NBS Occasional paper

No 2/2022

Incorporating Individual Retail Loan Data into the Macro Stress Testing Framework

Ján Klacso

NATIONAL BANK OF SLOVAKIA
EUROSYSTEM

research@nbs.sk

This publication is available on the NBS website

www.nbs.sk/en/publications-issued-by-the-nbs/research-publications

ISSN 2585-9277 (online)

Incorporating Individual Retail Loan Data into the Macro Stress Testing Framework*

Ján Klacso[a]

Abstract

Macro stress testing has become an increasingly important part of central banks', and macroprudential authorities' toolkits after the global financial crises. Estimation of credit risk losses under adverse circumstances is one of the most important parts of the stress testing framework within the EU/Euro area. However, standard satellite models based on econometrics of time series may not be well suited for countries with short time series or an incomplete credit cycle. This paper shows how to incorporate microdata into the stress testing framework. The paper uses a unique set of individual retail loan data available to the NBS with a large number of data items provided for each loan. The new framework using micro data yields to a much larger increase of NPLs than using time series data in the case of Slovakia. On the other hand, overall losses estimated under the adverse scenario are comparable to losses estimated using the previous framework. Last but not least, the new framework using micro data enables us to estimate the change in risk weights caused by the adverse scenario as well.

JEL code: C58, G51

Keywords: Macro stress testing, microdata, credit risk, retail loans

* We are grateful for Claus Puhr, Pavol Jurča, Reiner Martin and Pavel Gertler for their valuable comments.

[a] Research Department, National Bank of Slovakia. E-mail: jan.klacso@nbs.sk

Non-technical summary

Macro stress testing is an important tool of central banks and macroprudential authorities and a key part of their risk analysis and policy framework. Estimating possible loan losses banks can face under adverse macro-financial circumstances is one of the most important parts of the risk analysis framework within the EU and the euro area. In general, most of the stress test frameworks deploy satellite models based on econometric time series to estimate losses from corporate or household loans. However, for countries with short time series, an incomplete credit cycle or structural breaks in the time series, using such an approach may cause misleading results.

To overcome this issue, it is possible to use micro-data such as survey data or credit register data. In this paper, we introduce a framework capable of incorporating individual retail loan data into the overall stress testing exercise. To do so, we use a unique set of retail loan data collected by the NBS since the second quarter of 2018 for supervisory purposes. The data cover the whole retail loan portfolio of Slovak banks and subsidiaries and consist of a rich set of information about the loans, the underlying collateral and the debtors.

The main aim of the framework is to link the development of macroeconomic variables under different scenarios to households' Probabilities of Default (PDs) and banks' Losses given Default (LGD) at the micro level. As a first step, macroeconomic scenarios for regular stress testing are constructed. For the household credit risk, the estimated development of the unemployment rate is usually the most important macroeconomic factor. Second, the impact of socio-demographic factors (such as age or education) on the probability of becoming unemployed is estimated using a logit model. Then the logit model is adjusted so that the average probability of becoming unemployed in the loan sample matches the change in the overall unemployment rate in each quarter. Finally, Monte Carlo simulations are used to determine which debtors will lose their jobs. Besides this, several assumptions are used regarding the development of the income of other debtors as well.

Those households whose monthly income does not cover monthly instalments and the subsistence minimum are assumed to default. If the household has financial assets, these assets can be used for monthly instalments as well. In case the loan is collateralised, the (stressed) value of the collateral is considered for the estimation of loss given default.

Results based on end-2019 micro data, i.e., data not affected by the COVID pandemic, suggest that under the adverse scenario, retail NPL ratios are considerably higher than in the original stress testing exercise, based on time series data. This holds especially for housing loans, with a 5 p.p. increase using micro data compared to only a 2 p.p. increase using time series.

Even if not completely comparable, in 2020, due to the impact of the Covid pandemic, households were enabled to use loan payment deferral up to a period of 9 months. In the case of housing loans, the repayment of 12% of the loans was postponed. While some of the households could have used the deferral only for preventive or speculative purposes, most borrowers asked due to financial constraints. These figures are even higher than the estimated increase of NPL ratio under the new framework, pointing to the plausibility of the estimations using micro data.

1 Introduction

Macro stress testing has become an increasingly important part of the central banks' and macroprudential authorities' toolkits after the global financial crises. As a forward-looking approach, it is a very useful instrument that helps to identify potential vulnerabilities in the banking sector and to assess its resilience during severe but plausible turmoil on the financial markets and negative economic development. The importance is stressed not only by national authorities, but multinational institutions such as the ECB (Dees et al, 2017) or the IMF (Adrian et al, 2020) as well.

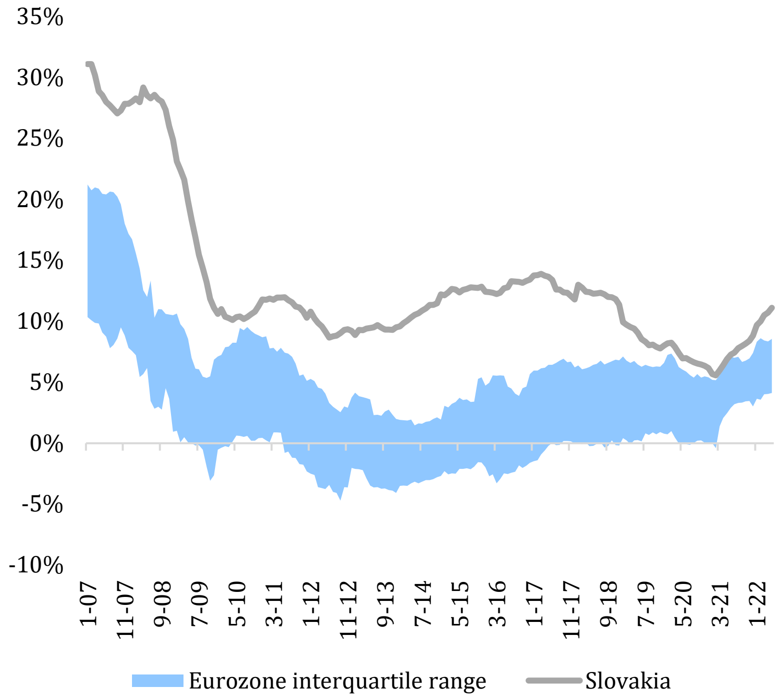
Stress testing is a relatively complex process with a lot of assumptions needed to assess systemic risks during severe but plausible adverse scenarios. It should capture the main risks for the given financial or banking sector it is applied to. Banking sectors in the EU in general face under the adverse scenarios losses mainly from credit risk, a significant part of which are losses from household credit risk (EBA, 2018). Household credit risk is even more important in countries with traditional banking sectors focusing on financing the real economy, such as in Slovakia, Czech Republic (CNB, 2019) or Hungary (MNB, 2019). Loans granted to NFCs by Slovak banks are more sensitive to negative shocks compared to household loans. During the Great Financial Crisis, the NPL ratio of Slovak NFCs increased between 2008 and 2010 by more than 5 p.p. and stayed at relatively high levels until 2015, also due to the decreasing volume witnessed in 2009-2010 and in 2012-2014 due to the sovereign crisis. Furthermore, losses from corporate loans increase more in the adverse scenario compared to the baseline scenario than those from household loans. On the other hand, losses from loans granted to households are larger or at least comparable under the adverse scenarios based on the recent macro stress testing results (NBS, 2020a, 2021, 2022)[1].

The importance of household credit risk for the Slovak banking sector is still increasing. While low in the early 2000s, household indebtedness has been continuously rising since 2002, when the housing loan market started after the destructuralisation of the banking sector (Tkáčová I - III, 2001). Currently, indebtedness in terms of household credit to GDP ratio is exceeding

[1] The framework described in this paper was already used to conduct stress testing based on December 2020 and December 2021 data. Results are described in the May 2021 and May 2022 Financial Stability Report.

levels in all peer CEE countries and is an increasing source of systemic risk to financial stability (NBS, 2017b).

Chart 1 Annual change of retail loans in Slovakia and in the euro area



Source: ECB SDW.

While increasing in importance, several factors make the proper estimation of losses from household credit risk using econometric techniques relatively hard in the case of Slovakia.

