the house price index ca. 25% below pre-crisis level. The main reasons for this are banks credit losses, which resulted in a revision of credit granting standards and a deteriorating in their availability. On the other hand, households have experienced increased uncertainty, both as a result of financial difficulties, experienced during the crisis years and political instability in the post-crisis years. It is therefore essential to identify the true risk drivers and to analyse them. Based on existing researches in other countries, the author has identified several dozen macro-economic indicators, such as the unemployment rate, wage growth, housing price index, etc. and micro factors such as the age of the borrower, total debt to income, loan-to-value, etc., have developed univariate and multivariate econometric models and have examined their statistical stability. Consequently, through a consistent application, it is possible to take sound credit decisions, both in banks and by households, and to contribute to the sustainable development of the housing market.

## Keywords:

Econometric Models;  
Housing Loans;  
Risk Drivers  
Macro Level Risk Drivers;  
Micro Level Risk Drivers.

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## 1- Introduction

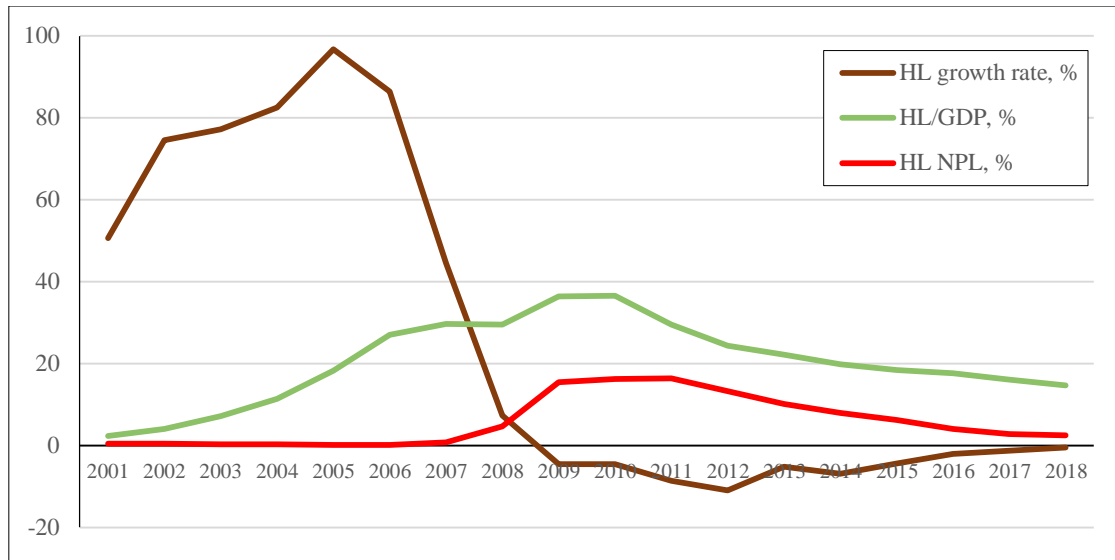
In the last decade of the 20th century, and also in the first years of this century the residential mortgage loans market in Latvia was stagnant due to low household income level and high credit interest rates. Coming closer to join NATO and the EU, foreign investment flowed rapidly, the costs of bank resources declined and confidence in the long-term growth of household incomes strengthened. As a result, housing lending and the ratio of loans to GDP increased significantly, see Figure 1. Unfortunately, most of borrowers had no credit experience until then. Lack of understanding of the housing market, high inflation and overall euphoria lead to disproportionate against stable and regular income borrowing and disregarding of risks until mid-2007, when anti-inflation measures were approved by Latvian Cabinet of Ministers came into force. With the new framework loans granting fell sharply, followed with decrease in demand in housing market and much more difficult refinancing of existing commitments. In 2008 the impact of the global financial crisis on Latvia's financial market became critical, in the autumn the largest bank went bankrupt, GDP fell sharply and unemployment began to rise. As a result, the proportion of non-performing housing loans (HoNPL) increased rapidly - from 0.7% at the end of 2007 to 15.4% and 16.2% at the end of 2009 and 2010, respectively [1]. Although HoNPLs have declined significantly starting from 2013 and have fallen below 2.5% at the end of 2018, the consequences are evident – at the end of last year housing loans volumes were 40% below pre-crisis level [2].

As residential mortgage loans play a key role in improving household living conditions, it is important to be aware of the main risk drivers and to work to prevent the mistakes that have been experienced in the past.

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**Figure 1. Housing loans growth rate, housing loans proportion to GDP and NPL development in Latvia (FCMC and CSB of Latvia data).**

## 2- Literature Review

Studies on the residential mortgage loans delinquencies include wide variety of variables, which can be divided into three groups: borrower and transaction characteristics, and macroeconomic ones.

