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DISCUSSION PAPER

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SURVEY-BASED ASSESSMENT OF HOUSEHOLD BORROWERS' FINANCIAL VULNERABILITY

1·2014

CONTENTS

ABBREVIATIONS

AUROC – area under the ROC curve
bp – basis point
CR – Credit Register of Latvijas Banka
CSB – Central Statistical Bureau of Latvia
ECB – European Central Bank
EURIBOR – euro interbank offered rate
FCMC – Financial and Capital Market Commission
GDP – gross domestic product
Ltd. – limited liability company
LTV – loan-to-value
MFI – monetary financial institution
pp – percentage point
ROC – receiver operating characteristics
SH – solvent household
US – United States of America
VH – financially vulnerable household

SUMMARY

This Discussion Paper is an attempt to provide insight into the debt servicing capacity of Latvian households and its sustainability under the impact of different macroeconomic shocks based on individual household data obtained by surveying households with at least one loan for house purchase. To assess the financial situation of these households, changes in the household solvency are modelled under the impact of different economic shocks (shrinking employment income, rising interest rates, loss of jobs) and the obtained results are generalised to the aggregate portfolio of loans granted by Latvian credit institutions to households for house purchase. The results obtained lead to a conclusion that following the financial crisis household solvency is still fragile and possible negative shocks might contribute to higher potential losses of credit institutions. At the same time possible losses to lenders arising from such adverse shocks might be lower than two years ago since the value of collateral has increased with real estate prices moving up, while outstanding loans granted for house purchase have declined.

Key words: analysis of household solvency, stress tests, sensitivity analysis, financial margin, macroeconomic shock scenario, microdata

JEL codes: C15, C35, D14, E21, G21

The views expressed in this publication are those of the authors, who are employees of the Financial Stability Department of Latvijas Banka. The authors assume responsibility for any errors and omissions.

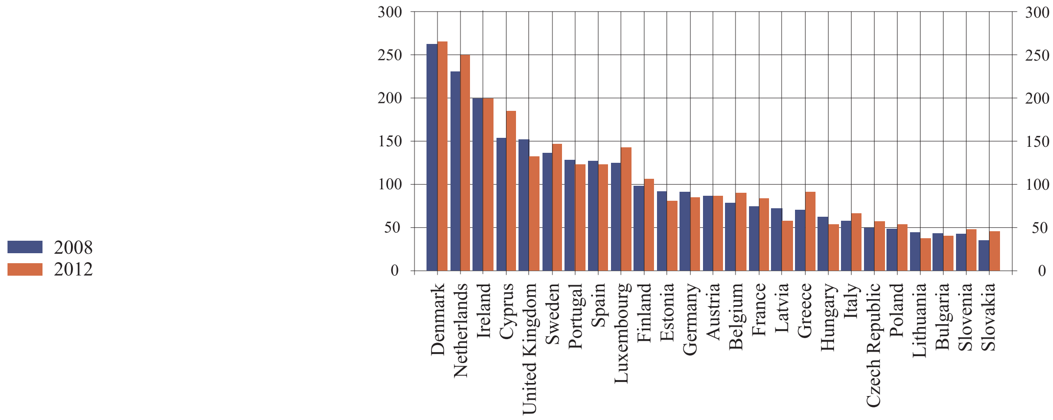
INTRODUCTION

The debt servicing capacity of households has important financial stability implications. First, credit institutions may incur direct losses due to households' inability to make their loan payments. Second, with private consumption weakening, credit institutions may incur indirect losses, since domestic demand for goods and services would decline as a result and debt servicing capacity of companies would also be impaired. Furthermore, households also represent a significant part of the economy and their financial position impacts the economy as a whole and its development, hence it is important to track changes in household solvency and the relevant driving factors.

In the last decade, debt ratios have increased rapidly in the East European countries and become comparable to the ratios in the developed countries. Household debt has surged, with Latvia reporting a very buoyant increase as well (see Chart 1). Traditionally high level of household debt is associated with the financial stability risks. Latvia explicitly demonstrated the materialisation of the above risks. The global economic and financial crisis exerted severe impact on Latvia, aggravating the fall of real estate prices that had already begun in 2007 upon the burst of the real estate price bubble. The deepening of the crisis resulted in a substantial economic downturn, unemployment rose to 18% and the average wage declined by 20%. This development had an adverse effect on the financial position of households. The share of loans past due increased sharply, giving rise to substantial losses for credit institutions (in 2008–2010, losses exceeded cumulative profit, generated in 2002–2007).

Chart 1

Loans granted to households in 2008 and 2012 (data from quarterly financial accounts; % of gross disposable income)



Source: The ECB Statistical Data Warehouse.

Despite the recovery of Latvian economy and declining unemployment, the share of loans past due declines at a very slow pace and the number of insolvency petitions filed by natural persons still reports an upward trend, hence there are still concerns about the Latvian household debt servicing capacity, their vulnerability under adverse changes in the national economy and the related potential risks to the stability of financial system.

The assessment of household debt servicing capacity based on macro indicators has a number of drawbacks. Aggregated disposable income only roughly reflects indebted households' paying ability, as it combines information about indebted and debt-free households; vulnerable households with low income are "masked" by those who are financially sound. Besides, it is also not possible to link information about the household liabilities to their savings and housing wealth with a sufficient degree of confidence.

The objective of this Discussion Paper is to assess the household resilience to unfavourable macroeconomic shocks (shrinking income, growing unemployment and increasing interest rates) based on the survey of household borrowers conducted on the order of Latvijas Banka in May and June 2013. Data on credit liabilities of each individual household and loan payments as well as income, basic living expenditures, value of a real estate (if used as a collateral) and detailed information on all members of the household (adults, children and number of employed) have been obtained from the survey. The survey data were complemented by the Credit Register data on average loan to value ratio for different loan groups. The obtained data allow to study the responses of each individual household in the sample to different simulated macroeconomic shocks and assess potential losses incurred by credit institutions in the event of the materialisation of such shocks.

Section 1 of the Discussion Paper presents a review of literature, Section 2 provides a general description of the household survey, Section 3 describes a logistic regression model for the assessment of household's solvency, Section 4 outlines the methodology applied to the stress test of household financial vulnerability and Section 5 is devoted to the key results of the stress test. The final Section concludes.

1. REVIEW OF LITERATURE

Shortcomings of the aggregated data have stimulated the central banks and other economic researchers of many countries to increasingly use micro data for risk analysis of borrowers' financial vulnerability, supplementing the stress tests at the portfolio level of credit institutions with borrowers' stress tests at the level of individual households. Studies that employ micro data for stress testing household debt servicing capacity constitute a relatively new field of research in literature on credit risk stress testing. Interest in this topic has grown as household debt has considerably increased in many countries. The central banks of Austria (Albacete and Fessler (2010)), Canada (Djoudad (2012)), the United Kingdom (May and Tudela (2005)), Sweden (Johansson and Persson (2006)), Norway (Vatne (2006)), Poland (Zajączkowski and Żochowski (2007)), Finland (Herrala and Kauko (2007)), Hungary (Holló and Papp (2007)), Chile (Fuenzalida and Ruiz-Tagle (2009)) and Lithuania (Financial Stability Review 2009) have published the results of their studies. The objective of stress tests is to assess household ability to continue debt servicing after facing negative external shocks (a decline in employment income, rise in interest rates, fall in real estate prices, increase in unemployment), as well as to examine and analyse the impact of such shocks on the domestic financial system.

The most widespread type of individual household borrowers' analysis is calculation of the household financial margin based on the survey data regarding household income and expenditure. The financial margin is the amount of money at the disposal of households after deduction of debt servicing and living costs. Households with a negative financial margin constitute the most vulnerable part of borrowers. Thus, the share of liabilities of these households in the total outstanding amount of household liabilities allows to assess credit institutions' credit risk relating to loans granted to households. When calculating the hypothetical decrease of the household financial margin resulting from adverse shocks (e.g. a rise in interest rates or increase in unemployment), an increase in share of households with a negative financial margin makes it possible to assess sensitivity of household financial vulnerability to this shock. Johansson and Persson (2006) have used the financial margin approach when examining the Swedish household debt servicing capacity. Vatne (2006) in Norway, Lietuvos bankas (Financial Stability Review 2009), Albacete and Fessler (2010) in Austria and many others have employed a similar approach.

Djoudad (2012) has used a slightly different method in the Bank of Canada. A household is considered vulnerable provided that its debt service ratio (the monthly loan payment to income ratio) exceeds 40%. Karasulu (2008) used both approaches, i.e. the debt service ratio and financial margin when performing debt stress tests of Korean households.

Holló and Papp (2007) supplemented the nonparametric approach used for calculation of the financial margin with the parametric approach when examining the credit risk of Hungarian households. They employed the binary variable that describes household insolvency problems to assess the models that help to determine the probability of each household's default. Such an approach reduces the uncertainty surrounding information on income and expenditure provided individually during surveys and consequently also the uncertainty linked to the financial margin.

The results obtained through the use of micro simulation models that are based on the financial margin usually reveal high sensitivity to interest rate changes, but sensitivity to an increase in unemployment is low. This effect can be explained by a short test horizon (the analysed period is usually a year) during which the income level of a household does not fall too fast due to unemployment benefits.

May and Tudela (2005), the Bank of England, have used the British Household Survey Panel of 1991–2004 to estimate the dynamic probit model for identification of the probability of household mortgage loan repayment problems. The use of the panel data made it possible to discover that unemployment has a major impact on insolvency, i.e. unemployment in the previous year increases the probability of non-payment next year by 13.5 pp.

Taking account of the available data, the most widespread approach – calculation of the financial margin by employing the survey data has been used in this discussion material. The use of the Credit Register data to reduce the sampling error[1] is an innovative approach compared with other studies.