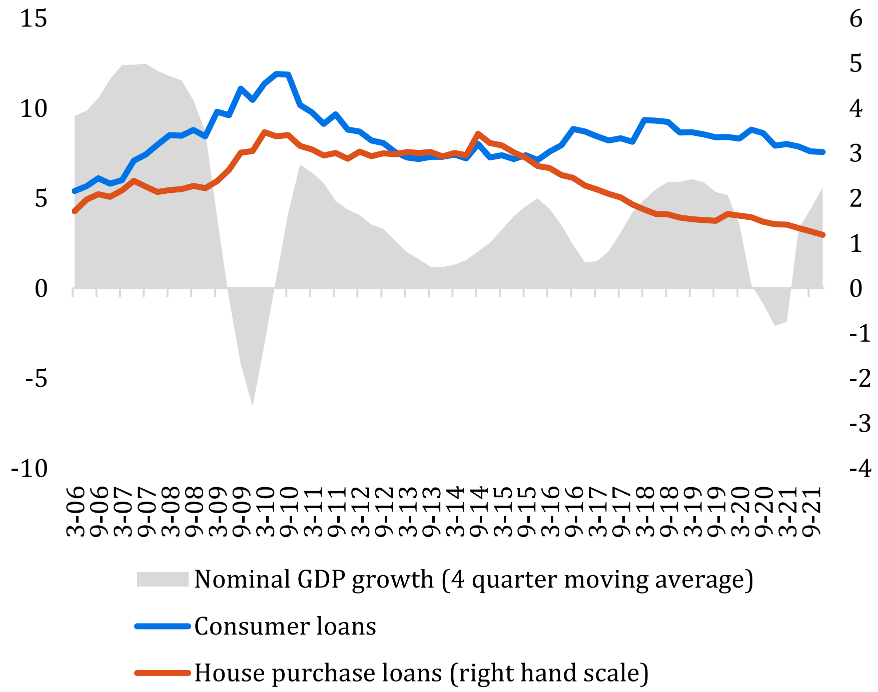
- Based on a sample of advanced economies, Mian and Sufi (2018) show that there is a predictable decline in household debt following a positive shock to this debt in respective countries. They also show that a shock to household debt generates a boom-bust cycle in the real economy that is similar to the credit cycle. While this was also the case for some eurozone countries after the Great Financial Crisis[2], household loan growth only decelerated in Slovakia but remained well above zero (Chart 1). While demand and supply were both negatively affected by increasing economic uncertainty and unemployment rate in 2009, high interest margins had a positive impact on the supply, while decreasing interest rates and low property prices boosted demand in the second half of 2009 (NBS, 2009). Not having a full credit cycle also means that the

[2] At most 8 eurozone countries experienced a decrease in the volume of loans to households right after the impact of the GFC in 2009, this number increased to 12 in 2012.

estimation of NPLs or NPL ratios using econometric techniques can underestimate the impact of adverse scenarios.

- NPL ratios increased because of the crises, mainly due to consumer loans, but remained relatively elevated and even increased also during the boom phase of the economy in 2016 – 2018 (Chart 2). The increase of the NPL ratio in the segment of consumer loans was to a large extent related to supply-side factors and a consequence of credit standard easing by some banks (NBS, 2017a). On the contrary, the corona crisis, mainly because of a broad set of government measures, has not resulted in a significant increase of NPL ratios of these loans.
- The implementation of a comprehensive set of borrower-based measures by the National Bank of Slovakia started in 2014 and has so far been done in several iterations. As a consequence of this, there are several structural breaks affecting the development of time series used for estimation.

Chart 2 Retail loans – development of the NPL ratio



Source: NBS.
Note: the chart shows the development of the stock of NPL ratios.

All these obstacles point to the necessity of using alternative approaches for estimating losses from household credit risk in the case of Slovakia. One possible approach is to use micro-level data. The National Bank of Slovakia has been receiving since 2018 detailed data about retail loans from domestic banks, subsidiaries as well as branches. These data contain a comprehensive set of information about the loan at the granted date as well as report date, about socio-demographic characteristics of the debtors at the granted date and a range of information about the collateral used.

As these individual data allow a proper in-depth analysis of the retail loan portfolio of the Slovak banking sector, it is a natural candidate to be used for macro stress testing purposes as well. In this paper, we exploit the dataset and suggest a framework for the overall stress testing exercise. We use estimated macroeconomic variables in the stress testing exercise under the baseline and adverse scenarios to obtain estimates of PDs and LGDs.

The paper is structured as follows. The next section gives a brief description of the related literature. Section 3 describes in more detail the database used for the estimations. Section 4 introduces the framework that links estimated macroeconomic development with microdata. Section 5 describes the results based on end-2019 data[3]. Finally, we conclude.

2 Literature review

Macro stress testing is now an integrated part of the toolkits of most central banks and macroprudential authorities. After the great financial crisis, this tool has become more important in the forward-looking assessment of the systemic risks the financial and particularly the banking sector can face during severe but still plausible adverse scenarios. Most of the financial stability reports contain results of actual stress testing exercises. Stress testing frameworks are being developed by national authorities as well as international organisations (see, e.g. Borio et al, 2014, Kanas & Molyneux, 2018 or Schmieder et al, 2011). The macro stress testing framework of the National bank of Slovakia is also described in Klacso (2014).

One of the key steps of the stress testing exercise is the translation of the development of the macroeconomic and global financial variables into estimated losses from different types of risks (credit risk, interest rate risk, FX risk, etc.). In the case of credit and particularly household credit risk, the framework usually includes satellite models to link the development of NPL ratios or PDs and LGDs to the development of selected macroeconomic variables using different econometric techniques, e.g. simple ADL processes (Dees et al, 2017), Bayesian techniques (Dees et al, 2017, Adrian et al, 2020) or quantile regressions (Adrian et al, 2020, Kanas & Molyneux, 2018).

While microdata, often based on different surveys, have been used for some time to assess household credit risk (see, e.g., Holló & Papp, 2007), they have become more widely used only recently. An exhaustive summary of literature focusing on the use of microdata for the assessment of households' credit risk can be found in Jurča et al. (2020), discussing the

[3] We refer to end-2019 data in the paper because this is the latest date when stress testing results for household credit risk were derived by econometric estimates. In 2020, the use of the econometric models for households' credit risk was terminated. Afterwards, the framework described in this paper has been used. Furthermore, 2019 is the latest year not impacted by the COVID pandemic and the related government measures. In 2020, the drop in GDP together with the positive NPL ratio development would make the use of standard econometric models even more challenging.

evolution of literature from focusing on different vulnerability metrics and being largely descriptive of literature dealing with multi-period stochastic simulations.

The above cited paper studies the effects of the borrower-based measures implied by the National Bank of Slovakia on the risk characteristics of retail loans (PD, LGD, loss rate) granted by Slovak banks under stressed circumstances. The paper uses data from the third wave of the Household Finance Consumption Survey (HFCS). The paper expands the macro-micro model introduced in Gross & Población (2017) that implements a framework translating the development of macroeconomic variables such as unemployment rate into micro-level household data. The original framework was also enhanced and extended to other, mainly EU countries in Gross et al. (2021) and in Ampudia et al (2021). In this paper, we expand and adjust the framework in two ways: first, we apply the framework to retail loan data covering the overall retail portfolio of Slovak banks as opposed to survey-based data used in the above cited studies. Second, we show how to implement the framework into the general process of stress-testing. The main adjustment of the framework is related to the use of retail loan data. As opposed to survey data, these micro data are from a different point in time and are not representative of the overall population.

In general, there are three types of data that can serve as an input into the estimation of household credit risk. The first is time series (of NPLs or PDs), the second is survey data and the third is loan-level data. In the table below, we give a very brief overview of the advantages and disadvantages of using these data for stress testing purposes.