**Table 1. Residential mortgage loans delinquencies affecting factors analysis summary from literature review.**

Group	Parameter	Author
<b>Borrower</b>	Age	Avanzini (2015) [3]; Campbell (2015) [4]; Csizmadý (2017) [5]; Gerlach-Kristen (2018) [6]; Lydon (2013) [7]; Van Ooijena (2016) [8]
	Credit score	Elul (2010) [9]; Foote (2018) [10]; Fuster (2015) [11]; Goodman (2010) [12]; Gyourko (2014) [13]; Harrison (2011) [14]; Jones (2015) [15]; Lee (2016) [16]
	Debt service ratio	Figueira (2005) [17]; Foote (2018) [10]; Harrison (2011) [14]; Jones (2015) [15]; Kelly (2018) [18]; Kukk (2016) [19]; Lee (2016) [16]; Lydon (2013) [7]; Van Ooijena (2016) [8]
	Education	Avanzini (2015) [3]; Gerlach-Kristen (2018) [6]; Van Ooijena (2016) [8]
	Employment conditions	Gyourko (2014) [13]; Harrison (2011) [14]; Jones (2015) [15]; Lydon (2013) [7]; Van Ooijena (2016) [8]
	Family status	Csizmadý (2017) [5]; Jones (2015) [15] etc.
<b>Transaction</b>	Initial LTV	Avanzini (2015) [3]; Campbell (2015) [4]; Elul (2010) [9]; Foote (2018) [10]; Fuster (2015) [11]; Goodman (2010) [12]; Harrison (2011) [14]; Hott (2015) [20]; Jones (2015) [15]; Kelly (2018) [18]; Lee (2016) [16]; Lydon (2013) [7]; Van Ooijena (2016) [8]
	Current LTV	Avanzini (2015) [3]; Bian (2018) [21]; Campbell (2015) [4]; Elul (2010) [9]; Foote (2008) [22]; Foote (2018) [10]; Fuster (2015) [11]; Gerlach-Kristen (2018) [6]; Goodman (2010) [12]; Gyourko (2014) [13]; Hott (2015) [20]; Jones (2015) [15]; Kelly (2018) [18]; Lee (2016) [16]; Lydon (2013) [7]; Van Ooijena (2016) [8]
	Interest rate volatility	Campbell (2015) [4]; Csizmadý (2017) [5]; Foote (2018) [10]; Fuster (2015) [11]; Harrison (2011) [14]; Hott (2015) [20]; Jones (2015) [15]; Van Ooijena (2016) [8]
	Foreign currency loan	Beckmann (2015) [23]; Csizmadý (2017) [5]
	Loan to income ratio	Campbell (2015) [4]; Figueira (2005) [24]; Fuster (2015) [11]; Gerlach-Kristen (2018) [6]; Harrison (2011) [14]; Kukk (2016) [19]; Lee (2016) [16]
	Negative equity	Aron (2016) [25]; Gerlach-Kristen (2018) [6]; Linn (2019) [26] etc.
<b>Macro factors</b>	GDP growth	Hott (2015) [20]; Lee (2016) [16]
	House price index	Aron (2016) [25]; Avanzini (2015) [3]; Campbell (2015) [4]; Foote (2018) [10]; Gerlach-Kristen (2018) [6]; Harrison (2011) [14]; Hott (2015) [20]; Jones (2015) [15]; Lydon (2013) [7]
	Income volatility	Foote (2018) [10]
	Interest rate volatility	Beckmann (2015) [23]; Campbell (2015) [4]; Fuster (2015) [11]; Goodman (2010) [12]; Harrison (2011) [14]; Hott (2015) [20]; Lee (2016) [16]
	Unemployment rate	Aron (2016) [25]; Elul (2010) [9]; Foote (2018) [10]; Gerlach-Kristen (2018) [6]; Gyourko (2014) [13]; Hott (2015) [20]; Lydon (2013) [7] etc.

Aron and Muellbauer (2016) based on mortgage data from UK analysis discovered strong correlation between arrears and aggregate debt–service ratio, the proportion of mortgages in negative equity and the unemployment rate [25]. Campbell and Cocco (2015) developed model incorporating household income, house price, inflation, and interest rate risk [4]. Created model highlights that mortgage default depends not only on the extent to which a borrower has negative home equity, but also on other factors, e.g. interest rates and income volatilities etc. Fuster and Willen (2012) also highlight the impact of negative equity and variations in interest rates on mortgages delinquencies [11]. They study was based on US mortgage micro-data. Gerlach-Kristen and Lyons (2018) applied regression analysis to national-level panel data to examine mortgage arrears in 15 EU countries [6]. Researchers conclude that the isn't clear evidence that negative equity per se is associated with higher arrears, but the combination of affordability problems and negative equity, which makes it impossible for financially strained households to move to cheaper places and which the literature refers to as a dual trigger situation, seems to matter for longer-term arrears. Hott (2015) developed mortgage loss model calibration based on US and Switzerland data and conclude that loss rates are positively influenced by the house price level, the loan-to-value of mortgages, interest rates, and the unemployment rate, but negatively influenced by the growth of house prices and the income level [20]. Kelly and O'Toole (2018) found that default increases with originating loan-to-value and falling with origination debt service ratio [18].