2. SURVEY DESCRIPTION

In May and June 2013, a survey of household borrowers was conducted. This is the second survey of its kind. The first, a pilot survey, was conducted in 2011 and its results were not made public, albeit used for internal reporting of Latvijas Banka. The survey data obtained are unique for Latvia as information about household income, expenses and savings and detailed information on credit liabilities and collaterals are combined in one source. 1 002 households with at least one loan for house purchase participated in the survey. Latvijas Banka commissioned TNS Ltd. to conduct the survey. The survey sample was obtained by applying stratified random sampling, based on statistical region[2]. Slightly more than one third of the interviews (37%) were conducted at the respondents' place of residence, other – via the Internet.

The objective of the survey was to assess the financial position of Latvian household borrowers as well as to obtain data for the assessment of their resilience to potential unfavourable shocks.

The survey respondents had to answer the questions about the factors describing housing loan (the initial loan and the outstanding amount of the loan, loan currency, time period of loan amortisation, interest rate, amount of a monthly payment, provided collateral), other liabilities and their inherent features (purpose of a loan, outstanding amount and amount of regular payments), self-assessment of household's financial position at that time and future expectations, household composition, employment, income, household expenses and savings.

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[1] Post-stratification of the survey data was performed with respect to the distribution of the outstanding amounts of loans for house purchase in the Credit Register, as well as the Credit Register data on the loan-to-value ratio were used.

[2] Pursuant to the Order of the Cabinet of Ministers No. 271 "On the Republic of Latvia Statistical Regions and the Respective Administrative Units" of 28 April 2004.

Data on 974[3] households with 1 040 loans granted overall (an average of 1.07 loans per household) and 432 other loans (an average of 0.44 loans per household) were analysed. The survey represents 0.76% of total loans granted to Latvia's residents by volume and 0.35%[4] by amount outstanding.

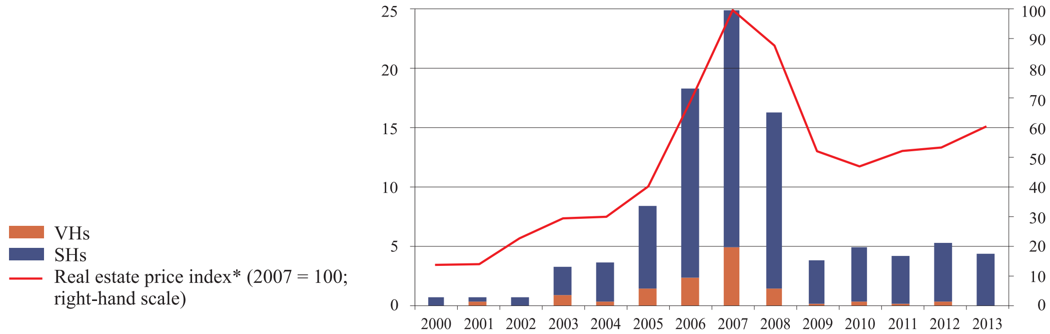
In the breakdown by regions, 35.6% of the respondents were from Riga, 20.1% – from Pierīga, 14.2% – from Kurzeme region, 13.2% – from Vidzeme region, 10.7% – from Zemgale region and 6.2% – from Latgale region.

Most of the respondents (53.6%) had taken loans specifically for house purchase, while 32.0% – to cover other costs (reconstruction, renovation, land purchase).

In the Discussion Paper households are divided into two groups, based on their balance of income and expenses: solvent and vulnerable households (for a more detailed explanation see Subsection 4.1). Households are deemed solvent (hereinafter, the SH) if their annualised[5] income and savings exceed annualised listed expenses or are equal to them, while households are deemed vulnerable (hereinafter, the VH), if their income is lower than the reported expenses. It should be noted that VHs amount to 10.2% of the total sample households (99 households) and SH comprise 89.8% (875 households).

The results of the survey show that the most vulnerable households were the ones which undertook credit liabilities when economic growth was the fastest and real estate prices – the highest (see Chart 2) and thus their loans and loan redemption repayments were also the highest. Moreover, several years after the beginning of the crisis some of the households have not been able to regain the lost solvency, and they are still facing challenges of balancing their income and expenses. Of the total sample housing loans, 59.7% were granted in 2006–2008 (the period of the highest real estate prices). Moreover, the number of VHs in the survey, which had taken loans for house purchase in 2006–2008, amounted to 56.8% of the total number of VH loans granted for house purchase, while their housing loans outstanding amounted to 68.6% of the total outstanding amount of VH loans respectively.

Chart 2
Distribution of household housing loans by the year of taking a loan, and real estate price index



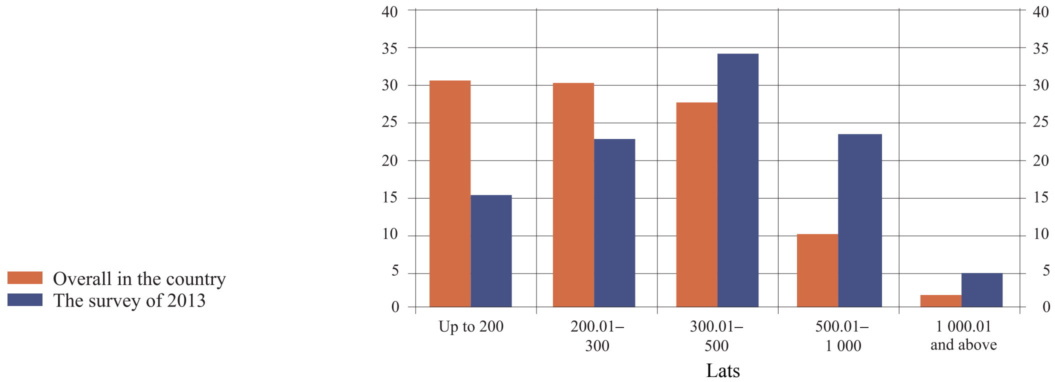
* Real estate price index calculated by Latvijas Banka.

3 The total number of households amounted to 1 002; however, upon verifying the data, households whose replies were insufficient for the performance of the analysis were excluded from any further analysis.
4 Comparison with the housing loans granted by Latvian credit institutions to households in June 2013.
5 Annualised to a full calendar year.

The average employment income in the sample was 420.7 lats in June 2013 (see Chart 3). In comparison with the CSB data on the net wage and salary in the country, employment income of the borrowers was overall higher than the national average (in June 2013, the average net wage and salary was 362 lats), moreover, higher concentration of income of the surveyed persons in the sample was evidenced in the groups with higher wages and salaries. Income of 62.0% of the employed respondents exceeded 300 lats per month, compared to 39.3% of employed on the national level. In comparison with the survey of 2011, the share of households whose total household income per employee is below 500 lats has declined. Thus, the share of households with higher income has expanded suggesting that overall the income of borrowers has followed an upward path along with the growing remuneration in the national economy (see Chart 4).

Chart 3

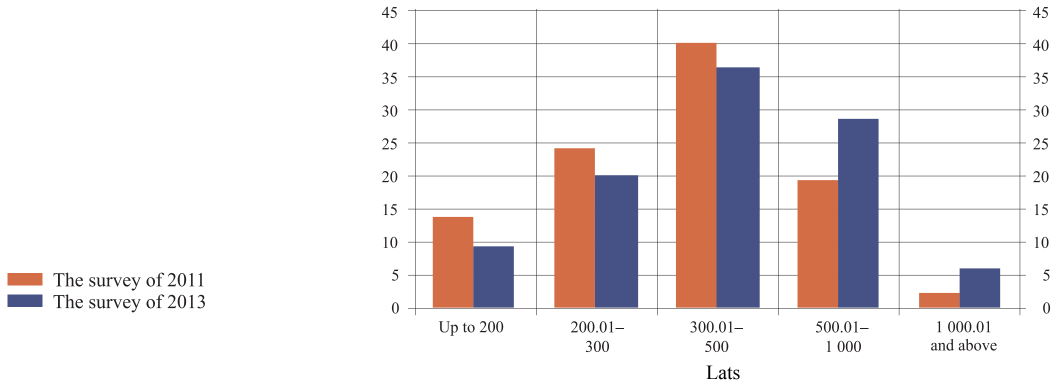
Comparison of the distribution of average net employment income per employee in the sample of 2013 and overall in the country (%)



Sources: Sample data and CSB.

Chart 4

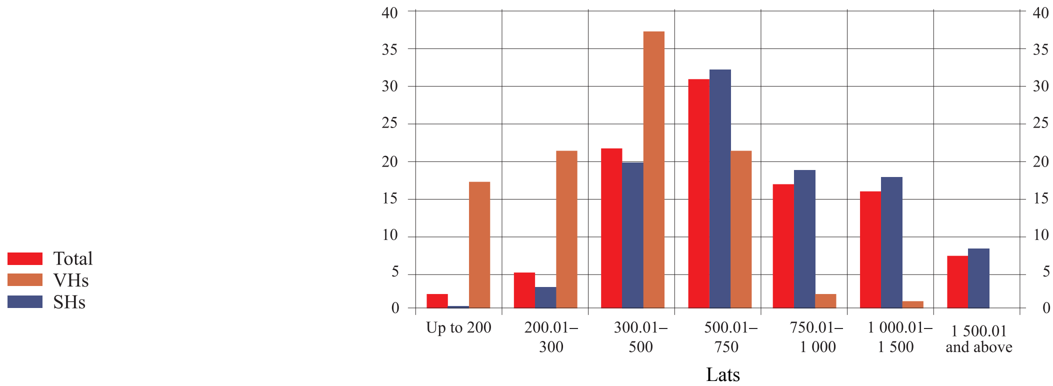
Comparison of the distribution of the average net household income per employee in the surveys of 2011 and 2013 (%)



Sources: Sample data and CSB.