Table 1 Data types used for stress testing household credit risk

Data type	Advantages	Disadvantages
Time series	Cover the whole portfolio of retail loans Historical relationship between macroeconomic variables can be detected	Structural breaks and incomplete credit cycle can make the proper estimation of future development challenging
Survey data	Representative data usually not just of the loan portfolio but also of the whole population Point-in time data not affected by structural breaks	Only part of the loan portfolio is covered Hard to incorporate historical relationships into the estimates
Loan-level data	The whole loan portfolio is covered Point-in time data not affected by structural breaks	Cover information only about indebted households Not all the available data are up to date

3 Description of the retail loan database

Table 2 Information available in the database

Type of information	Data item	Description
Information at the granted date	Aim of the loan	Information about whether it is a new loan, refinancing loan or renegotiated loan
	Granted and drawn amount of the loan	
	Granted date	
	Original maturity date	
	Initial interest rate	
	Initial monthly instalment	
Information at the reporting date	Outstanding amount of the loan	
	Actual maturity date	
	Actual interest rate	
	Actual monthly instalment	
	Actual interest rate fixation	
	Date of the next refixation	
	Days overdue	
	Volume of provisions	
	Default flag	Dummy indicating whether the loan is at default at the time of reporting
	Forbearance	Dummy indicating whether any changes in the loan contract have been realised due to the credit quality (forbearance)
Information about the debtor/household at the granted date	Education of the first and second (if exists) debtor	Primary, secondary or higher level of education
	Minimum subsistence amount	Minimum subsistence amount of the household that is used for the calculation of DSTI
	Income of the debtors	3 (consumer loans) or 6 (housing loans) month average of net income
	Income source of the debtors	Employee, self-employed or other
	Financial assets of the debtors	Financial assets of the debtor at the reporting bank or at the asset management company held by the bank
	Overall debt of the debtors at the granted date	The volume of all loans granted to the debtors
	Overall monthly instalment of the debtors at the granted date	
	DTI at the granted date	
	DSTI at the granted date	
Information about the collateral (if exists)	Number of collaterals	
	Region	Region of the collateral
	Collateral value entering the calculation of LTV	
	Different measures of the collateral value	Market value, internal value (set by the bank), external value (external appraisal)
	LTV at the granted date	
	LTV at the reporting date	
	Date of the last revaluation of the collateral	

Source: NBS.

Note: as collateral in the form of real estate is practically the only one used in the case of housing loans, the database contains only information about this type of collateral.

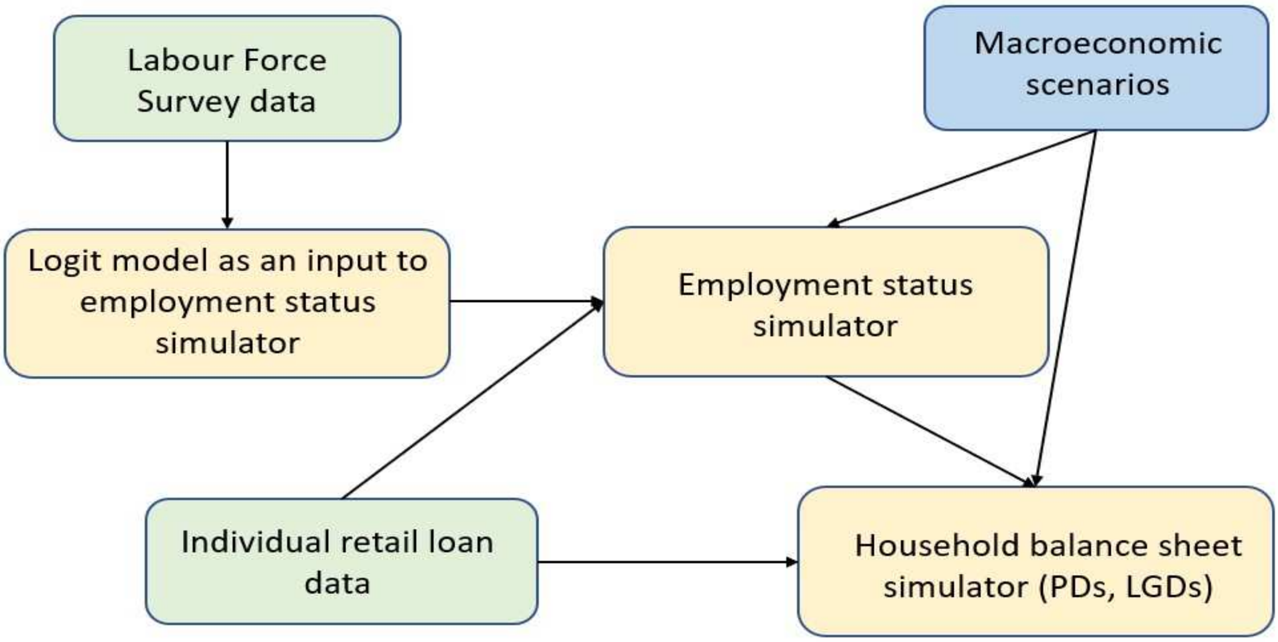
Since the second quarter of 2018, the NBS has been obtaining quarterly data from all Slovak banks, subsidiaries and branches. Data are collected for supervisory purposes, as the introduction of borrower-based measures by the National Bank of Slovakia as a national macroprudential authority makes it necessary to i) regularly control the compliance of the banks with the limits and ii) to assess the effectiveness of the measures. A description of the reasons for introducing BBMs and the set of BBMs is available in Harrison et al. (2018) and on the website of the NBS[4]. The dataset consists of an exhaustive list of data items for each loan, depending on the type of loan. The most important data items are described in Table 2.

The database contained overall approximately 3.5 million individual data points (loans) as of end-2019, 650 thousand housing loans and almost 3 million other loans. The overall volume of loans in the database as of end-2019 matches the volume of loans reported by banks via official supervisory reports relatively well.

4 Stress testing individual data – methodology

The main aim of the framework is to link the development of macroeconomic variables under different scenarios to households' PDs and LGDs at the micro level. In this part, we describe the necessary steps to obtain estimation of losses from households' credit risk using micro data. The scheme of the framework is described in Chart 3.

Chart 3 Scheme of the methodology for individual loan data



Source: NBS.

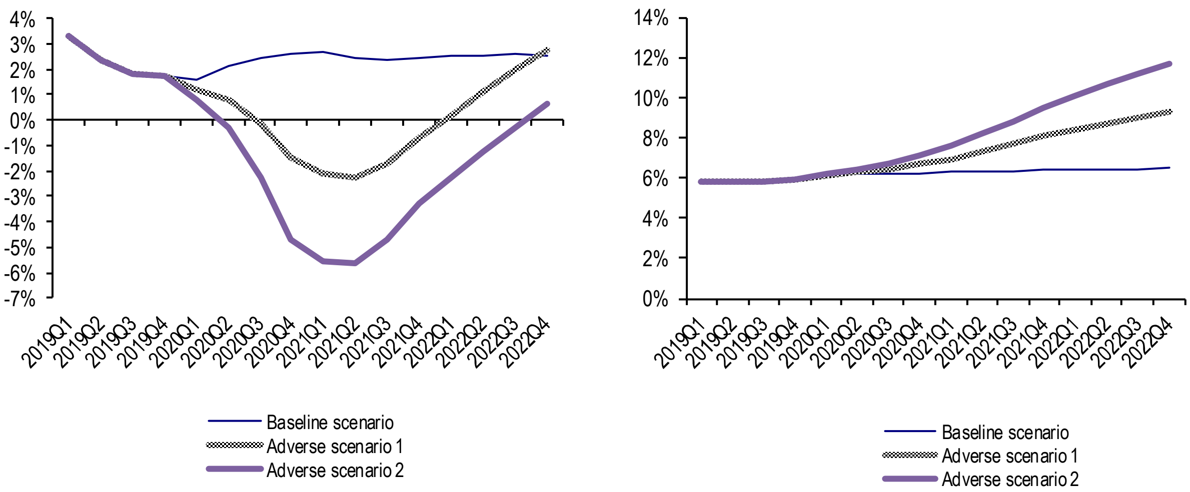
[4] https://www.nbs.sk/en/financial-market-supervision1/macroprudential-policy/current-status-of-macroprudential-instruments/current-setting-of-instruments-for-retail-loans

The key adjustments of the framework compared to the one used in Jurča et al. (2020) are related to the use of retail loan data instead of HFCS survey data. While HFCS data are a representative sample of the whole population, retail loan data cover only the indebted part of the population. Therefore, the logit model estimating the probability of employment cannot be based on the retail microdata and data from the Labour Force Survey are used instead. These data are used to estimate flows between different employment stages[5] in Klacso & Štulrajterová (2021). In this paper a similar approach is applied, however the focus is on the flow from the employed to the unemployed status. In addition, while there are several possible explanatory variables available in the survey, we use only those that are available also in the retail loan data so we can apply the results to the dataset used.

