A HEATMAP FOR MONITORING SYSTEMIC FINANCIAL STABILITY RISKS IN UKRAINE[1]

ADAM GERŠL[a], PERVIN DADASHOVA[bc], YULIYA BAZHENOVA[b], VLADYSLAV FILATOV[c], ANATOLII HLAZUNOV[bc], ROMAN SOLTYSIAK[b]

[a]Charles University
E-mail: adam.gersl@gmail.com
[b]National Bank of Ukraine
E-mail: pervin.dadashova@bank.gov.ua
yuliia.bazhenova@bank.gov.ua
anatolii.hlazunov@bank.gov.ua
roman.soltysiak@bank.gov.ua
[c]National University of Kyiv-Mohyla Academy
E-mail: vladyslav.filatov@ukma.edu.ua

Abstract This study presents an updated risk map of the Ukrainian financial sector – an analytical tool for identifying and monitoring the buildup and materialization of systemic risks. The risk map methodology that the National Bank of Ukraine used until 2021 has been revised to ensure that risk assessment is based on reliable quantitative indicators rather than expert judgements, as well as to extend the list of risks considered. The instrument allows the stability of the financial system to be assessed across key risks, such as macroeconomic risk, the credit risks of households and non-financial corporations, capital adequacy risk, profitability risk, liquidity risk, and foreign exchange risk. We introduce indicators that capture a wide range of economic and financial vulnerabilities and group them by risks. Each risk category contains from four to seven indicators that combine both actual data and expectations. Statistical checks show that the indicators clearly signal previous crisis episodes, as well as the buildup of vulnerabilities during the research period. We find that macroeconomic risk and foreign exchange risk have the best explanatory and predictive power, while the weaker performance of other risks could result from structural changes in the banking sector over the past decades that have affected the overall risk profile of the financial sector.

JEL Codes G01, G10, G18, G21, G28

Keywords risk map, systemic risks, macroprudential policy, financial stability

1. INTRODUCTION

One of the fundamental goals of most central banks is to promote financial stability, which is a prerequisite for sustainable economic growth. To achieve this goal, they implement policies to prevent the buildup and materialization of systemic risks in order to reduce the probability and severity of crises, and to strengthen the resilience of the financial sector.

In Ukraine, the task of maintaining financial stability is especially relevant – over the past 30 years the country has experienced five deep crises. While a number of risks accumulated at the macroeconomic level, the severity and depth of Ukraine's systemic crises were exacerbated by the financial sector. Therefore, an appropriate risk assessment should be based on the analysis of the development of both the macroeconomic environment and the financial system.

As a macroprudential authority in Ukraine, the National Bank of Ukraine (NBU) promotes financial stability, including the stability of the banking system, provided that this does not impede the achievement of price stability. Its powers include the identification and monitoring of the buildup of systemic

[1] The authors thank the Bilateral Assistance and Capacity Building for Central Banks (BCC) programme for supporting this research. The BCC programme is funded by Swiss State Secretariat for Economic Affairs (SECO) and implemented by The Graduate Institute, Geneva. The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the National Bank of Ukraine.

risks, and the selection and introduction of macroprudential regulatory measures if the situation requires it.

The choice of macroprudential policy instruments depends on the type of risk that arises or is expected to arise at a particular moment. The NBU has a wide range of tools for monitoring the risks affecting financial stability. In 2016, the NBU developed a *risk map* of the banking sector, which captures such risk categories as credit risk, capital adequacy risk, liquidity risk, profitability risk, foreign exchange risk, and legal risk. The assessment of the risk level for each category was to a large extent based on expert judgements of NBU staff, which could lead to biased conclusions. Recently, we revised the risk map methodology to ensure that risk assessment is based on reliable quantitative indicators rather than personal views, as well as to extend the types of risks captured.

In this study, we present an updated risk map for the Ukrainian financial sector as an analytical tool for identifying and monitoring the buildup and materialization of systemic risks, and as a communication tool to raise stakeholder awareness of financial stability risks. The risk map allows for an assessment of financial system resilience across seven key risks, namely macroeconomic risk, credit risk of households, credit risk of non-financial corporations, capital adequacy risk, profitability risk, liquidity risk, and foreign exchange risk. We identified indicators in each risk category that reflect a wide range of economic and financial vulnerabilities. The selection of indicators is based on their ability to signal an accumulation and materialization of risks, as well as the availability of historical data and their comparability with data from other countries. The indicators were aggregated by simple averaging within each risk category. Finally, the obtained risk assessments were tested for the ability to predict crises.

According to the results, the aggregate risk level can explain and predict crises well. Macroeconomic risk and foreign exchange risk estimates have the better explanatory power compared to other risks. The weaker performance of other risk categories could be a result of structural changes in the banking sector over the past decades, which have affected the overall risk profile of the financial sector, and the limited availability of data for certain periods.

The paper is organized as follows. Section 2 describes the related literature. The methodology framework is presented in Section 3. Section 4 specifies data and indicators. The results of the paper are discussed in Section 5. Section 6 provides conclusions.