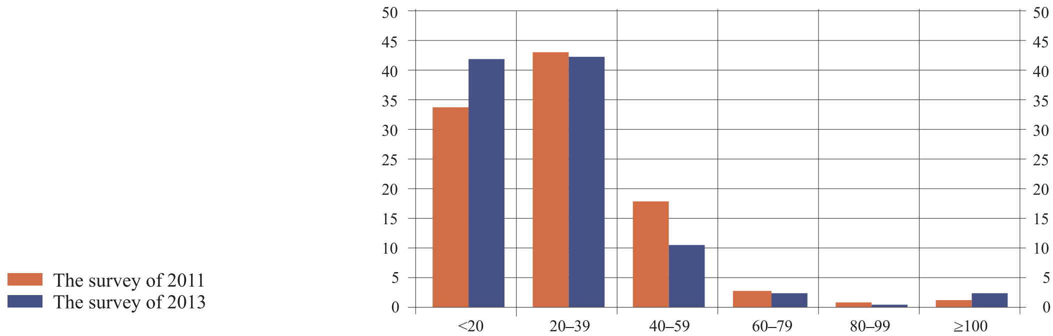
Income comparison between SHs and VHs reveals a pronounced difference in monthly household income of the two groups. Income of only 23.3% of households was below 500 lats per month in SH group, while 75.8% of such households were reported in VH group (see Chart 5). The average income of VHs, in turn, was by 55% lower than that of SHs (863 lats and 386 lats respectively).

Chart 5
Distribution of household total monthly net income (%)



Initial assessment of borrowers' solvency shows that the monthly payment of all loans exceeded 40% of income (deemed to be a threshold of reasonable debt burden)[6] for 15.7% of households at the moment of survey (May and June 2013; see Chart 6). The average debt service ratio (the ratio of a household's total loan payments to income) in the sample was 28.7%. However, the debt service ratio increases with the size of the loan. The above ratio was 45.0% for households, whose total loans amounted to 50–100 thousand lats at the moment of survey, suggesting that households with larger loans mainly granted in the last few years prior to the financial crisis might be very vulnerable in the event of an unfavourable scenario of the economic development. It should be noted that improvements have been observed over the past two years in comparison with the survey of 2011. According to the survey of 2011, the monthly payment of all loans exceeded 40% of income for 23.0% of households, pointing to a decreasing overall debt burden of borrowers.

Chart 6
Comparison of the distribution of respondents by debt service ratio in the surveys of 2011 and 2013 (%)



The breakdown by SHs and VHs also shows that the payment burden of VHs is substantially higher (see Chart 7). The average monthly payment of housing loan of

[6] The debt service ratio is one of the macro-prudential instruments which may be applied to mitigate cyclical development of the national economy. In international practice, the debt service ratio exceeding 30%–40% is deemed to be a threshold of excessive payment burden. In South Korea its maximum threshold is stipulated in the amount of 40% (Igan and Kang (2011)). The *Regulations for Responsible Lending* adopted by Lietuvos bankas took effect on 1 November 2011. The above Regulation also stipulates the introduction of such threshold with respect to the debt service ratio for new loans.

SHs amounted to 20.0% of income, while that of VHs stood at 70.5% (more than three times higher). The debt service ratio of other loans was also higher for VHs than for SHs (9.1% and 18.7% respectively). Nevertheless, it should be noted that the debt service ratio of VH housing loans was quite uneven among households. The median of the SH housing debt service ratio was 17.9% (very close to the average), while the median of VH was 46.0% (considerably below average), confirming that the debt service ratios of VHs were very dispersed (see Chart 8) and outliers had affected the average.

Chart 7
Average monthly debt service ratio (%)

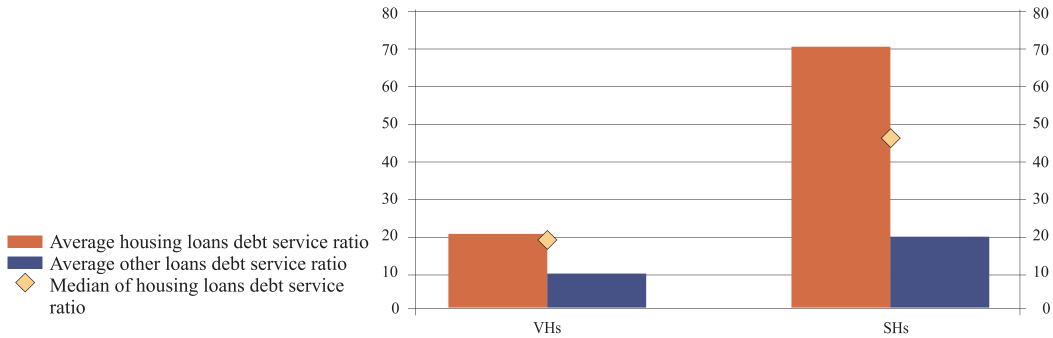
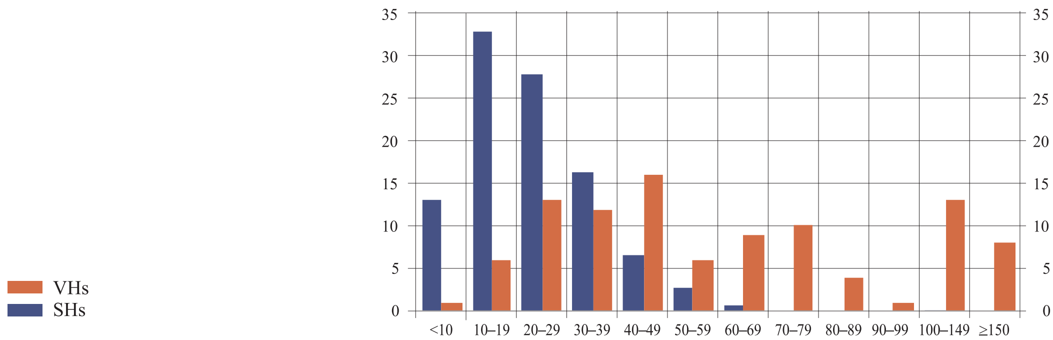


Chart 8
Household distribution by debt service ratio (%)



According to the survey results, in June 2013 the average outstanding liabilities of households (including all housing loans, consumer credit, leasing, credit lines and other liabilities) amounted to 19.7 thousand lats, of which the average housing loans comprised 19.1 thousand lats. The average monthly payment for the settlement of all liabilities was 191 lats, of which the repayment of housing loans comprised 163 lats. In the breakdown of households by solvency indicator, it may be observed that a housing loan of SH is on average smaller than that of VH (18.5 thousand lats and 23.8 thousand lats respectively). Taking into account the above differences in income and payment burden of SHs and VHs, it might be concluded that VHs have suffered more in the financial crisis – their loans were taken shortly before the crisis when residential property prices were the highest, and their income is lower as they have relatively more suffered from an increase in unemployment and income fall during the crisis. Moreover, their income has remained stagnant.[7] In the survey, a

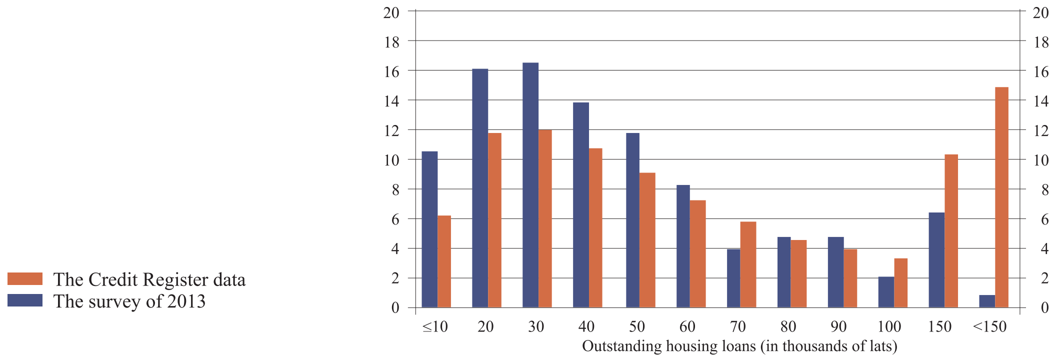
[7] 23.8% of respondents admitted that their income had declined in comparison with the previous year (in the survey of 2011 – 44.9%), while this share was sufficiently higher among VHs – 54.5% (in the survey of 2011 – 57.3%).

higher share of unemployed persons, compared to the sample average, has been reported among VHs that took loans in 2006 and 2007, as well as there were less employed persons among VHs on average than in SHs (1.4 and 1.8 employed respectively). Moreover, the employed persons in VHs are more often employed in the construction sector, which faced a substantial decline during the crisis. The survey data also suggest that the employed persons of VHs are more frequently employed in low-wage sectors and are less likely to have higher education.

For comparison with the survey data, the distribution of the total housing loans for individual borrowers[8] was obtained from the Credit Register. The share of small-amount loans is higher, while the share of loans exceeding 100 thousand lats is lower in the survey sample than recorded in the Credit Register (see Chart 9). This can be explained by the challenges encountered upon surveying households with high income: residents with high income and high credit liabilities are more reluctant to participate in the survey, and the number of such large loans is relatively small (in accordance with the Credit Register data their share in the total number amounts to 4% only; see Chart 10). Taking into account the fact that the sample contains only one household with a loan exceeding 150 thousand lats, the above household has been excluded from further analysis and all conclusions are generalised only with respect to the households whose liabilities do not exceed 150 thousand lats.