The literature analysis provides some valuable guidance on housing loans risk drivers. The ability of borrowers to pay a mortgage can be affected by external circumstances such as unemployment and income decline, particularly during periods of crisis and recession, and by households themselves – the ability to balance their cash flow and competitiveness in the labour market. In the years of crisis, a sharp decline in housing prices is also playing an important role, and consequently less could refinance existing liabilities or sell mortgage without significant losses. Another important conclusion from the literature analysis is that there are different laws in different countries and consequently the results of studies cannot be interpreted unambiguously without taking into account these specificities.

### 3- Macro Level Risk Drivers and Models

#### 3-1- The Model

Let  $HoNPL_t$  be dependent variable 'Housing loans nonperforming ratio' in year  $t$ . Further, let  $x_{1t}, \dots, x_{kt}$  denote independent variables and  $b_{1t}, \dots, b_{kt}$  denote regression coefficients of independent variables, than the model can be expressed as in Equation 1:

$$HoNPL_t = f(x_{1t}, \dots, x_{kt}) + \varepsilon_t \quad (1)$$

Where  $\varepsilon_t$  – the error term.

#### 3-2- Data

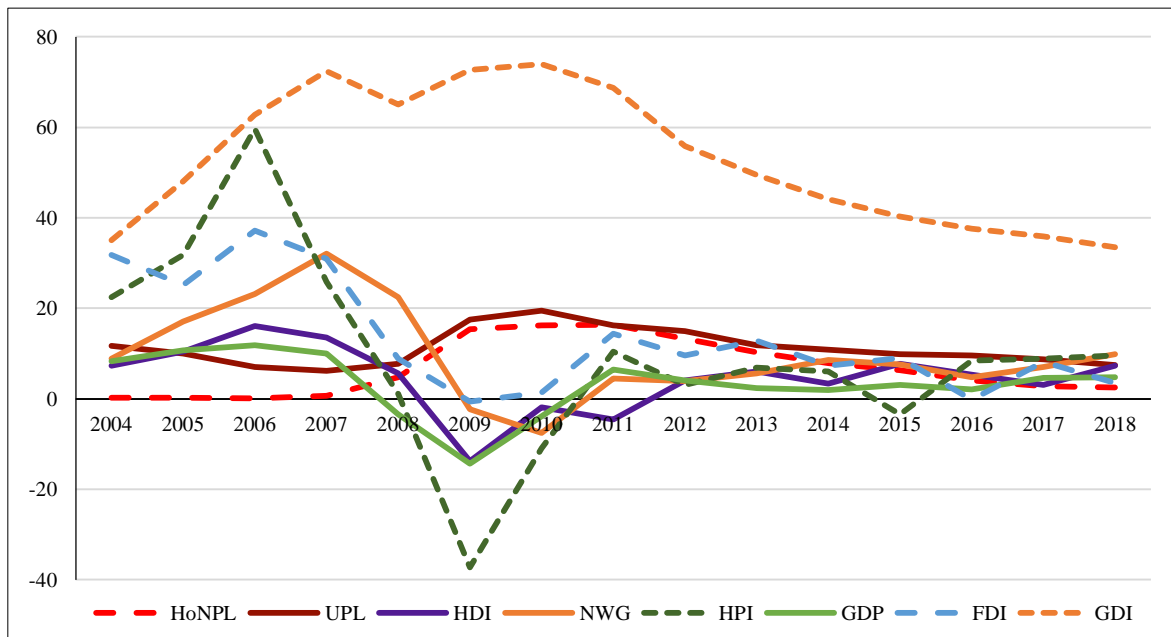
For research macro indicators on first stage where selected based on the literature review, indicators list, data source and correlation coefficients with 'Housing loans non-performing ratio' are presented in following table.

**Table 2. Macro indicators and their correlation with HoNPL.**

Indicator	Unit of measure	Abbreviation	Data source	Correlation
Consumer price index	%	CPI	CSB [2]	-0,4299
Foreign direct investments growth	%	FDI	BoL [27]	-0,5826
GDP growth	%	GDP	CSB [2]	-0,6371
House price index	%	HPI	CSB [2]	-0,7016
Household disposable income growth	%	HDI	Eurostat [28]	-0,8125
Household gross debt-to-income	%	GDI	Eurostat [28]	0,5068
Housing loans interest rate	%	HIR	ECB [29]	-0,1665
Net wages growth	%	NWG	CSB [2]	-0,7315
Unemployment rate	%	UPL	Eurostat [28]	0,8885

Macro indicators data for research where collected from Bank of Latvia (BoL) [27], Central Statistical Bureau of Latvia (CSB) [2], European Central Bank (ECB) [29] and Eurostat [28].