Another need for adjustment is because, as opposed to the HFCS data, retail loan data are from a different point in time based on the date the loan was granted. For those indebted households that have more than one loan, some data like education or income could be included multiple times in the database with potentially different values. This makes necessary the proper adjustment of the data before their use. Below we give a step-by-step explanation of the approach[6].

4.1 Linking macroeconomic development with microdata

Chart 4 Baseline and adverse scenarios for stress testing based on end-2019 data: annual real GDP growth (left) and unemployment rate (right)



Source: NBS.

[5] Employed, unemployed and inactive.

[6] The current environment of elevated uncertainty stemming from geo-political risks and the increased level of inflation means also new challenges for the modelling framework. The future improvement of the framework may focus on capturing, among others, the (i) increase of basic living costs, (ii) increase of interest rates and (iii) heterogenous changes in income across households, including a possibility that the income could increase less or even shrink in some households. These changes are however subject to ongoing research and are out of the scope of this paper.

As a first step, macroeconomic scenarios are constructed for the regular stress testing. The stress testing exercise in Slovakia is conducted annually and usually consists of three scenarios, one baseline and two adverse. The baseline scenario is based on the official medium-term forecast of the National Bank of Slovakia. The adverse scenarios consist of severe but still plausible development of the main macroeconomic and financial variables affecting banks' profitability. The adverse scenarios are generated in a two-step procedure. First, an exogenous path of a set of macroeconomic variables is decided by expert judgement[7]. Second, the structural error correction-based macro model of the NBS is used to estimate the endogenous development of the domestic macroeconomic variables based on this set. A detailed description of this macro model is available in (Reľovksý & Široká, 2009)[8]. These scenarios reflect the main systemic risks and their potential triggers. The development of real GDP and unemployment rate from the stress testing exercise based on end-2019 data are shown in Chart 4. The stress testing exercise is described in more detail in NBS (2019).

The main macroeconomic factor affecting households' credit risk via negative impact on cash flow in the case of the adverse scenarios is the increased unemployment rate. PDs, or defaults of individual loans, depend on the cash flow of the indebted household. The inflow can be influenced by the possible change in income due to a negative impact of the scenario on the income (due to the expected adverse economic development, causing, e.g., less working hours or a cut in bonuses[9]) or on the economic status of the household members (i.e. if any of the family members become unemployed). The cash flow of unemployed household members is then affected by the possible eligibility for unemployment benefit. When there is a drop in income, it is assumed households can also use their financial assets to cover expenses. While the unemployment rate in general significantly increases under the adverse scenario, macroeconomic estimations usually does not lead to a drop of income[10]. Therefore, while we use the estimated development for the unemployment rate, for the income we assume in the base setup a decrease of 10% for household members not becoming unemployed. In the retail loan database, we have information only about the financial assets of the household members that are deposited in the same institution who provided the loan. These assets are not impacted by the development on the financial markets[11].

---

[7] A more detailed list of these variables is available in Table 4 of the Annexes to the Analysis of the Slovak Financial sector 2019 (NBS 2019)

[8] A short description of the structural model is provided in Box A1 in Jurča et al. (2020).

[9] While the cashflow can be affected also by unexpected expenditure increase, this is not reflected in the framework.

[10] In the case of the adverse scenario used for the end-2019 data, the unemployment rate increased from 6% to more than 11% while even real income remained on a decreasing path.

[11] While we do not have complete information about the financial assets of indebted households, Slovak households still have one of the lowest ratios of financial assets to financial liabilities within the EU (FSR, November 2021).

On the outflow side, households can face changes in their expenses or changes in the monthly instalments. As the framework is applied for stress testing purposes, it is assumed that under the adverse scenario, households under financial pressure will cut their expenses as much as possible to cover their monthly instalments. Therefore, we assume expenses in the form of minimum monthly living costs are related to the subsistence minimum. In the case of the monthly instalments no change is assumed[12]. LGD is important for collateralised loans. It is affected mainly by the assumed development of residential real estate prices, as in practice residential properties are the most widely used collateral for house purchase loans. It means that overall, from the macroeconomic factors affecting households' PD, the only important and estimated factor is the unemployment rate.

The probability of a household member losing their job depends on both macroeconomic and socio-demographic factors. The impact of socio-demographic factors on the probability of becoming unemployed is estimated using a logit model. As mentioned above, we use data from the Labour Force Sample Survey to estimate the probability of becoming unemployed. This dataset allows us to construct quarterly flows from employed to unemployed or economically inactive status from 2005. We estimate a logit model where the explained variable is the quarterly number of employees not losing their job, it means the probability of staying employed[13]. Explanatory variables are chosen to be available also from the retail loan database so the results can be used for stress testing purposes, i.e., it is a more focused version of the logit model estimated in Klacso & Štulrajterová (2021). The variables are summarised in Appendix 1.

Time series are available since 2005Q1, therefore it is possible to estimate the logit model on the whole period, but also for the period of increased stress, when the global financial cycle had the most pronounced effect on the economic development in 2009 and 2010. This allows the estimation of possible different elasticities of the variables used during periods of increased stress when the increase of unemployment rate is higher. Estimation results are summarised in Table 3.

One of the most important explanatory variables is the level of education. The higher the education, the higher the probability of staying employed. The effects of education even increase during a crisis period, as the impact of tertiary education is significantly higher than during the whole period.

Being married increases the probability of staying employed as well. Self-employed people are also less likely to lose their job/business. Younger people have a higher probability of becoming

[12] While a possible change in interest rates can also negatively affect debt-servicing capacity of the indebted households as the monthly instalment can increase, in 2019 in an environment of extremely low interest rates this was not an issue. Moreover, in the adverse scenarios a continued relaxed monetary policy is expected with a downward impact on interest rates. As loans granted to Slovak households are practically only denominated in EUR, FX risk is also negligible and thus not included in this paper.
[13] The probability of losing a job can be then calculated as 1 – probability of staying employed.

unemployed, while all these effects are similar during crises and normal periods. Based on the estimations, while during the whole period male employed have a higher probability of staying employed, this changes in crisis times where female employed have higher probabilities.

Table 3 Logit regression – estimation results

	Whole period		2009 - 2010	
	Coefficients	Marginal effect	Coefficients	Marginal effect
Explained variable				
Probability of staying employed				
Explanatory variables				
Intercept	2.747**		2.048**	
Sex	-0.090**	-0.0005	0.130	0.0009
Reference: at most primary				
At most secondary	0.928**	0.0065	0.803**	0.0074
Tertiary	1.586**	0.0055	2.234**	0.0092
Marital status	0.344**	0.0019	0.320**	0.0024
Type of activity	0.853**	0.0045	0.922**	0.0050
Reference: up to 45 years				
Up to 25 years	-0.675**	-0.0048	-0.658**	-0.0063
Up to 35 years	-0.151**	-0.0008	-0.225*	-0.0017
Up to 55 years	0.065	0.0003	0.208*	0.0014
Up to 65 years	0.114*	0.0006	0.348**	0.0022
More than 65 years	12.293	0.0059	12.495	0.0078

Notes: ** significant at 1% significance level
* significant at 5% significance level
Coefficients are the estimated coefficients of the logit model. They don't have a clear economic interpretation. Marginal effects show how much the probability of staying employed increases/decrease by a 1 unit change in the explanatory variable.