Chart 9

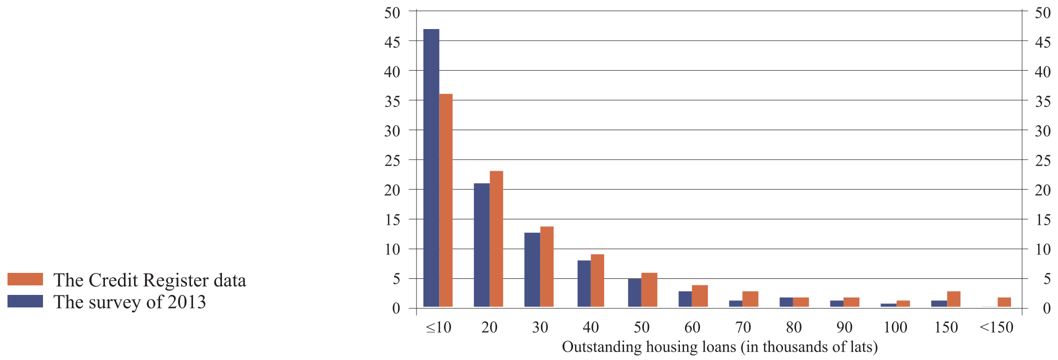
Distribution of housing loans in the Credit Register and in 2013 survey sample by size of housing loan (in % of total amount outstanding)



For the surveyed household sample to reflect the population of borrowers more accurately, the sample was post-stratified with respect to the total housing loans of households, with weights applied to the sample data so that the distribution of the household housing loans would be consistent with the distribution of housing loans in the Credit Register. Section 4 presents a more detailed calculation of weights.

8 The given comparison is not entirely accurate since data providing for the identification of individual households are not available in the Credit Register where only identifiers of individual borrowers are provided for.

Chart 10
Distribution of borrowers in the Credit Register and in the survey sample by size of housing loan (in % of total number of borrowers)



3. PARAMETRIC CREDIT RISK ASSESSMENT

This Section presents a logistic regression model for default probability prediction. Assuming that nonfinancial assets of households and debt to credit institutions remain unchanged over the analysed period (one year), an individual probability of default is calculated for each household in the sample based on its financial and demographic characteristics. The main advantage of applying this model is a lower dependence of the obtained results on the household's reported ambiguous income and expenses. First, household's statement that it has already failed to make payments (see description in Subsection 3.1) is used as an indicator of its default, rather than the financial margin (see Section 4). Thus, this indicator is not directly dependent on the disclosed income and expenses. Second, to lessen the dependence on reported level of household income (that could be inaccurately reported), the level of income is transformed into quartiles, hence only the relative position of household's income in ordered income distribution matters rather than the amount of such income. Third, a non-linear method is applied to determine the probability of default, therefore, an average conditional probability of default is less sensitive to the uncertainty of income than the financial margin.

3.1 Logistic regression model

The problem of household default can be analysed within a binary choice framework. A household either made (Y = 0) or did not make (Y = 1) credit payments at the moment of the survey. It has been assumed that the household did not make credit payments (Y = 1), if:
– the question "Does your family face any problems due to a loan repayment?" was answered as follows: "It faces serious problems, the repayment is already past due";
– the question "How would you assess your loan repayment capacity, if your monthly loan payments rose by 20–25%?" was answered as follows: "I have already failed to make monthly payments in full."

It is assumed in the model that a household's payments decision is explained by a variable vector *x*:

$$P(Y = 1\lfloor x) = F(x, \beta) \tag{1}$$

and

$P(Y = 0 \lfloor x) = 1 - F(x, \beta)$ (2),

where $F(x, \beta)$ – some cumulative distribution function.

The parameters β reflect the impact of changes in the explanatory variables x on the probability of default. Assuming that the error term is logistically distributed[9], the conditional probability of default is calculated as follows:

$P(Y = 1 \lfloor x) = \frac{\exp(x'\beta)}{1+\exp(x'\beta)} = \Lambda(x'\beta)$ (3),

and model is referred to as the model of logistic regression or *logit* model.

3.2 Estimation of the logit model

To allow for the model's goodness of fit assessment, the original sample was divided into two groups – estimation sample (75% of observations), where model parameters were estimated, and test sample (25% of observations), used for model validation purposes. The observations were randomly selected in each group.

The explanatory variables were divided into three categories: financial, demographic and geographical indicators. The category of financial indicators contains the quartile of household's disposable income, the monthly debt service ratio, the debt to income ratio (total debt to yearly disposable income) and savings. The group of demographic indicators shows the composition of a family: the total number of family members, the number of dependents, the number of employed, the number of unemployed, the number of unemployed pensioners, the number of unemployed students, the number of residents employed abroad (the binary variable shows that the household members are employed abroad). Geographical indicators include the type and region of residence.

For selection of the explanatory variables in the model, the method of purposeful selection of variables allowing for obtaining the optimal regression function was employed (see Hosmer, Jr., Lemeshow and Sturdivant (2013)). The inclusion of irrelevant variables not only fails to help in prediction, but also reduces the accuracy of estimates due to noise or systemic bias.

The explanatory variables selected at this stage were the debt service ratio, the level of income (in quartiles), the number of dependents and savings.

An interaction between variables was also studied after the estimation of the basic model and interaction between geographical characteristics and number of unemployed was included in the equation.

The coefficients of the estimated model are presented in Table 1.

9 The assumption regarding a normal distribution of error term is also used in the binary selection models. In this case, the model is called probit model. Although both the probit and logit models have been estimated yielding similar results, the Discussion Paper presents only the results of the logit model due to a more straightforward interpretation.

Table 1
Parameters of the estimated model and the relevant marginal effects

Variable	Coefficient	P-value	e^{β}	Marginal effect (ME)	
				ME at means*	Average ME
Constant	–3.29	0.000	0.037		
Number of dependents	0.48	0.001	1.61	0.020	0.028
Debt service ratio	4.08	0.000	59.06	0.174	0.244
Savings (binary variable)	–0.92	0.043	0.40	–0.039	–0.055
Number of unemployed and rural regions	1.55	0.013	4.71	0.066	0.093
Income in the second quartile	–0.89	0.010	0.41	–0.038	–0.053
Income in the third quartile	–2.237	0.000	0.09	–0.101	–0.142
Income in the fourth quartile	–1.96	0.002	0.14	–0.084	–0.117
Goodness of fit measure					
McFadden R^2					0.341
Nagelkerkrke R^2					0.414

* Calculated based on the sample mean values of the explanatory variables.

To assess the logit model quality, ROC curve[10] and AUROC (for the description see Appendix 2) are widely used, while the pseudo determination coefficients (see Table 1) have only some informational value. In brief, the closer the value of AUROC to one, the better the model quality, whereas the value of AUROC 0.5 suggests that the model fails to distinguish solvent households from defaulted ones. Table 2 features in-sample and out-of-sample AUROC values obtained by applying the fitted model to the estimation sample and test sample.

Table 2
Estimated area under the ROC curve and its confidence interval

	Area under ROC (AUROC)	Standard error	Asymptotic p-value	Asymptotic confidence interval (95%)	
				Lower bound	Upper bound
Estimation sample (75%)	0.883	0.019	0	0.845	0.921
Test sample (25%)	0.847	0.056	0	0.738	0.956

An out-of-sample AUROC value of the model close to 85% points to good prediction properties of a model (for in-sample and out-of-sample ROC curves see Appendix 2).

The results of the model (see Chart 1) reveal that the debt service ratio, the level of income, the number of dependents and existence of savings exert notable impact on the probability of default, and direction of such impact is consistent with the economic intuition. The higher the share of income devoted by a household to payments, the higher the probability of encountering solvency problems since the above household's capacity to make savings is limited, and it is more exposed to risk in the case of rising loan payments or household expenses, or loss of income. A positive relationship also exists between the probability of default and the number of

[10] ROC curve – receiver operating characteristics. It illustrates the performance of a binary classifier graphically and depicts its sensitivity against proportion of false positive observations.

dependents since a household is more vulnerable to expenditure shocks, given a larger number of dependents. The impact of the income level is also apparent since having income in the highest quartiles mitigates the possibility of encountering payment problems. The number of unemployed is also significant in combination with the geographical variable (rural regions, excluding Pierīga), and it contributes to the probability of default considerably.

Marginal effects[11] (shown in Table 1 along with the coefficients of the model) provide a better insight into the magnitude of the impact of the changes in explanatory variable on the default probability. As regards the analysed factors, the debt service ratio exerts the most substantial impact on the probability of default. Income level ranks next in terms of impact, followed by the existence of savings. The impact of binary variables may be shown not only as one number, calculated at the sample means of the explanatory variables, but also as a whole probability P(Y = 1) distribution curve within the range of changes of $x'\beta$ evaluated at both values of the binary variable[12]. Chart 11[13] representing the dependence of the probability of default on the number of dependents and existence of savings has been created in line with the above description. The probability of facing debt service problems is twice lower for the households with savings. At the same time, the higher the number of dependents, the higher the probability to face default problems.

Chart 11

Probability response curve of savings as a function of the number of dependents

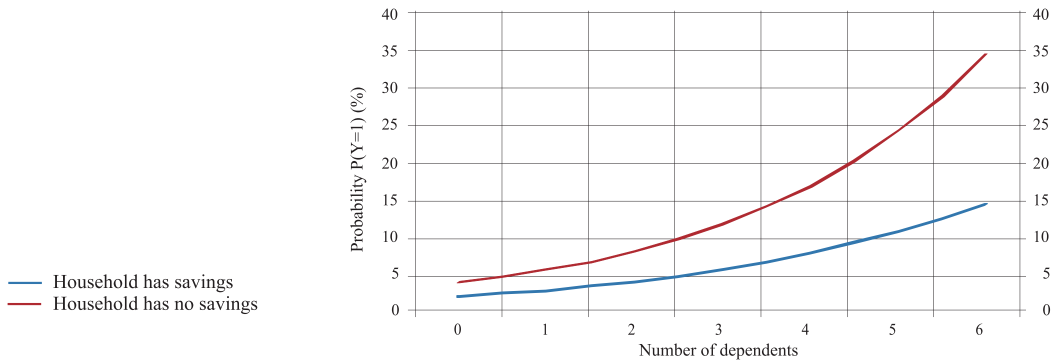


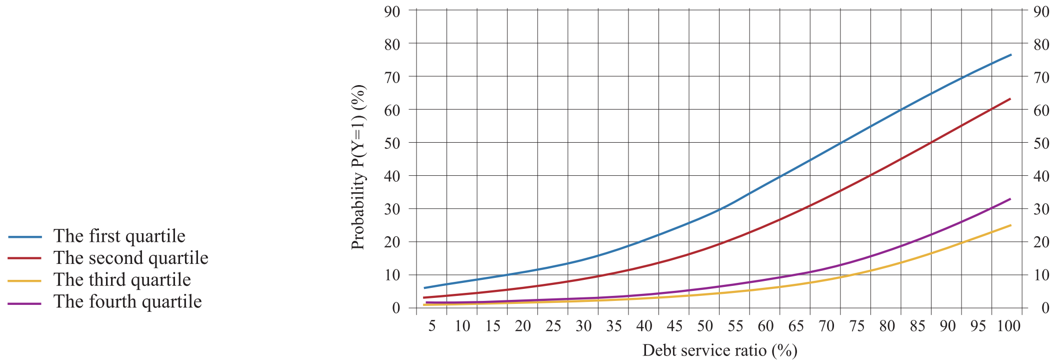
Chart 12 shows the probability of default as a function of the debt service ratio and income quartile. The chart illustrates that not only the balance of income and payments is vital, but also the level of income itself. If the amount of payments constitutes 25% of income, the probability of default for households in the lowest income quartile is by 10 pp higher than in the third income quartile; while the difference doubles as the amount of payments exceeds 45% of income. A slightly higher probability of default among the households in the fourth quartile (the highest income) than among the households in the third quartile can be explained by the fact that households in the highest income quartile borrow more: the average amount of liabilities increases 1.5 times upon moving from the third income quartile to the fourth income quartile.