From table 2 one can see that the highest correlation with housing HoNPL in Latvia during years 2004-2018 showed following indicators: ‘Unemployment rate’ (0.8885), ‘Household disposable income growth’ (-0.8125), ‘Net wages growth’ (-0.7315), ‘House price index’ (-0.7016) etc. In the same time ‘Housing loans interest rate’ had low impact (-0.1665) on HoNPL, which isn’t consistent with revealed in studies, e.g. Campbell (2015) [4], Csizmadya, (2017) [5], Foote, (2018) [10], Fuster (2015) [11], Harrison (2011) [14], Hott (2015) [20] and Jones, (2015) [15].



**Figure 2. Macro indicators and HoNPL (Eurostat, BoL, FCMC, CSB of Latvia data).**

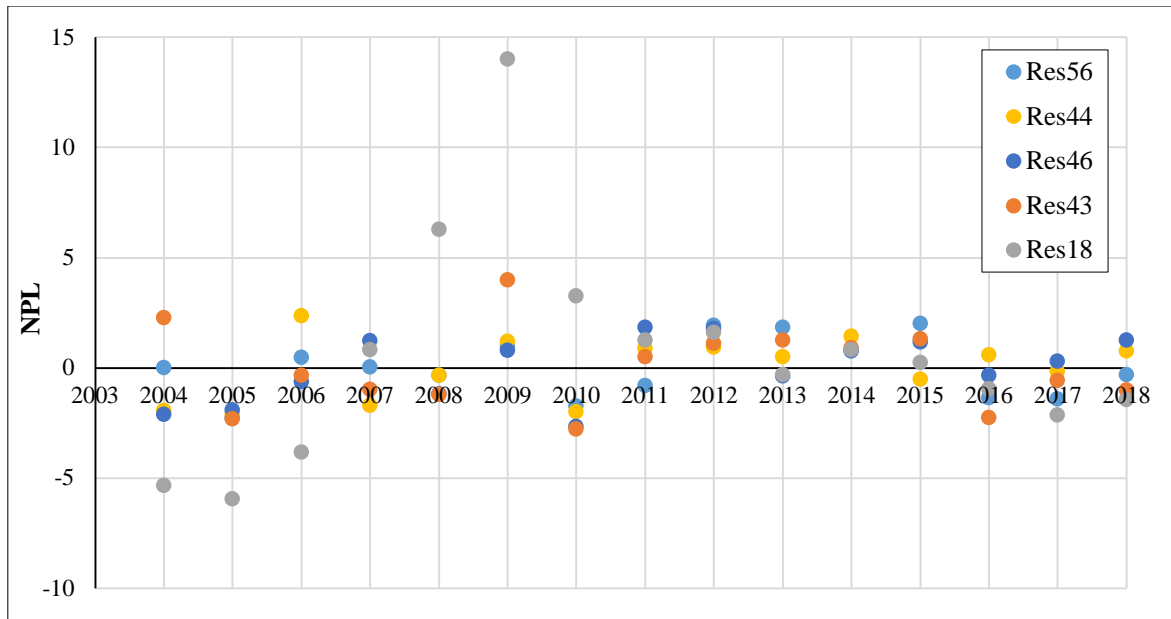
### 3-3- Results

In the first stage based on the method of least squares 59 regression models (7 linear univariate, 7 nonlinear and 45 multivariate) have been created, which faced trough  $F$  test at confidence level of 0.95 ( $\alpha=0.05$ ). In the second phase, those who failed regression coefficient statistical stability  $t$ -test at confidence level of 0.95 were removed. The statistics of regression models faced trough  $t$ -test are aggregated in following table.