The employment status simulator is used to match the estimated unemployment rate at the macro level to the implied unemployment rate in the adjusted database of household loans. The employment simulator works similarly to the one introduced in Jurča et al. (2020). Based on the estimated logit model, for every employed or self-employed debtor the probability of staying employed in the next quarter can be calculated for each quarter of the 3 years of stress testing period. It is further assumed that the development of the unemployment rate during the period of the stress test under the adverse scenarios will be the same in the population of indebted households and the overall population[14]. To achieve this assumption, the intercept in the logit model is adjusted to match the change in the overall unemployment rate in each quarter. The intercept is changed in a way that the average probability of becoming unemployed in a given quarter is equal to the unemployment rate at the end of that quarter. Thus, 12 different values of the intercept are calculated for the 3-year period. In the baseline scenario it is assumed that the share of debtors becoming unemployed will be proportionate to

[14] While this assumption can overestimate the increase in the unemployment rate in the population of indebted households, it takes into account that all indebted households are covered, including those having only consumer loans. Based on the 3rd wave of the Household Finance and Consumption Survey form 2017, the share of unemployed persons in the total weighted number of employed and unemployed persons was 9% in the overall population and 8% in the population of indebted household members.

the share of defaulted loans in the latest non-crisis year. This assumption is necessary, as debtors default even in normal times, however in the baseline scenario usually a decrease of unemployment rate is foreseen.

There are, however, a few adjustments of the data from the loan database needed in order to properly feed the employment status simulator. As opposed to survey data, information about the economic status and other characteristics of the household members is not from a given point in time but can differ for each debtor based on the granted date of the loan. Moreover, if a household member has more loans granted on different dates, there can be different information available about his/her economic status and other characteristics. Therefore, for each individual client having multiple loans, only the economic status, education, income source and income available from the latest loan enter the estimation. The income is indexed for each employed and self-employed to end-2019 (the date as of the stress testing is conducted) by the index of average income available from the Slovak Statistical Office.

After calculating the probability of becoming unemployed for each employed or self-employed debtor for each quarter, Monte Carlo simulations are used to determine which debtors will lose their job[15]. This is the last step necessary to estimate potential losses from the household loan portfolio. As losing a job has a significant impact on the cash-flow of the household, some further assumptions are made affecting this cash flow. If an employed debtor becomes unemployed, they have a 50% chance of qualifying for unemployment benefit for 6 months representing 70% of his/her salary[16]. After 6 months, and debtors not qualifying for unemployment benefit (including all self-employed losing their job/closing their business), will receive material need assistance representing €66.30 per month. In the case of other employed or self-employed debtors, under the adverse scenarios it is assumed that their income decreases. This is to reflect possible decrease of working hours or cuts in bonuses due to the adverse economic development. During the baseline scenario no decline of the income is assumed.

4.2 Estimation of loan losses

After estimating the impact of macroeconomic scenarios on households' cash flow, we can estimate defaults of households on their debt. We assume that the probability of default is equal to one, or that the household defaults on its debt if the monthly income, together with the value of their financial assets, do not cover monthly instalments and the subsistence minimum.

---

[15] As the portfolio of retail loans is very homogenous, results are very robust after a relatively small number of simulations, up to 100.

[16] As under the adverse scenario the unemployment rate is increasing throughout the whole period, we do not include in the framework a probability of reemployment. On the other hand, we assume if a household under financial pressure can pay back its debt for one year, it does not default (see section 4.2).

$$PD_t = 1 <=> \sum_{All\ loans} Monthly\ instalments_t + k * subsistance\ minimum \geq \sum_{All\ household\ members} Monthly\ net\ income_t + \sum_{All\ household\ memebrs} Financial\ assets/12$$

It means we assume indebted households can use their income or financial assets to pay monthly instalments. As we have information reported by banks, we do not have proper information about the actual size of the household. The size of the household can be estimated by checking all debtors that can be related to each other via being codebtor in any loan granted. The income and financial assets are then the sum of the income of all members and financial assets reported for each first debtor by the banks. Similarly to Jurca et al (2020), we assume that if a household can pay its monthly instalments for a year, the household will not default on its debt[17]. We also require indebted households to have a buffer covering minimum monthly living costs that are proportionate to the subsistence minimum for the household. In the basic framework, we assume minimum monthly living costs are 1.5 times the subsistence minimum, i.e. $k = 1.5$ in the above equation.

If the subsistence minimum is not reported by banks, we estimate this amount using the estimated number of household members. In case the income and financial assets of the household do not cover monthly instalments and the minimum living costs, the household defaults on the loan with the smallest outstanding amount. In case other loans can be paid, the household will do so. If not, the household defaults on the loan with the second smallest outstanding amount, too. This procedure is repeated until the household has enough liquidity to pay back the remaining loans or no loan remains. If the household has more loans in one bank, defaulting on any of these loans means the household defaults on all loans in that bank.

Loss given default is affected by the value of collateral (if available) and by administrative costs. If the household defaults on a loan, the bank must cover losses stemming from this loan. In case the loan is not secured or there is no information about the value of the collateral, we assume the loss is 80% in the case of uncollateralised loans and 20% in the case of collateralised loans[18]. In case we have information about the value of collateral from the database we use this value to estimate loss given default. First, we update the value of the collateral as of the date of the stress testing exercise based on the last revaluation date (available in the database) and the average change in property prices. If possible, we use

[17] The latter assumption is consistent with the financial crisis experience in Slovakia, where a reasonable forbearance extension supported the recovery of household capacity to service debt without defaulting. In addition, the computation of debt service assumes that the loan principal and interest payments are serviced from origination until the moment of default.

[18] These values are based on the internal reporting of banks about provisioning.

regional statistics for the property price changes. Then, in the adverse scenario, we adjust the value of the collateral by the expected decrease of the property prices. As banks have to create provisions for defaulted loans based on lifetime expected losses, for each defaulted loan the value of the collateral is adjusted by the full expected decrease of the property prices. We also assume a fixed cost of foreclosure representing 10% of the outstanding amount of the loan[19]:

$$Loss\ given\ default_t = \max(0, L_t - CV_t) + 0.1 * L_t$$

where L_t is the outstanding amount of the defaulted loan at the time of default and CV_t is the indexed value of the collateral adjusted by the expected decrease of the value under the adverse scenario. In the case of the baseline scenario the indexed collateral value is not adjusted further. At the end, the volume of defaulted loans and loan losses are adjusted to reflect the estimated development of the total volume of retail loans. This estimation is derived using a satellite model in the overall stress testing framework, the description of which is available, e.g., in NBS (2018)[20].

5 Results based on end-2019 data

5.1 Results under the base assumptions

The latest stress testing not affected by the COVID-19 pandemic was conducted based on end-2019 data. The stress test assumes in the more severe adverse scenario an increase of the unemployment ratio to more than 11.5% as of end-2022, from less than 6% as of end-2019 (Chart 4). The baseline scenario assumes only a mild increase in the unemployment ratio, to less than 6.5% as of end-2022. In the paper, we provide results for the baseline and the more adverse scenario. Our basic assumptions for the stress testing are summarized in Table 4 below.

Results point to a possible rapid increase of the ratio of non-performing loans in the case of the adverse scenario. The ratio for housing loans would increase by nearly 5 p.p.; for consumer loans even more, by 9.4 p.p. The baseline scenario, which replicates PDs from the latest non-crisis year, foresees only a mild increase both for housing and consumer loans. Note that this ratio would be affected also by possible write-offs, therefore would be lower in reality.