[11] For the calculation of marginal effects in the logit model see Appendix 1.

[12] Those curves are called Probability Response Curves, see Green (2008) for details on calculations.

[13] To take into account all information available in the sample, the probability response curves were created by using coefficients obtained upon the evaluation of the same model in a full sample (100% observations); see Appendix 3.

Chart 12
Probability response curve of income level as a function of debt service ratio



4. METHODOLOGY OF STRESS TESTS OF HOUSEHOLD FINANCIAL VULNERABILITY

4.1 Financial margin of a household

To assess household vulnerability to the changes in income, interest rates and employment, the so-called financial margin (balance of income and expenses) was calculated for each household for the year 2014 (see equation 4). The financial margin shows the share of the household's disposable income remaining after deduction of debt servicing costs and basic living expenditure. In the event that the financial margin is positive, a household is able to cover both household expenses and loan payments. In turn, if the financial margin is negative, a household has solvency problems. As mentioned above, households with negative financial margin are referred to as vulnerable for the purposes of the present Discussion Paper.

$$B_i = DI_i + HS_i - BE_i - LP_i \quad (4),$$

where:

B_i – financial margin of i-th household (balance of income and expenses);
DI_i – total disposable income of i-th household;
HS_i – savings of i-th household;
BE_i – basic living expenditure of i-th household for the purchase of food and consumer goods and utility payments;
LP_i – total payments of i-th household for the settlement of liabilities.

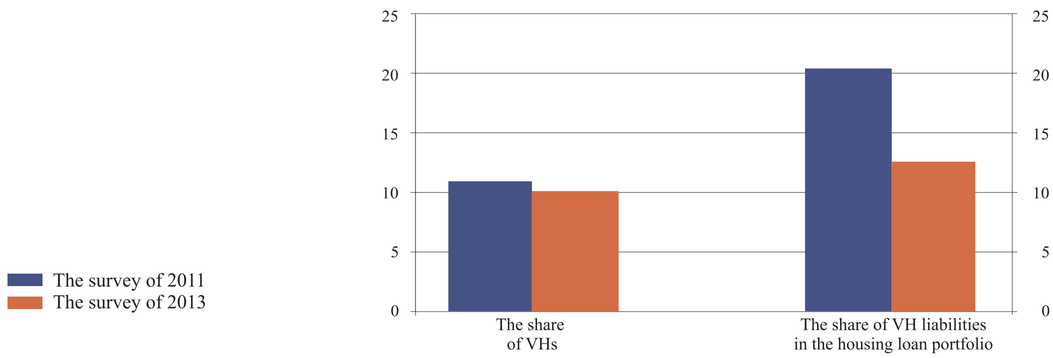
The assessment of an individual household's income (DI_i) for 2014 is obtained by annualising the total monthly household income reported in the survey. The level of income is assumed to remain unchanged in 2014. Savings (HS_i) are derived from the responses of the surveyed households, and such savings are not subject to adjustment upon assigning them to the year 2014. It is assumed that a household may use its savings to cover expenses. Household expenses (BE_i) are derived from the consumption expenditure reported by a household: the purchase of food and consumer goods and utility payments as well as other urgent expenses, excluding, however, recreation costs (travel, theatre performances etc.). The level of household expenses is also assumed to remain unchanged in 2014. Total household payments for the redemption of liabilities (LP_i) are calculated for the year 2014, based on the surveyed information on outstanding liabilities, maturity of loans, interest rates and payments. For the purposes of initial analysis it is assumed that interest rates remain unchanged in 2014.

VH is not necessarily a defaulted household right away. It may reduce its expenses, gain additional income (for instance, with the help of relatives or friends). However, such adjustments are not subject to modelling since they depend on a given situation of a household, therefore it has been assumed in the further analysis that households do not adapt to a challenging situation. It is also assumed that a household is not able to increase its debt, should it face solvency problems.

The share of VHs amounts to 10.2% in the total sample, and the share of such households' liabilities is 12.7% in the aggregate portfolio of loans granted by credit institutions to households for house purchase (see Chart 13). It is in line with the share of household loans for house purchase past due over 90 days (12.3% – in June 2013)[14] and the results of research carried out in other countries. The researchers of the Central Bank of Chile, Fuenzalida and Ruiz-Tagle (2009) applied a different methodology and found out that 9.5%–13.6% of households were vulnerable (the share of liabilities of these households amounted to 14.5%–17.1% of the aggregate portfolio of loans granted by credit institutions for house purchase); researchers of Oesterreichische Nationalbank, Albacete and Fessler (2010) revealed in their study of 2010 that the share of VHs constituted 9.2%–15.6% (depending on the applied methodology of the financial margin calculation) and the share of liabilities of these households amounted to 14.3%–26.5% of the aggregate portfolio of loans granted by credit institutions to households for house purchase. Zajączkowski and Żochowski (2007) of Narodowy Bank Polski stated in their publication that 12% of Poland's households were vulnerable in 2006 and their share of liabilities stood at 15% of the loan portfolio of households.

Chart 13

Comparison of the share of VHs and their liabilities in the portfolio of loans granted for house purchase in the surveys of 2011 and 2013 (%)



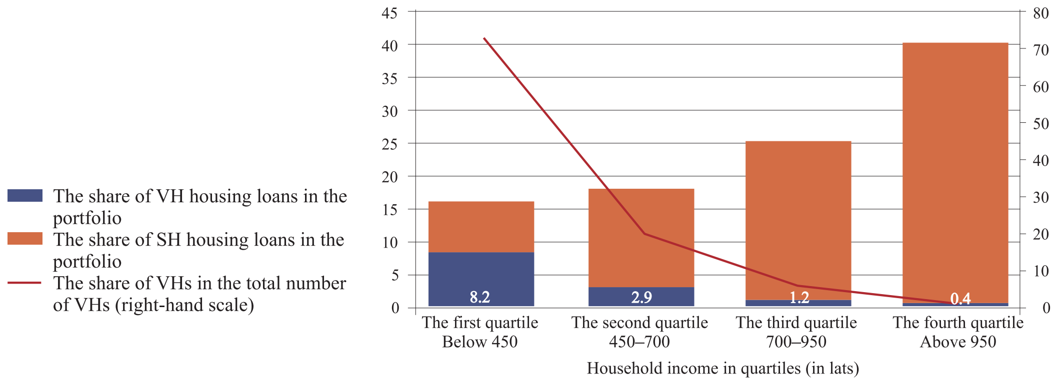
A slight improvement can be observed in comparison with the survey carried out in 2011, i.e. according to the previous survey 11.2% of households could be considered VHs. This minor difference suggests that the position of household borrowers still remains problematic. Although household income has increased over the past two years, some of the households still find it very difficult to balance their expenses with income. The share of VH liabilities in the portfolio of loans granted for house purchase has declined more rapidly.

[14] The FCMC data.

In Latvia, similar to other countries, households with a higher income have the largest share of housing loans (40%). It is obvious since households with higher income are able to receive larger loans. As regards households with lower income, their housing loans constitute approximately 16% of housing loans (see Chart 14).

Chart 14

Distribution of VH loans and SH loans for house purchase and distribution of VHs by income quartiles (%)



A distribution of housing loans into quartiles is similar to the distribution of housing loans of other countries not only in qualitative, but also in quantitative terms, for instance, the study by Albacete and Fessler (2010) of Oesterreichische Nationalbank reveals that the first lower income quartile comprises 9% of loans granted by credit institutions, the second quartile comprises approximately 17%, the third quartile – approximately 33% and the highest income quartile – approximately 38% of all loans granted for house purchase.

It is rather logical that the distribution of the number of VHs into income quartiles represents a trend opposite to that of loans: more than 70% of all sample VHs are in the first income quartile (with the lowest income), 20.2% – in the second quartile, 6.1% – in the third quartile and only 1.0% of VHs are in the highest income quartile (for the breakdown of the number of VHs by quartiles see Chart 14).

The share of liabilities of VHs and SHs in the aggregate loan portfolio depending on a household income quartile has been provided in Chart 14. It is similar to the distribution of the number of VHs in the income quartiles. The quality of loans granted in the lowest income quartile is the worst since half of the outstanding loans are VH liabilities.

4.2 Expected losses

The share of VHs in the total number of borrowers is the most significant indicator describing the overall resilience of households to various shocks. However, it does not allow for an assessment of the potential impact on lenders. To assess impact on credit institutions (lenders), should various shocks and adverse scenarios materialise, the share of VH liabilities in the total loans as well as the value of assets held by these households is to be taken into account. Therefore three indicators are calculated – the share of VH liabilities in the total loans outstanding, additionally required provisions for loans past due and ratio of the expected losses of credit institutions to the total housing loans.