**Table 3. Final regression models statistics.**

#	Model type	Variable	$R^2$	$F$	$p$ - value	Durbin-Watson
1.	1-factor, linear	UPL	0.7895	48.7568	<0.0001%	0.8687
3.	1-factor, linear	HDI	0.6601	25.2500	<0.0001%	0.8037
5.	1-factor, linear	NWG	0.5351	14.9625	<0.0001%	0.4347
7.	1-factor, linear	HPI	0.4903	12.6018	<0.0001%	0.6964
9.	1-factor, linear	GDP	0.4058	8.8799	<0.0001%	0.5330
11.	1-factor, linear	FDI	0.3394	6.6789	<0.002%	0.4991
18.	2-factor, linear	UPL, GDP	0.9098	60.5098	<0.0001%	0.7224
20.	2-factor, linear	UPL, GDI	0.5787	8.2401	<0.0003%	0.8415
43.	3-factor, linear	UPL, FDI, GDI	0.9066	35.5770	<0.0001%	2.5773
44.	3-factor, linear	UPL, HPI, GDI	0.9478	66.6114	<0.0001%	2.4345
46.	3-factor, linear	UPL, GDP, GDI	0.9432	60.9273	<0.0001%	1.9141
47.	3-factor, linear	UPL, FDI, HIR	0.8338	18.3981	<0.0001%	2.7174
48.	3-factor, linear	UPL, GDI, HST	0.7330	10.0682	<0.0001%	1.4827
56.	4-factor, linear	UPL, HDI, FDI, GDI	0.9507	48.1749	<0.0001%	1.7572

Statistics in Table 3 show that 5 of the models created allow to explain at least 90% and three of them at least 94% of housing non-performing loans ratio fluctuations with changes in variables included. In order to compare those five model and select the model with highest statistical stability residuals were analyzed, see following figure.



**Figure 3. Best fit model's residuals.**

Residuals analysis shows that all five models considered provide a sufficiently high level of stability and a minor error during periods of sustainable development, while in crisis years individual models, e.g. #18, are becoming manifestly unstable.

Based on Durbin-Watson statistic the preference should go to model #46:

$$HoNPL_t = 1,0551 * UPL_t - 0,5896 * GDP_t + 0,0794 * GDI_t - 7,7595 \quad (2)$$

The results are statistically significant ( $F = 60.9273$ ,  $p < 0.00001\%$ ). Model (2) allow to explain  $> 94\%$  of housing loans non-performing variations with  $UPL_t$ ,  $GDP_t$  and  $GDI_t$  variations.

**Table 4. Model #46 regression coefficients and  $p$ -values**

Variable	Regression coefficient	$p$ - value
Unemployment rate	1.0551	0.0002%
Gross domestic product	-0.5896	0.0004%
Household gross debt-to-income	0.0794	2.7194%
Intercept	-7.7595	0.2595%

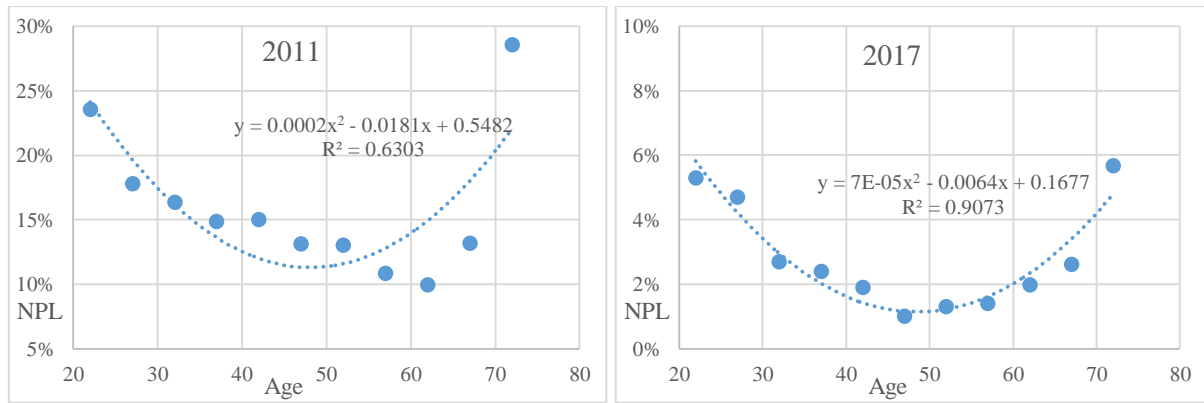
## 4- Micro Level Risk Drivers and Models