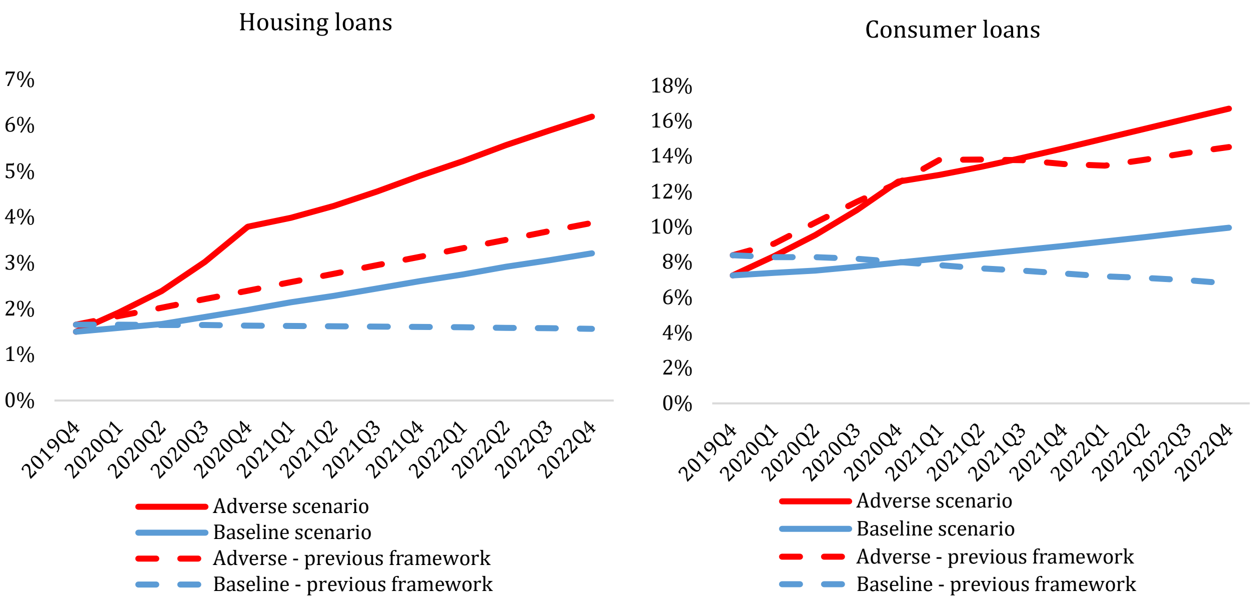
[19] This value is consistent with the one used in Jurca et al (2020) and is calibrated to match the estimated losses under the baseline scenario and the latest non-crisis year.

[20] The adjustment is relatively straightforward. As we have micro data available only at the beginning of the stress testing period, the estimated flow of the volume of non-performing loans and losses in each quarter of the stress testing period is adjusted by the quarterly growth rate of the outstanding volume of loans estimated by the satellite model. This is to reflect the estimated change in the volume of outstanding loans that serve as the basis for the flow of non-performing loans and loan losses.

Table 4 Stress testing – main assumptions		
	Baseline scenario	Adverse scenario
Unemployment rate, change in pp.	0.5	5.7
Income change	0%	-10%
Property price change	0%	-30%
Minimum living costs	1.5*subsistence minimum	1.5*subsistence minimum
Number of month until recovery	12	12
Administrative costs	10%	10%

The last stress testing conducted based on the previous framework estimating NPL ratios using quarterly time series and Bayesian Model Averaging methodology was based also on end-2019 data. The estimation of NPLs under this framework is described in Klacso (2014) and in the Annexes to the Analysis of the Slovak Financial Sector[21]. The availability of the results makes it possible to compare the outcome of both scenarios.

Chart 5 NPL ratio estimates under the baseline and adverse scenario



Source: NBS.
Note: as the portfolio of retail loans is very homogenous, Monte Carlo simulations lead to very narrow confidence bands. Hence, these bands are not displayed in the charts.

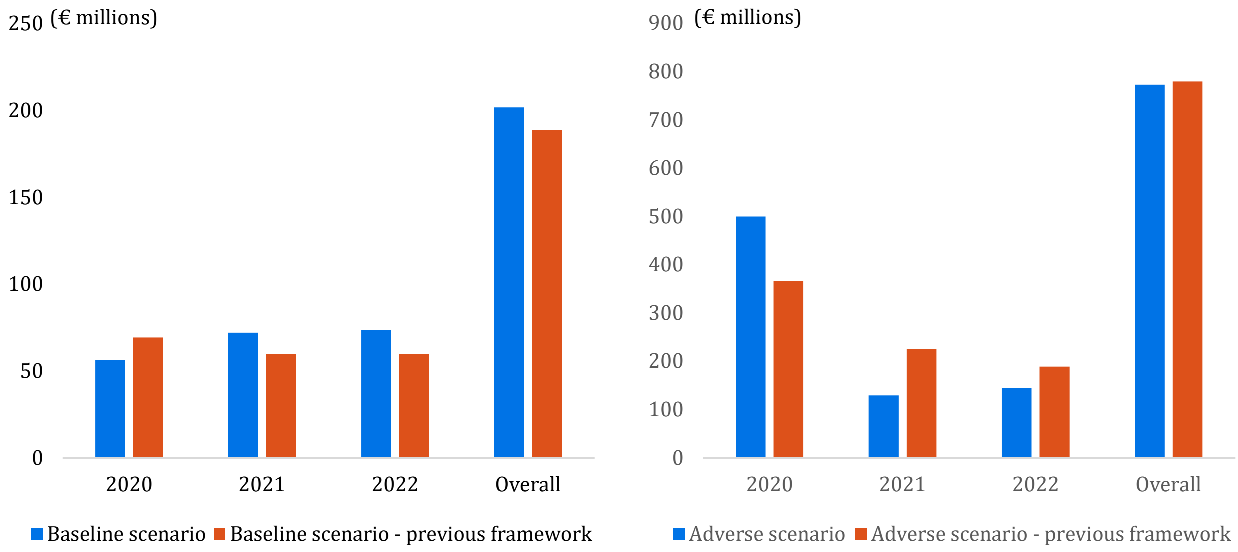
NPL ratios, especially for housing loans, are considerably higher in the case of the adverse scenario than in the original stress testing exercise conducted on end-2019 data. Using the previous framework, the NPL ratio for housing loans would increase by only slightly more than 2 p.p. While this result could be the consequence of the relatively positive development of the housing loan portfolio even during stressed periods in the past (as described in the introduction), it is possible that it does not capture the current level of accumulated risk in the loan portfolio. Even if not completely comparable, in 2020, due to the

[21] The Analysis of the Slovak Financial Sector was a regular publication terminated in 2020 and is available on the website of the NBS: https://nbs.sk/en/publications/analyses-of-the-banking-and-financial-sector/

impact of the Covid pandemic, households were enabled to use loan payment deferral up to a period of 9 months. In the case of housing loans, the repayment of 12% of the loans was postponed. In the case of consumer loans, this share reached 18% (NBS, 2020b). While some of the households could have used the deferral only for preventive or speculative purposes, most borrowers asked due to financial constraints (Cupák et al., 2020). These figures are even slightly higher than the estimated increase of NPL ratio under the new framework, pointing to the plausibility of the estimations. After the end of loan repayment deferral, slightly more than 5% of households asking for such a deferral had problems with paying back their debt.

Losses estimated under the adverse scenario are comparable to losses estimated using the previous framework, even slightly lower for the overall three year horizon. This is also true for the baseline scenario, where losses are to a large extent comparable between the two frameworks. The latter is, however, because both frameworks take the latest non-crisis year as a benchmark for calibrating credit risk losses.

Chart 6 Losses estimated under the baseline and the adverse scenario



Source: NBS.

The comparable amount of losses under the two frameworks, together with higher estimated NPLs using microdata means that the estimation of losses under the previous framework was stricter. This could be caused by the decreasing average LTV of the new business in case of housing loans due to the LTV limits imposed by the NBS. Decreasing average LTV of the loan portfolio, together with the gradual increase of property prices means that the losses from housing loans will be, even under the adverse scenario, lower on average than the previously assumed 20%[22]. However, it is worth noting that as described in section 4.2, the calculation of

[22] In 2019, the majority of housing loans were granted with an LTV lower than 80%. If a loan with 80% LTV defaults and we assume a 30% decrease of property prices under the adverse scenario, the losses from this loan

LGD takes into account only an expected administrative cost of 10% and the assumed drop in real estate prices. No additional haircuts on the properties, due e.g. to write-offs or selling to third parties, are included in the current framework due to lack of data.

5.2 Sensitivity analysis

Results of stress testing are, naturally, highly dependent on the assumptions used. Our basic assumptions summarised in Table 4 are mostly in line with those used in previous stress testing exercises. We assumed minimum living costs are equal to 1.5 times subsistence minimum[23]. If we assume that under stressed conditions a household can decrease rapidly its monthly expenditure and assume minimum living costs can decrease to 1 times subsistence minimum (similarly to the assumption used in Jurca et al, 2000), the estimated increase of NPL ratio would be lower by nearly 2 p.p. for housing loans and by more than 4.7 p.p. for consumer loans (Chart 7). Total loan losses under this assumption would be lower by more than 300 million EUR (Chart 8), equalling to 1.2 p.p. of the volume of loans (Appendix 2).