The share of VH liabilities in the total outstanding liabilities (exposure at default, $EAD_{\%}$) is a significant credit risk indicator (it is actually the proxy of the share of loans past due) and it is calculated using the following equation:

$$EAD_{\%} = \frac{\sum_{i=1}^{N} I_{\{B_i<0\}} \cdot L_i}{\sum_{i=1}^{N} L_i} \cdot 100 \quad (5),$$

where L_i – outstanding liabilities of i-th household, and $I_{\{B_i<0\}}$ – indicator function of a negative financial margin of i-th household, which takes the value one, if the financial margin of a household is negative:

$$I_{\{B_i<0\}} = \begin{cases} 0, \text{ if } B_i \geq 0, \\ 1, \text{ if } B_i < 0 \end{cases} \quad (6).$$

The second indicator – **additionally required provisions** – is calculated according to the methodology[15] applied in the credit risk sensitivity analysis, stipulating that credit institutions make provisions for loans past due. Provisions are made in the amount of 60% for the projected increase in the share of loans past due over 90 days. To proxy the increase in the share of loans past due over 90 days under the impact of shocks, the difference between the percentage share of total debt held by VHs after a shock and this share in the absence of shocks was calculated:

$$\Delta EAD_{\%} = EAD_{\% shock} - EAD_{\% no\ shock} \quad (7).$$

The third indicator – **expected losses** – represents losses, taking into account the average LTV ratio based on the Credit Register data. Although, with the number of VHs increasing, lenders may incur initial losses directly due to the increase in the provisions for loans past due. Eventually, losses would be equal to the difference between the outstanding amount of the defaulted loan and sales value of the real estate pledged as loan collateral.[16] The expected losses represent the above losses.

To make a more precise assessment of potential losses incurred by credit institutions due to the loans granted for house purchase, the Credit Register data on the average LTV ratio by housing loan size groups (see Table 3) are used. In the stress test, the loan collateral values V_i were calculated as follows:

$$V_i = L_i / LTV_i \quad (8),$$

where LTV_i is the value of the LTV ratio consistent with the total housing loan of i-th household and L_i – outstanding liabilities of i-th household. The loss incurred by a credit institution in the event of a household's default equals the difference between the outstanding amount of the defaulted loan and collateral value. In the case of a negative difference (the value of collateral exceeds outstanding loan), loss equals zero. The expected total losses incurred by credit institutions due to the loans granted for house purchase may be expressed by the following equation:

$$EL = \sum_{i=1}^{N} I_{\{B_i<0\}} \cdot \max(L_i - V_i, 0). \quad (9).$$

[15] See Subsection 2.6 " Credit Risk Shock-Absorption Capacity" of Latvijas Banka Financial Stability Report for 2012.

[16] Potential income arising from the discharge of liabilities during insolvency proceedings of a natural person are not taken into account. The study of the Association of Commercial Banks of Latvia "Statistics of Insolvency Proceedings of Natural Persons" evidences that income generated from the discharge of liabilities are insignificant compared to the outstanding loan which is not covered by a collateral.

Table 3

Comparison of housing loans distribution in the household survey and Credit Register, the weights applied and average LTV from the Credit Register by housing loan size

Size of a housing loan (in thousands of lats)	Share in the total housing loans (%)		Share in the loans up to 150 thousand lats	Applied weight	LTV ratio (%)
	Survey	Credit Register	Credit Register		
Below 10	9.98	6.73	7.74	0.78	52.2
10–20	17.17	13.01	14.96	0.87	94.0
20–30	17.20	12.76	14.68	0.85	112.2
30–40	12.67	11.07	12.73	1.00	122.8
40–50	12.42	9.09	10.46	0.84	128.4
50–60	8.99	7.26	8.35	0.93	130.7
60–70	4.42	5.64	6.49	1.47	130.2
70–80	3.73	4.52	5.20	1.39	129.9
80–90	4.81	3.89	4.47	0.93	134.1
90–100	2.16	3.03	3.49	1.62	135.2
100–150	6.46	9.92	11.42	1.77	136.5
Above 150	–*	13.09	–	0	136.1
Total	100	100	100	–	–

* The number of households with a housing loan above 150 thousand lats in the survey sample is insufficient (only one household), hence it has been excluded from further analysis and conclusions were generalised only to loans below 150 thousand lats.

The expected losses $EL_{no\ shock}$ are calculated using equation 9 in absence of any shocks and, therefore, represent losses caused by households that already had failed to comply with their liabilities at the beginning of the year. We assume that credit institutions had already made provisions for the above expected losses. Taking this into account, the impact of a shock is represented by an increase in the expected losses due to the shock:

$$\Delta EL_{shock} = EL_{shock} - EL_{no\ shock} \quad (10).$$

To generalise the conclusions obtained using the survey data to all loans below 150 thousand lats granted for house purchase, the expected losses are expressed as a percentage of the total housing loans:

$$\Delta EL_{\%} = \frac{\Delta EL}{\sum_{i=1}^{N} L_i} \cdot 100 \quad (11).$$

However, it should be noted that actual losses incurred by lenders would be lower due to three reasons. First, households may also own other real estate properties (not disclosed in the survey) which may be used for covering debt or as an additional collateral. Second, insolvent households will cover part of their outstanding liabilities during their insolvency proceedings. Third, solvency of a household may be restored in cooperation with the lender by applying a postponement of principal payments temporarily or reducing the payments and extending loan maturity term at the same time. However, a simplified calculation of the expected losses has been applied to the above analysis (see equations 8 and 9) and it is sufficiently conservative to consider the result as the upper limit of the expected losses.

5. RESULTS OF STRESS TESTS OF HOUSEHOLD FINANCIAL VULNERABILITY

5.1 Results of a sensitivity analysis

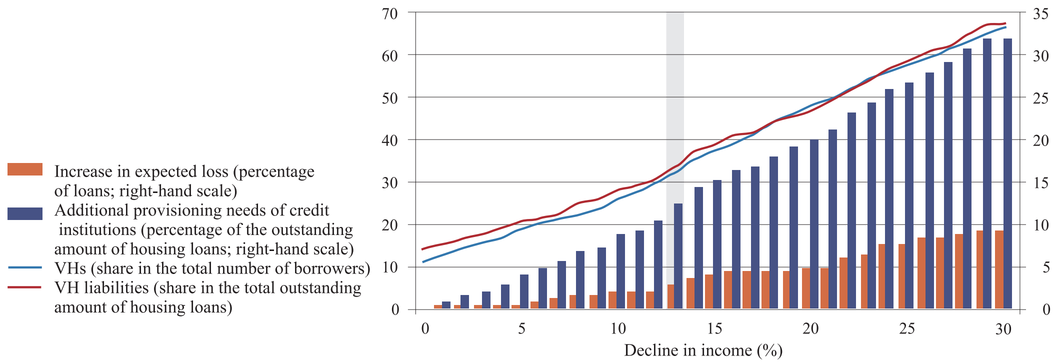
Based on the established relationships, the sensitivity of household financial vulnerability to the reduction of employment income, interest rate increases and rise in unemployment was analysed; the impact of two unfavourable macroeconomic scenarios was also assessed. The sensitivity analysis was carried out by gradually changing the respective exogenous variable (household employment income, interest rates, unemployment rate) and by calculating the changes of the VH share and potential losses of credit institutions in accordance with the changes in exogenous variable.

When assessing the effect of the shock induced by employment income reduction, the income level is decreased proportionally for all households and the financial margin is calculated, taking into account the reduced income, while other factors remain unchanged. Analogically, the impact of an interest rate rise is assessed by increasing interest rates on household housing loans, while keeping other factors unchanged.

Initially (i.e. without applying a fall in employment income or an increase in interest rates) at the end of 2014, 11.0% of households can be considered vulnerable (their financial margins are negative) and the share of liabilities of these households constitutes 13.8% of the housing loan portfolio. The expected losses of credit institutions in the initial situation are 3.3% of housing loans. Although household employment income has increased over the past years and the average wages and salaries have even reached the pre-crisis level[17], part of households still find it very difficult to balance their expenses with income.

Households are very sensitive to the decline in employment income. The drop in income by 5% increases the share of VHs to 18.4%, but the share of VHs' loans in the loan portfolio – to 19.8% (see Chart 15).

Chart 15
Household sensitivity to a decline in employment income



This means that credit institutions should increase their provisions for household housing loans approximately by 160 million euro (3.6% of the housing loan portfolio). In turn, assessment of lenders' expected loss based on the LTV ratio

[17] Based on CSB statistics, the average net wages and salaries have reached the pre-crisis level. However, at the same time it also points out that wages and salaries in the public sector are still lower than before the crisis.

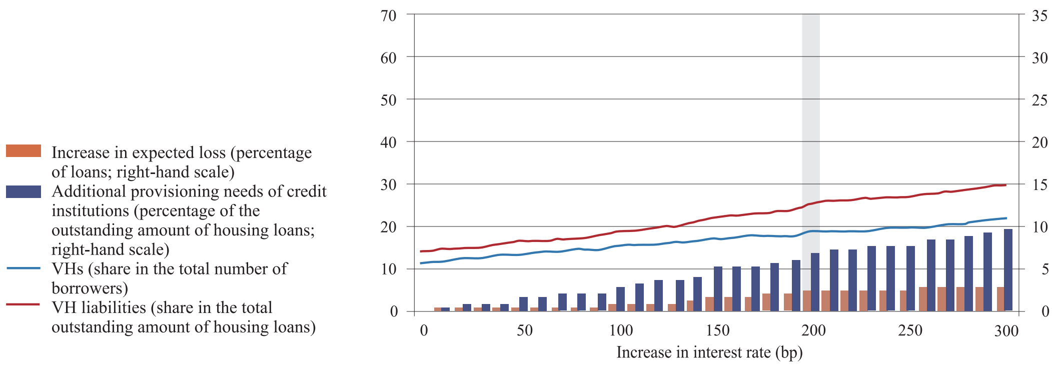
values calculated employing the Credit Register data suggest that the expected loss of the housing loan portfolio would grow by 0.7% if employment income fell by the above amount. This suggests that relatively small income shocks can still cause significant deterioration of household solvency, creating losses for lenders. Losses would be incurred mainly because of the need to make additional provisions, but the ultimate losses caused by insolvent borrowers would be relatively limited as most of the loan would be covered by selling the property used as collateral for the loan.