### 4-1- Data

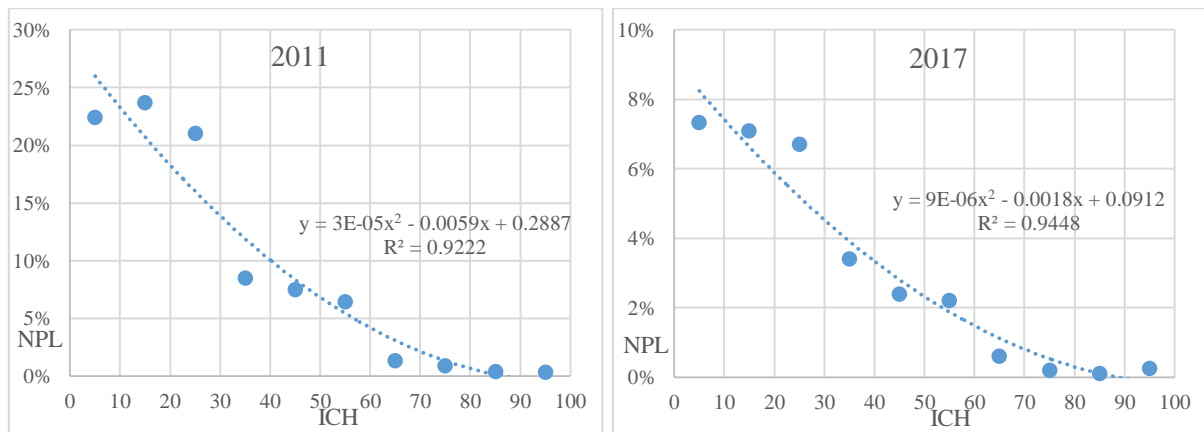
The primary data used in micro level study come from two housing loans samples – one include borrowers age, credit history, Loan-to-Value (LTV) and NPL status at the end 2011 and other at the end 2017. In order to solve NPL micro numerosity issues following indicators buckets were created:

- age – up to 25; 25-30; 31-35,...;
- credit history – score up to 10; 11-20; 21-30,...;
- LTV – up to 0.5; 0.5-0.6; 0.61-0.7,...

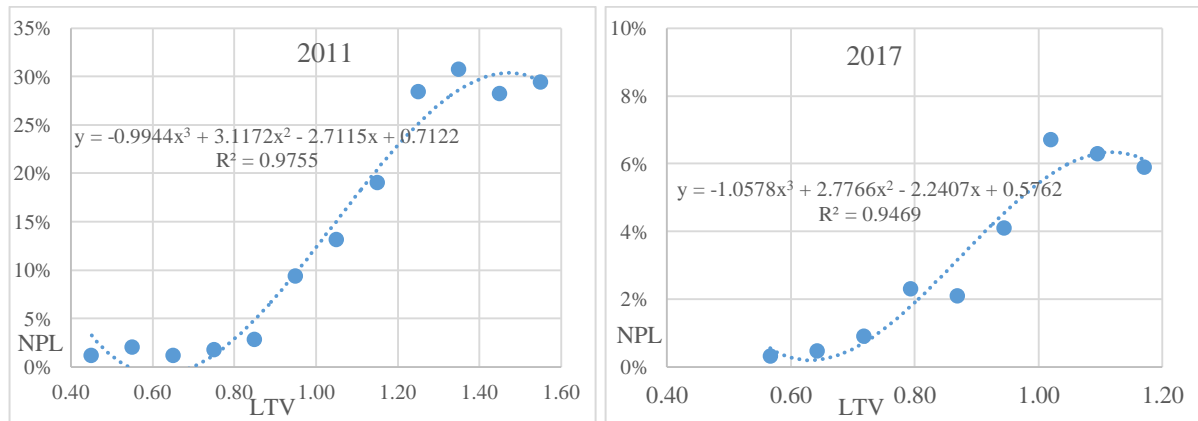
Following figures show borrowers age and NPL, credit history and NPL, LTV and NPL distributions.



**Figure 4. Borrowers age and NPL's distributions.**



**Figure 5. Credit history and NPL's distributions.**



**Figure 6. LTV's and NPL's distributions.**

#### 4-2- Results

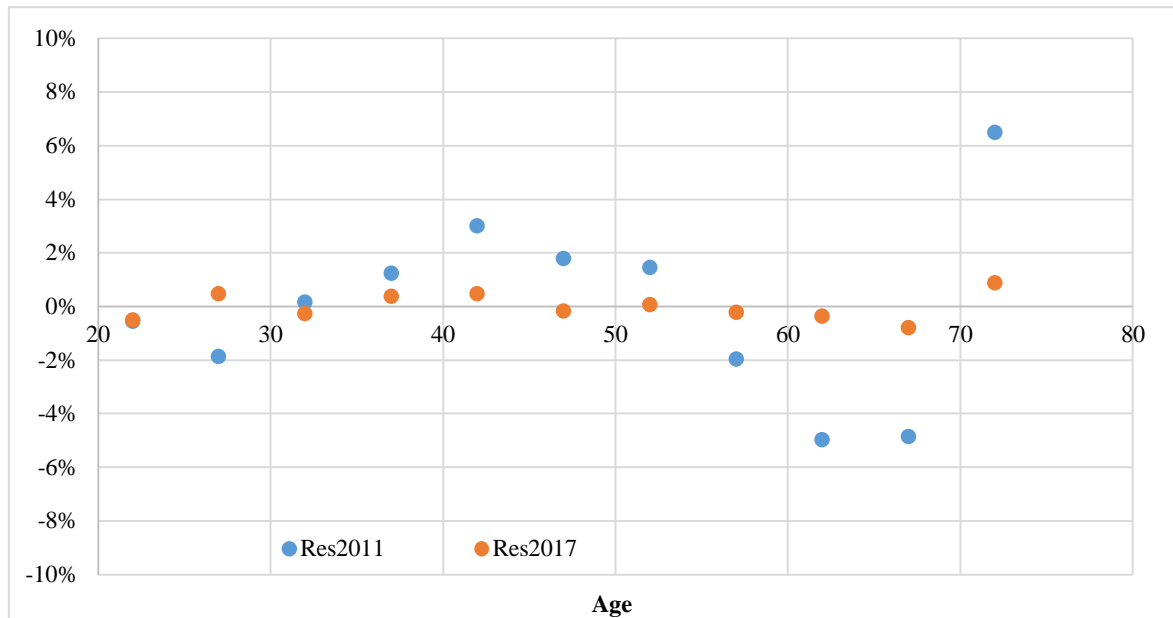
Using method of least squares linear and nonlinear models were created. Best fit model's statistics are aggregated in following table.