If, instead of decreasing minimum living costs, we expect a lower decrease of income, only 5%, the results would a bit stricter. The NPL ratio for housing loans would be lower by 1 p.p. and for consumer loans by 2.8 p.p. Naturally, overall losses would decrease as well, by around 180 million EUR (0.7 p.p.).

In the adverse scenario we assume a gradual decrease of income during the first year. As there are households having relatively high monthly instalments compared to their income, such a decrease of income would make them default even without becoming unemployed. The number of these households and the share of loans defaulting depends only on the assumed minimum living costs and the assumed decrease of income; the expected timing of the decrease has an impact only on the time of default.

In the base setup we assume households must repay for 12 months after they face a financial shock. During stressed periods this assumption can be relatively benign, therefore we provide the results also using an assumption of 18 months needed. In such case, the NPL ratio for housing loans would increase by more than 0.6 p.p. and for consumer loans by 1.1 p.p. Losses would increase by 90 million EUR (0.4 p.p.).

---

are 10%. Together with the assumed 10% administrative costs, the losses are 20% of the outstanding amount. It means that the 20% average loss used in the previous framework is more an upper limit currently.

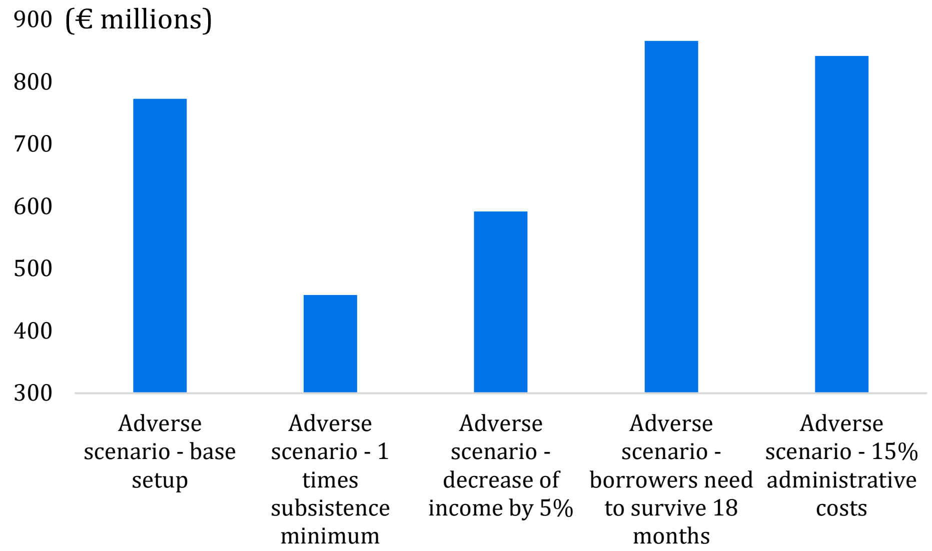
[23] The subsistence minimum is used also for the definition of the Debt service-to-Income ratio limits by the National Bank of Slovakia:
https://nbs.sk/en/financial-stability/fs-instruments/dsti/
While it is assumed in the DSTI ratio that households should have, after paying their monthly instalments, available at least the subsistence minimum, in the stress testing exercise we applied a more prudent approach using 1.5 times this subsistence minimum.

Another important assumption is about the administrative costs related to defaulted housing loans. While the 10% is calibrated based on the baseline scenario, in a stressed period when also the housing market is under stress, there can be other haircuts not captured solely by the decrease of the property price. Therefore, we also provide the results using an increased value of 15% for the administrative costs. As in this case NPL ratios are not affected, we only show the impact on the volume of losses. Overall, assuming an increase in administrative costs of 5 p.p., losses would increase by 70 million EUR (0.3 p.p. of the volume of loans).

Chart 7 NPL ratios under different assumptions

Source: NBS.

Chart 8 Loan losses under different assumptions



Source: NBS.
Note: the chart shows the overall volume of losses for the whole period and each loan type covered.

5.3 Impact of the increasing PDs on risk weights

Increased losses from credit risk lead to increased risk weights in the case of banks using the IRB approach. During adverse developments, when there is an increased share of loans defaulting, credit risk parameters like PD or LGD will also be higher. This automatically leads to increased risk weights negatively affecting the capital adequacy ratio of banks. Based on back-testing (Klacso, 2014) and bottom-up results, the annual increase in risk weights under the previous framework was set to 8% for the adverse scenario (NBS, 2019).

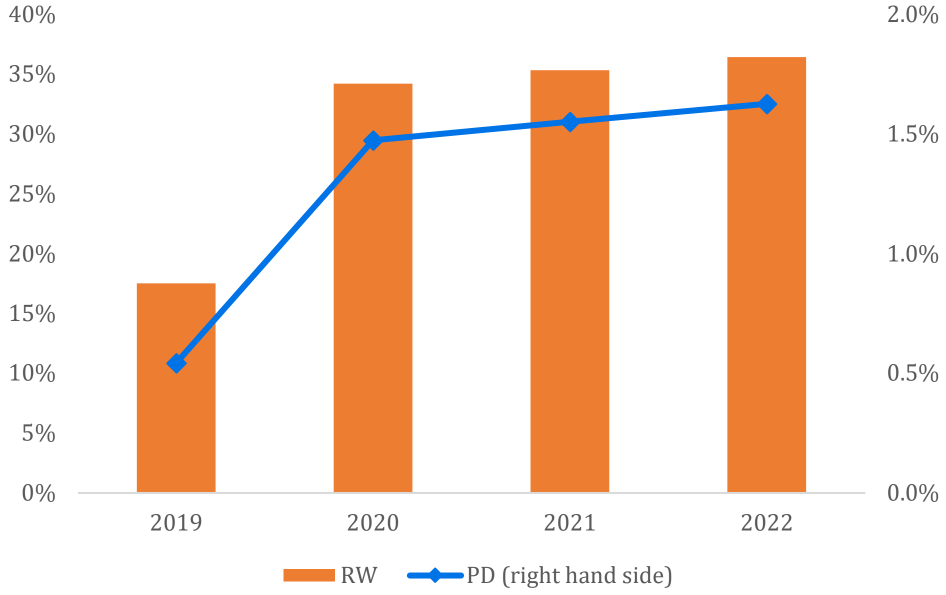
Microdata allows the calculation of the risk weights for IRB banks. As individual loan data are used to estimate NPL ratios and losses under the baseline and the adverse scenario, PDs can be calculated as well. Using calculated yearly PDs and LGDs based on the COREP report of respective banks, we can estimate the change in risk weights as well. The LGD for non-defaulted housing loans was reported by the banks at values around 20%. Using this value, we can estimate the risk weights for housing loans[24] using the standard formula:

$$RW = \left(LGD.N\left(\frac{1}{\sqrt{1-R}}.G(PD) + \sqrt{\frac{R}{1-R}}.G(0.999) \right) - LGD.PD \right).12{,}5.1{,}06$$

[24] We provide the estimation of risk weights based on 3 years average PDs.

where R = 0.15 in the case of housing loans collateralised by immovable property, $N(x)$ is the cumulative distribution function for a standard normal random variable and $G(Z)$ is the inverse cumulative distribution function for a standard normal random variable.

Chart 9 Estimated PDs and Risk Weights for housing loans under the adverse scenario



Source: NBS.

If we stick to the assumptions provided in Table 4, estimated risk weights would rapidly increase in 2020, to more than 30%. Thus, during an adverse scenario, the banking system's capital adequacy would be seriously affected by both decreasing capital and increasing risk weights, which should be considered when calibrating capital buffers.

Conclusions

Macro stress testing is an important toolkit of central banks and macroprudential authorities as part of their risk analysis and policy framework. Estimation of possible losses banks can face under adverse circumstances from their loan portfolio is one of the most important parts of the framework within the EU and Euro area. However, standard satellite models based on econometric of time series may not be well suited for countries with short time series, an incomplete credit cycle or structural breaks in the time series.

As Slovakia is one of those countries in the case of retail loans, in this paper we introduced a framework that enables incorporation of individual retail loan data into the macro stress testing framework. The paper uses a unique set of individual retail loans data reported by banks to the NBS with a large number of data items provided for each loan.