Over the past 10 years, the most significant reduction in wages and salaries within a year was 13.4%[18]. The sensitivity analysis shows that in the case of such an isolated shock the share of vulnerable households would rise to 32.4% of the total number of borrowers, but additionally required provisions – by 12.2% of housing loans (see the highlight in Chart 15). However, the ultimate losses of credit institutions would increase by 2.7% of the loan portfolio granted for house purchase.

The increase in interest rates also has a significant, however, smaller impact on households (see Chart 16). The interest rate rise by 100 basis points would increase the share of VHs in the total number of households to 14.7% and their share in the loan portfolio – to 18% thus necessitating credit institutions to expand their provisions for household housing loans by 2.5% of the outstanding amount of household loans. Assessment of the expected loss suggests that such a shock would increase losses by 0.6% of the outstanding amount of household loans. Unlike the income shock, a rise in interest rates has a stronger impact on households with large credits. This is evidenced by a more rapid increase in the share of VH loans in the total outstanding amount of housing loans and faster mounting of losses, with interest rates climbing.

So far the largest observed increase in the base interest rate of the 3-month EURIBOR within a year has been 204 basis points[19]. In the case of such an isolated rise in interest rates the share of VHs would increase to 18.2% of the number of borrowers. However, ultimate expected losses of credit institutions would be limited and would rise only by 2.1% of the loan portfolio (see the highlight in Chart 16).

Chart 16
Household sensitivity to an increase in interest rate



[18] Based on the CSB data on the average wages and salaries of employees.
[19] Based on the European Banking Federation's data on the index of the interest rates on interbank loans in euro.

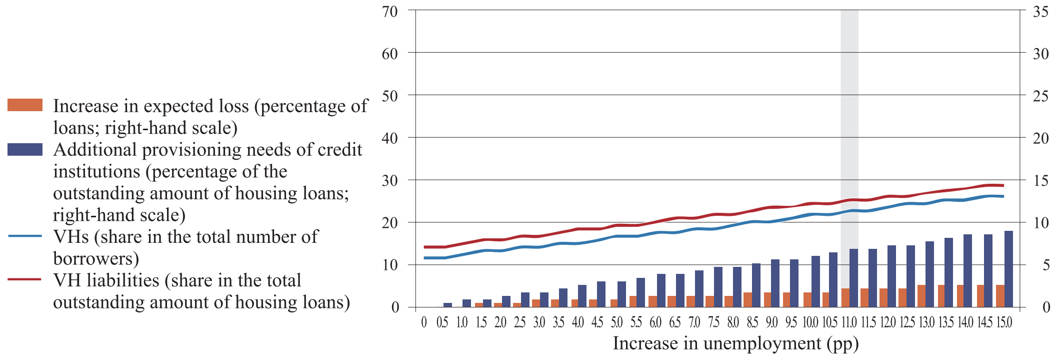
When assessing the effect of an increase in unemployment on the financial margin of the respective household, a problem of applying the increase in unemployment to the whole sample arises since it affects only individual persons but not all households as is the case in the previously analysed impact assessment of the decline in employment income or increase in interest rates. Monte Carlo simulations were carried out to address this problem. In each simulation individuals, assumed to become unemployed, were randomly selected, ensuring that becoming unemployed for each person in the sample employed in Latvia would be, first, equally possible and, second, the total number of the newly unemployed would correspond to the rise in unemployment in the stress test. If an employed person becomes an unemployed person, household income is recalculated by replacing employment income of the specific person with unemployment benefit calculated by taking account of the salary prior to job loss and the individual's age (which affects the length of service[20]). 1 000 simulations were carried out for each increase in the unemployment rate considered in the paper. The share of VHs and expected losses of lenders were averaged across simulations to assess the impact of unemployment shock not allowing peculiarities of individual households to influence the stress test results.

The produced results suggest that household sensitivity to an increase in unemployment is moderate (see Chart 17). The rise in unemployment by 5 pp increases the share of VHs to 16.1% but their share in the loan portfolio – to 18.7%. An equivalent increase in the number of VHs would cause reduction of employment income by 4.0%. This relatively low household solvency sensitivity to a rise in unemployment can be explained by the fact that the period analysed in the test is one year, and this analysis is based on the assumption that all persons employed receive unemployment benefits for nine months. However, this might not be the case due to the "envelope wages" as part of the employed pay taxes only for a share of their wages and salaries or do not pay taxes at all. Therefore, the calculated unemployment benefits would be considerably lower than income of these persons employed. Moreover, when modelling the impact of a rise in unemployment, the fall in income caused by job loss affects only individual households, but in the case of the income and interest rate sensitivity analysis changes refer equally to all households. It should also be taken into account that 3.9% of the employed persons in the sample work abroad and, therefore, are not affected by Latvian unemployment shock.

Over the past 10 years the most pronounced increase in unemployment rate within a year was 11.2 pp[21]. Such an isolated shock would increase the share of vulnerable households by 11.2% of the total number of borrowers (see the highlight in Chart 17). In turn, losses of credit institutions would mount by 6.5% of the outstanding amount of housing loans due to the necessary additional provisions; however, in a longer run – only by 1.7% of the outstanding amount of housing loans. Thus, comparing the major historically observed shocks, the impact of a rise in unemployment is comparable with the effect of an interest rate increase.

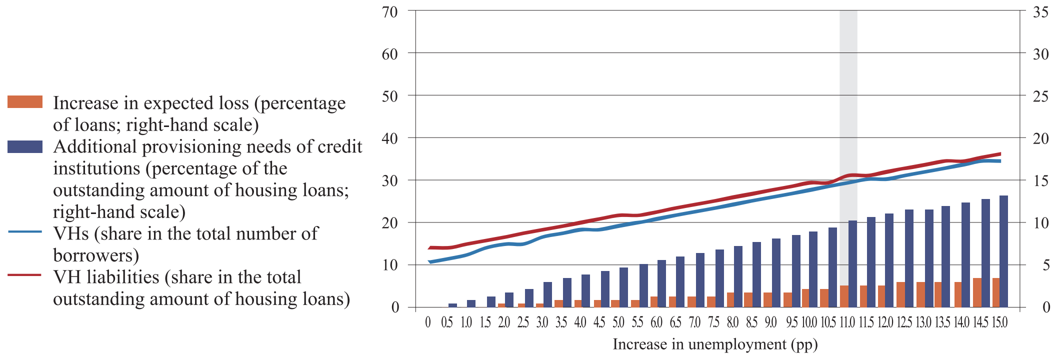
[20] Pursuant to the law of the Republic of Latvia "On Insurance against Unemployment".
[21] Based on the Eurostat data on the registered unemployment rate.

Chart 17
Household sensitivity to an increase in unemployment



Soaring unemployment is usually related to economic downturn and a drop in income; therefore, a sensitivity analysis was carried out by modelling a simultaneous rise in unemployment and fall in income. The impact of a rise in unemployment on an employment income decrease was assessed using the macroeconomic model of Latvijas Banka through simulating changes of external demand and investment. The increase in the unemployment rate by 1 pp causes the decrease in wages and salaries approximately by 0.47 pp. As a result of the combination of the impact of a rise in unemployment and decrease in income, household sensitivity becomes more pronounced (see Chart 18). For example, if the unemployment rate grew by 5 pp and income fell by 2.4%, the share of VHs would climb to 19.6% and the share of their loans in the loan portfolio – to 21.5%. The required increase in provisions for housing loans in this situation would be approximately 200 million euro (5.1% of the housing loan portfolio).

Chart 18
Household sensitivity to a rise in unemployment followed by shrinking employment income



5.2 Macroeconomic stress test

Based on the financial margin of household borrowers it is also possible to assess a simultaneous impact of several risks on household solvency. The sensitivity analysis was supplemented with a macroeconomic stress test that enables to assess reaction of household borrowers to the potential combination of the interconnected macroeconomic shocks according to a specific scenario. Two scenarios were considered, i.e. the stress scenario and severe scenario. When establishing the range of shocks to be included in the scenarios, the primarily focus is on the risks related to the external macrofinancial environment development that currently has been identified as one of the most important sources of systemic risks. Materialisation of the external risks would affect Latvia's economy through two primary channels.

First, external shocks can affect Latvia's economy via the foreign trade channel. The potential volatility on the global financial markets caused by the materialisation of the risk premia repricing risk and the related rise in interest rates can facilate an increase in the sales of financial assets not only in the markets of the emerging market economies but also in those of the developed countries. The related fall in confidence and economic activity would endanger the fragile economic recovery process in the euro area and slow down growth of other regions, including that of Latvia's main trade partners. Thus, a decrease in external demand would have a negative impact on Latvia's export developments.

Second, external shocks can affect Latvia's economy through the investment channel. Currently the uncertainty surrounding development of the external macrofinancial environment is one of the most important factors hindering investment activity in Latvia. Should the external risks materialise, the above uncertainty can substantially increase and progressively impair confidence of both domestic and foreign investors in Latvia.

With the external risks materialising, potentially adverse export and investment changes are the two most significant factors that could have a downward effect on Latvia's economic growth and result in a higher credit risk.

Taking account of the above, the **stress scenario** analysed the reaction of Latvia's economy to a combination of two shocks: a 10% fall in foreign demand and diminishing of investors' confidence leading to a 5% decrease in investment.