**Table 5. Best fit model's regression statistics.**

Model	Model type	$R^2$	SE	F	p-value	t-test max p-value
Age2011	Second order polyn.	0.6303	0.0378	6.8186	1.869%	<0.650%
Age2017	Second order polyn.	0.9073	0.0056	39.1297	0.007%	<0.002%
ICH2011	Second order polyn.	0.9222	0.0302	41.5111	0.013%	<6.064%
ICH2017	Second order polyn.	0.9448	0.0079	59.8934	0.004%	<4.235%
LTV2011	Third order polynom.	0.9755	0.0230	106.219	0.0001%	<0.395%
LTV2017	Third order polynom.	0.9469	0.0075	29.7198	0.130%	<7.405%

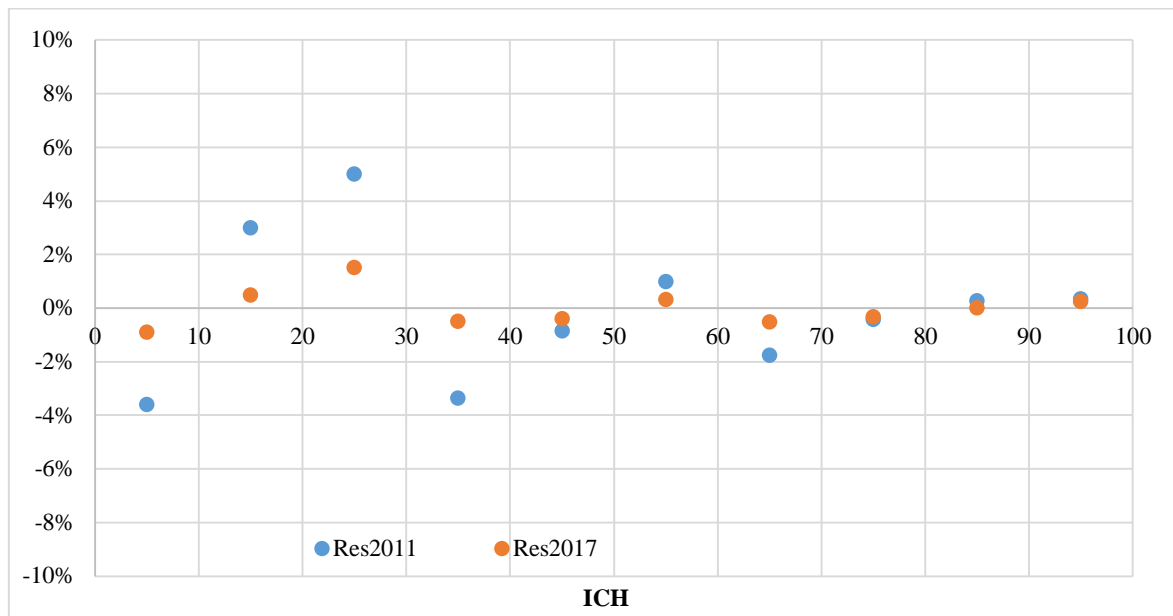
Regression statistics show that the statistical stability of the models created is high –  $F$ -test  $p$ -values  $< 2\%$ . Also regressions coefficients  $t$ -tests demonstrate model's stability. All models allow explaining more than 90% (except Age2011 with 63%) of HoNPL fluctuations with changes in variables included. Comparing models with 'Age' as variable, it can be seen that this risk indicator works not so well in time periods with fragile economic development (recessions and crises). Borrower's credit history is as stable risk indicator for both stable and volatile economic conditions periods of time. Meanwhile, LTV is slightly better risk indicator in fast-changing house price periods of time.