Within the framework we transpose the estimated development of the unemployment ratio into job losses in microdata. Together with using a broad set of assumptions, we are able to estimate the development of the NPL ratio under baseline as well as adverse scenarios. We also estimate losses stemming from defaulted loans and the potential increase in risk weights.

NPL ratios, especially for housing loans, are considerably higher in the case of the adverse scenario than in the original stress testing exercise conducted on end-2019 data. Based on the recent COVID experience and the share of indebted households opting for the possible loan instalment deferral, the higher increase of the NPL ratio in the case of housing loans under this framework compared to the previous framework, using the same increase in unemployment rate, is probably more plausible. While results based on time series can be the consequence of the relatively positive development of the housing loan portfolio even during stressed periods in the past, it is possible that they do not capture the current level of accumulated risk in the loan portfolio.

On the other hand, losses estimated under the adverse scenario are comparable to losses estimated using the previous framework, even slightly lower for the overall three-year horizon. This could be caused by the decreasing average LTV of the new business in the case of housing loans due to the LTV limits imposed by the NBS. Decreasing average LTV of the loan portfolio, together with the gradual increase of property prices means that the losses from housing loans will be even under the adverse scenario lower on average than the previously assumed 20%. However, when estimating losses from housing loans, only an expected administrative cost of 10% and the assumed drop in real estate prices is taken into account. No additional haircuts on the properties, due e.g. to write-offs or selling to third parties, are included due to lack of data.

References

Adrian, T., Morsink, J. & Schumacher, L. (2020). *Stress Testing at the IMF*. IMF Department Paper Series No. 20/04.

Ampudia, M., Lo Duca, M., Farkas, M., Pérez-Quirós, G., Pirovano, M., Rünstler, G. & Tereanu, E. (2021). *On the effectiveness of macroprudential policy.* ECB Working Paper No 2559

Borio, C., Drehmann, M. & Tsatsaronis, K. (2014). *Stress-testing macro stress testing: Does it live up to expectations?* Journal of Financial Stability Volume 12, June 2014, pp. 3-15

Česká národná banka. (2019). *Financial Stability Report 2018/2019*

Cupák, A., Klacso, J. & Cesnak, M. (2020). *Surveying the Impact of the Covid-19 Recession on the Financial Situation of Indebted Households.* NBS Working Paper 6/2020

EBA (2018). *2018 EU-Wide Stress Test Results.* European Banking Authority publications

Dees, S., Henry, J. & Martin, R. (2017). *STAMP€: Stress-Test Analytics for Macroprudential Purposes in the euro area*. European Central Bank

Gross, M. & Población, J. (2017). *Assessing the Efficacy of Borrower-based Macroprudential Policy Using an Integrated Micro-Macro model for European Households.* Economic Modelling, Vol. 61, pp. 510 - 528

Gross, M., Giannoulakis, S., Forletta, M. & Tereanu, E. (2021). *The Effectiveness of Borrower-Based Macroprudential Policies: A Cross-Country Perspective Using an Enhanced Integrated Micro-Macro Model Approach.* Mimeo

Harrison, O., Jurča, P., Rychtárik, Š., and others. (2018). *Credit Growth and Macroprudential Policies in the Slovak Republic.* IMF Country Report 18/242

Holló, D. & Papp, M. (2007). *Assessing household credit risk: Evidence from a household survey.* MNB Occasional Papers, No. 70, Magyar Nemzeti Bank

Jurča, P., Klacso, J., Tereanu, E., Forletta, M. & Gross, M. (2020). *The Effectiveness of Borrower-Based Macroprudential Measures: A Quantitative Analysis for Slovakia.* IMF Working Paper WP/20/134

Kanas, A. & Molyneux, P. (2018). *Macro stress testing the U.S. banking system.* Journal of International Financial Markets, Institutions and Money, Volume 54. May 2018, pp 204-227

Klacso, J. (2014). *Macro Stress Testing Framework at the National Bank of Slovakia.* NBS Policy Paper 1/2014

Klacso, J. & Štulrajterová, E. (2021). *Determinants of labour market flows in Slovakia*. NBS Working Paper 5/2021

Magyar Nemzeti Bank. (2019). *Financial Stability Report*, December 2019

Mian, A. & Sufi, A. (2018). *Finance and Business Cycles: The Credit-Driven Household Demand Channel.* The Journal of Economic Perspectives, Vol. 32, No. 3 pp. 31-58

Národná banka Slovenska. (2009). *Financial Stability Report 2009*

Národná banka Slovenska. (2017a). *Financial Stability Report May 2017*

Národná banka Slovenska. (2017b). *Financial Stability Report November 2017*

Národná banka Slovenska. (2018). *Annexes to the Analysis of the Slovak Financial Sector 2018*

Národná banka Slovenska. (2019). *Analysis of the Slovak Financial Sector 2019*

Národná banka Slovenska. (2020a). *Financial Stability Report May 2020*

Národná banka Slovenska. (2020b). *Financial Stability Report November 2020*

Náridná banka Slovenska. (2021). *Financial Stability Report May 2021*

Náridná banka Slovenska. (2022). *Financial Stability Report May 2022*

Reľovský, B., and Široká, J. (2009). *A Structural Model of the Slovak Economy*. Biatec,

Vol. 17, No. 7/2009, 9-14.

Schmieder, Ch., Hasan, M. & Puhr, C. (2011). *Next Generation Balance Sheet Stress Testing.* IMF Working Paper No. 11/83

Tkáčová, D. (2001). *Banking sector in the Slovak Republic Development, Restructuring and Privatisation Part I.* BIATEC, 8/2001 pp. 38 - 40

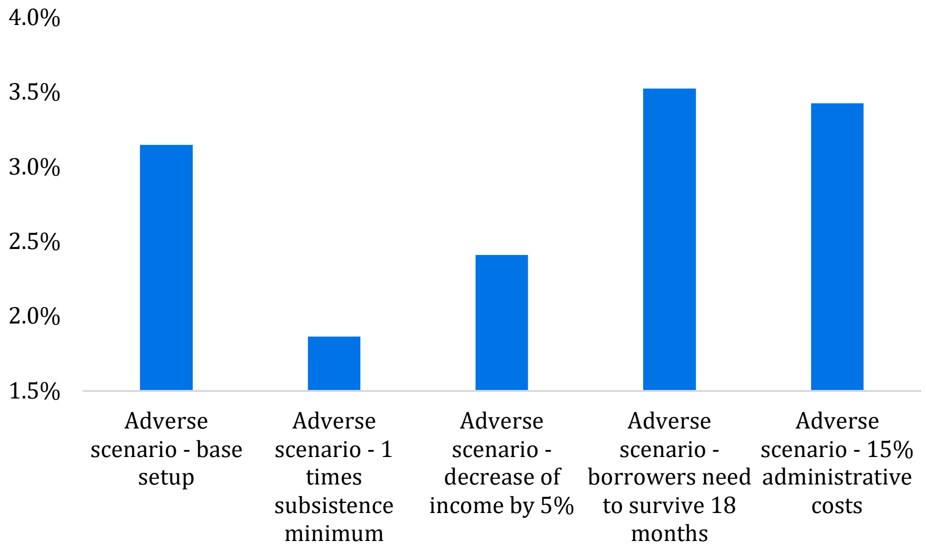
Tkáčová, D. (2001). *Banking sector in the Slovak Republic Development, Restructuring and Privatisation Part II.* BIATEC, 9/2001 pp. 38 - 40

Tkáčová, D. (2001). *Banking sector in the Slovak Republic Development, Restructuring and Privatisation Part III.* BIATEC, 10/2001 pp. 38 - 40

Appendix 1 Data used for the logit regression

Variable	Possible states
Change in economic status	1 – employed in quarter t-1 and t 0 – employed in quarter t-1, unemployed in quarter t
Sex	1 – male 2 - female
Education	0 – at most primary 1 – at most secondary 2 – tertiary
Marital status	1 – single 2 - married
Type of activity	1 – employed 2 – self-employed
Age: dummy	Up to 25 years Up to 35 years Up to 45 years Up to 55 years Up to 65 years More than 65 years

Appendix 2 Loan losses under different assumptions as a % of the volume of loans



Source: NBS, author's calculations.