In order to assess the credit risk shock-absorption capacity of credit institutions under extremely adverse circumstances, the **severe scenario** was analysed. This scenario is based on the same shocks as the stress scenario, but their size was doubled, i.e. it envisages a 20% fall in foreign trade and a 10% decrease in investment.

Changes in the average wages and salaries and unemployment under the impact of the above shocks were assessed within the stress scenarios by using the macroeconomic model of Latvijas Banka, while the satellite model was employed to assess the fall in real estate prices relevant to the scenario shocks. Table 4 reflects the macroeconomic parameters of the stress and severe scenarios for 2014, as well as the stress test results.

Table 4

Parameters of the macroeconomic stress test scenarios and the share of liabilities of the assessed VHs and additional losses incurred from loans granted to residents for house purchase at the end of 2014

Indicator	Stress scenario	Severe scenario
Increase in unemployment rate (pp)	1.1	2.2
Average wages and salaries (annual changes[22]; %)	–2.3	–4.7
Fall in real estate prices (%)	8.2	14.0
Share of VHs (%)	17.7	21.8
Rise in the share of VH liabilities in the loan portfolio (pp)	4.0	8.1
Additionally required provisions (in millions of euro)	94	191
Expected losses due to additional provisions (% of the total amount of housing loans[23])	2.4	4.8
Expected losses after enforcement of collateral[24] (%)	1.10	2.5

22 As compared to the baseline scenario.
23 Loans for house purchase, reconstruction and renovation granted to residents.
24 Deviation from losses without application of shocks which constitute 3.3% of the housing loan portfolio.

CONCLUSIONS

The survey of household borrowers has provided a valuable insight into the financial situation of borrowers. The obtained data suggest that the most vulnerable households are the ones that suffered most from unemployment and contracting income during the financial crisis, having at the same time higher credit liabilities than those of other borrowers as they took loans shortly before the onset of the crisis when real estate prices were the highest. Moreover, several years after the beginning of the crisis part of these households has not been able to regain the lost solvency, and they are still facing difficulties in balancing their income and expenses.

The results of parametric modelling indicate to a strong dependence of household default probability on the debt service ratio, as well as to the crucial role household savings play in mitigation of their default risks. Moreover, the results of the model reveal that the default risk of households grows as the number of dependents increases. These results show that households with several dependents have to be very cautious when assessing their ability to undertake credit liabilities.

Overall, household borrowers are still rather vulnerable to shocks caused by a small drop in employment income and rise in interest rates. However, the expected losses related to their solvency have become more moderate for lenders. This has been facilitated both by the increase in property value over the past years[25] and deceleration in the outstanding amount of housing loans[26]. In turn, the impact of a rise in unemployment is moderate as access to unemployment benefits mitigates this effect during the period analysed in the test. However, it can be intensified by the "envelope wages" phenomenon (the employed receive part of their wages or salary unofficially, without paying social security tax), i.e. the unemployed receive benefits only for the part of their salaries taxes are paid for. Therefore, the actual decline in income can be more pronounced in the case of unemployment. In turn, in the case of an adverse macroeconomic scenario credit institutions may need to substantially increase provisions for housing loans.

[25] The CSB housing price index reveals that housing prices between 2011 and 2013 grew on average by 8.2%, but the prices of standard apartments of Latio Ltd. in Riga – by 3.0%.

[26] The outstanding amount of loans granted to resident households for house purchase decreased by 15.5% between December 2011 and December 2013.

APPENDICES

Appendix 1. Calculation of marginal effects for the logit model

Since the binary choice models (including the logit model) are nonlinear, interpretation of coefficients differs from the customary interpretation of the linear regression model. In order to obtain information on the extent of the impact of the explanatory variable on probability, the marginal effects of these variables have to be calculated.

The marginal effect of a continuous variable within the logit model can be computed according to the following formula:

$$\frac{\partial E[y \mid x]}{\partial x} = \Lambda(x'\beta)[1 - \Lambda(x'\beta)]\beta \qquad (1.1),$$

but that of a binary variable – according to the formula:

$$M.e. = P[Y = 1 \mid \bar{x}_{(d)}, d = 1] - P[Y = 1 \mid \bar{x}_{(d)}, d = 0] \qquad (1.2),$$

where d is the binary variable under consideration, and it is assumed that the remaining variables take the sample mean values $\bar{x}_{(d)}$ (see Green (2008)).

Appendix 2. The ROC curve and AUROC

ROC curves are used to assess the ability of discreet choice models to classify data correctly.

Y = 1 is assumed to be a positive result which means default in the case of credit risk, but Y = 0 (a negative result) corresponds to fulfilment of liabilities. All households whose assessment of the probability of default P(Y = 1) exceeds threshold C are considered insolvent.

When classifying households in this way, four situations reflected in Table 1 may arise, where:

TP (true positive) means that a household has been classified as insolvent, and it does not fulfil its liabilities;

FP (false positive) means that a household has been wrongly classified as insolvent, but it fulfils its liabilities;

TN (true negative) means that a household has been classified as solvent, and it fulfils its liabilities;

FN (false negative) means that a household has been wrongly classified as solvent, but it does not fulfil its liabilities.

Table P2
Classification results

	True value	
	Y = 1	**Y = 0**
$\hat{P}(Y=1) > C$	TP	FP
$\hat{P}(Y=1) \leq C$	FN	TN

Sensitivity of the classifier is characterised by the proportion of correctly identified positive observations:

$$TPR(C) = \frac{TP(C)}{TP(C) + FN(C)} \quad (2.1),$$

but **specificity** – by the proportion of correctly identified true negative observations:

$$CNR(C) = \frac{TN(C)}{TN(C) + FP(C)} \quad (2.2).$$

1-specificity, also called FPR (false positive rate), is used for generation of the ROC curve:

$$FPR(C) = \frac{FP(C)}{TN(C) + FP(C)} \quad (2.3).$$

The ROC curve depicts sensitivity (TPR(C)) on the x-axis, but 1-specifity (FPR(C)) – on the y-axis for all threshold C values from the interval [0; 1]. The closer the curve to the point (0, 1), the better the model classifies the data.

AUROC (area under the ROC curve) can be calculated as follows:

$$AUROC = \int_0^1 TPR(FPR)d(FPR) \quad (2.4).$$

In the case of a perfect model AUROC would equal 1. This means that the probability of insolvency of all insolvent households is higher than that of the solvent ones. The AUROC value of 0.5 identifies a useless model as it does not distinguish insolvent households from the solvent ones.

Charts P2.1 and P2.2 show the in-sample and out-of-sample ROC curves of the logit model estimated in Section 3.

Chart P2.1
In-sample (75% of observations) ROC curve

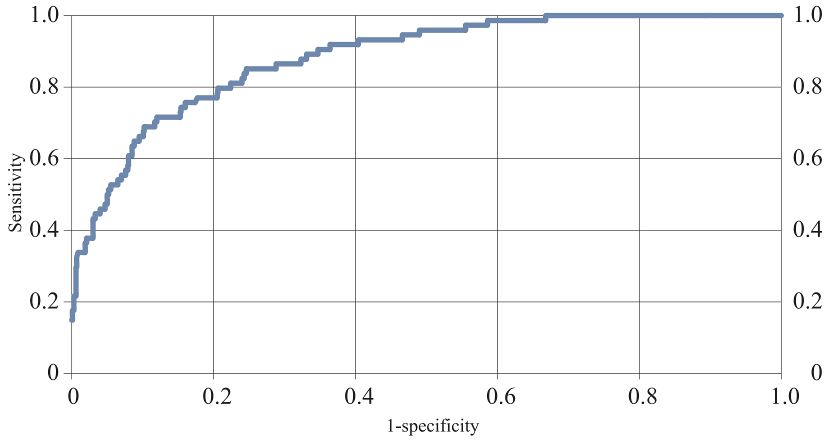
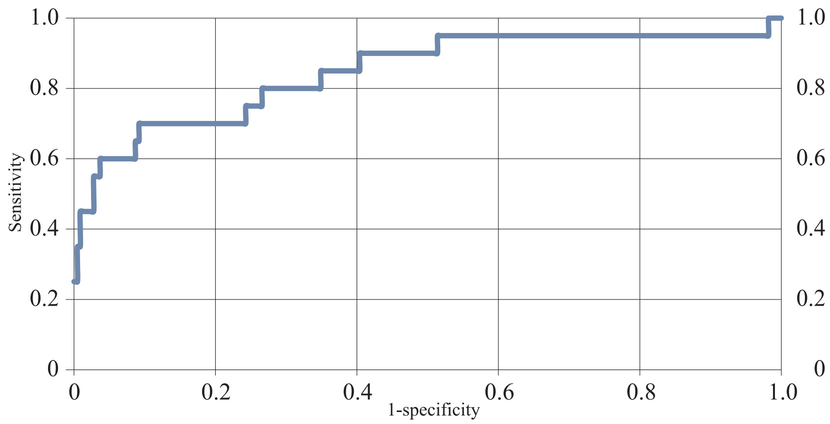


Chart P2.2
Out-of-sample (25% of observations) ROC curve



Appendix 3. Estimates of the logit model coefficients in the full sample

Variable	**Coefficient**	**P-value**	e^{β}	**Marginal effect**	
				ME at means*	**Average ME**
Constant	–3.36	0.000	0.035		
Number of dependents	0.39	0.002	1.47	0.002	0.022
Debt service ratio	4.31	0.000	75.15	0.181	0.242
Savings (a binary variable)	–0.68	0.068	0.51	–0.029	–0.038
Number of the unemployed and fields	1.34	0.018	3.80	0.056	0.075
Income in the 2nd quartile	–0.63	0.034	0.53	–0.027	–0.035
Income in the 3rd quartile	–2.28	0.000	0.10	–0.096	–0.128
Income in the 4th quartile	–1.91	0.001	0.15	–0.081	–0.107
Goodness of fit measure					
Mc Fadden R^2					0.337
Nagelkerkrke R^2					0.409
AUROC					0.876

* Calculated based on the sample mean values of the explanatory variables.

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