Residuals are shown in following figures.



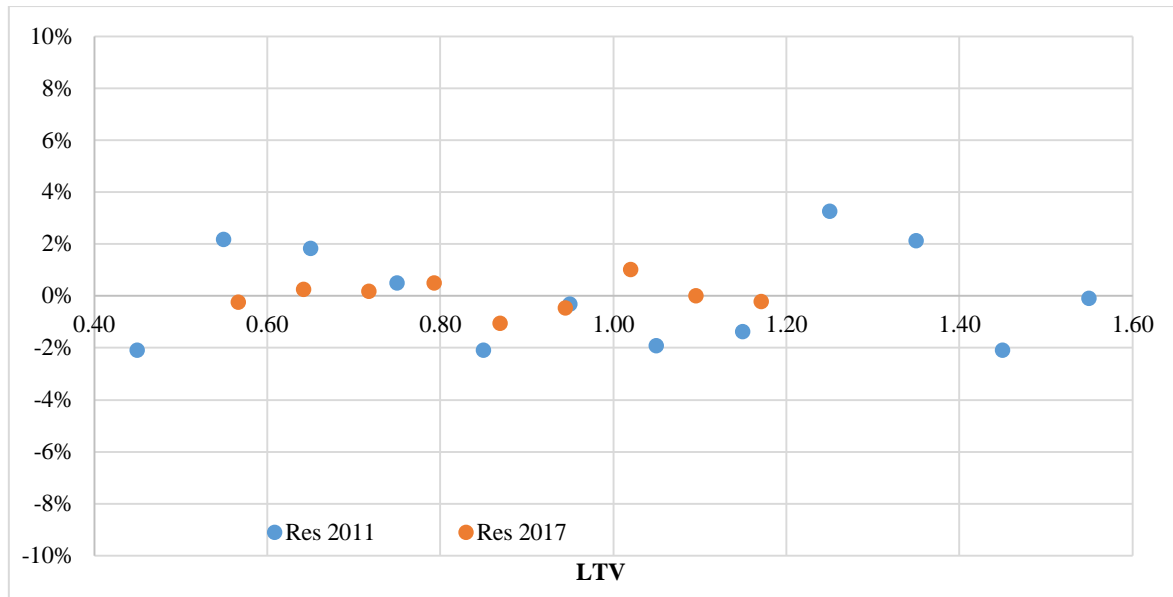
**Figure 7. Residuals distributions for models with age.**

Residuals analysis for created models with age shows that Age2017 provide a sufficiently high level of stability and a minor error for all age groups, while during crisis years forecasts for age 60+ is related with high uncertainty.



**Figure 8. Residuals distributions for models with ICH.**

Residuals analysis for created models with credit history shows that ICH2017 provide a sufficiently high level of stability and a minor error for all ICH scoring groups, while during crisis years forecasts for ICH scoring groups with risk 'above average' is related with high uncertainty.



**Figure 9. Residuals distributions for models with LTV.**

Residuals analysis for created models with LTV shows that LTV2017 provide a sufficiently high level of stability and a minor error for all LTV buckets, while during crisis years forecasts for LTV buckets 125% + is related with high uncertainty.

## 5- Conclusion

The severe financial crisis and the subsequent slow recovery in Latvia have had a significant impact on both the banking business, suffering massive losses from not always sufficiently carefully evaluated credit applications and forcing a review of the credit approval standards set to date, as well as the housing market, which has stagnated for years after the crisis, and households which have been unable to repay often the commitments created.

It is important to identify both macro and micro risk drivers, since credit risk management tasks cover the assessment of the total risk of the credit portfolio in perspective, such as the amount of expected losses and capital requirements for covering credit risk for business plan and internal capital adequacy assessment needs, and the credit risk causation study to make sound business activation or risk mitigation decisions.

The quality of the analysis of household credit risks can be ensured by the availability of a number of models and the possibility of use them in combination to assess expected risk levels, as a weighted average of a number of outcomes, for example, taking into account the availability of indicator forecasts, the level of its assurance and other considerations. Before applying the models drawn up and framed, it is important not only to verify their statistical stability, but also to carefully assess model errors (residuals), as the research carried out shows that each model has different behaviour over different periods of the economic cycle and should not be ignored.

According to the research carried out, the most influential macro risks drivers for housing loans are unemployment, household gross disposable income, GDP, house price index, wages growth, and from micro drivers - credit history, age, LTV etc. The results of the study in this respect largely coincide with those previously carried out and described in accessible literature. However, in addition, it can be concluded that each of these indicators has both certain advantages and shortcomings, which differ in the various periods of economic development. It is important to remember that once created econometric models cannot be considered non-changeable - they should be regularly tested and recalibrated if necessary.

## 6- Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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