2. RELATED LITERATURE

This study builds on an extensive literature that seeks to find empirical evidence for the ability of a macroprudential toolkit to predict the probability of the occurrence of financial crises, and to assess their severity.

The early literature, motivated by emerging market crises in the 1990s, found that international reserves, domestic credit growth, real exchange rate volatility (Kaminsky et al, 1998; Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 1999), and domestic inflation (Demirgüç-Kunt and Detragiache, 1998; Kaminsky et al., 1998) are good predictors of banking and currency crises.

Excessive growth in credit and asset prices have been identified in numerous studies as leading indicators of financial crises (Borio and Lowe, 2002; Mendoza and Terrones, 2008; Schularick and Taylor, 2012; IMF, 2011; Mitra et al., 2011; Dell'Ariccia et al., 2012; Arena et al., 2015).

Dell'Ariccia et al. (2012) identified factors frequently associated with the onset of credit booms: financial sector reforms, surges in foreign capital inflows, often in the aftermath of capital account liberalization. They also pointed out that credit booms generally start during or after a period of buoyant economic growth.

Mendoza and Terrones (2008) found major differences in credit booms in the industrial and emerging economies: (a) credit booms, and the macro and micro fluctuations associated with them, are larger in emerging economies; (b) not all credit booms end in crisis, but many of the emerging markets crises were associated with credit booms; and (c) credit booms in emerging economies are often preceded by large capital inflows and not by domestic financial reforms or productivity gains, while credit booms in industrial countries tend to be preceded by financial reforms or gains in total factor productivity.

Drehmann et al. (2010) and Drehmann et al. (2011) proved the importance of the credit-to-GDP gap as a leading indicator for predicting the expansion phase of the credit cycle, as well an as anchor for the countercyclical capital buffer setup. In response to the critics of the credit-to-GDP gap's relevance for emerging markets and transition economies (World Bank, 2010; Geršl and Seidler, 2015; RBI, 2013), Drehmann and Tsatsaronis (2014) emphasized the need to rely on a wide range of indicators rather than solely on the mechanical use of the credit-to-GDP gap.

This study contributes to the existing literature on financial stability risk measures. These metrics are commonly based on a set of indicators, which are aggregated into composite measures and visualized via heatmaps, risk dashboards, spider, radar, coxcomb or sun-burst charts etc. They either provide an assessment of risk evolution over time or a snapshot of risk at a given point in time. Some such tools for monitoring financial stability risks across countries are summarized in Table 2 (Appendix A).

Risk maps usually comprise indicators that characterize credit growth and debt burden in the non-financial private sector, current lending standards, banking sector leverage, liquidity and profitability, real estate price growth, macroeconomic imbalances, and financial market trends. Non-bank financial segments are also often captured. These indicators are typically grouped into different categories, which can be defined by intermediate macroprudential policy objectives according to the European Systemic Risk Board (Mencía and Saurina, 2016; NBB, 2019; Central Bank of Ireland, 2020), sectors of the economy (Aikman et al., 2018; IMF, 2019), or risks (Arbatli and Johansen, 2017; Lepers and Sánchez Serrano, 2017; Latvijas Banka, 2018; Venditti et al., 2018; EBA, 2020).[2]

Different techniques can be applied to aggregate risk assessments of indicators into groups or general risk level. This is often done linearly, by taking a simple or weighted

[2] According to ESRB (2013) the intermediate objectives of macroprudential policy should be to: (a) mitigate and prevent excessive credit growth and leverage, (b) mitigate and prevent excessive maturity mismatch and market liquidity, (c) limit direct and indirect exposure concentration, (d) limit the systemic impact of misaligned incentives with a view to reducing moral hazard, and (e) strengthen the resilience of financial infrastructure.

average of the standardized (or not) indicators within categories (Venditti et al., 2018; IMF, 2019; NBB, 2019; EBA, 2020). Commonly, the weights of indicators depend on their ability to predict a future crisis – indicators with better predictive power have higher weights. Mencía and Saurina (2016) also set weights depending on the correlation between indicators so as to avoid multiple counting of sources of the same risk – the lower the correlation, the higher the weight of the indicator. Some of the risk maps do not contain aggregate measures, such as those of Latvijas Banka (2018) and the Central Bank of Ireland (2020).

The setting of thresholds that determine the assignment of risk levels is another important aspect of risk map analysis. Typically, thresholds are set according to the national or cross-country historical distributions of the indicators (Mencía and Saurina, 2016; Aikman et al., 2018; IMF, 2019; EBA, 2020). Other approaches use early warning models, levels prescribed by legislation, guidelines or regulations, and expert judgments (Latvijas Banka, 2018; Venditti et al., 2018; NBB, 2019; Central Bank of Ireland, 2020).

In this study, we used the above-mentioned experience of other central banks and regulators to select indicators that can signal an incipient crisis, set thresholds for risk levels, and aggregate risk assessments, adjusting and supplementing them with information specific to Ukraine.

3. METHODOLOGY

When refining the risk map, we proceeded from the fact that the methodology should be straightforward and clear, so as to be easily interpreted by all stakeholders, such as policymakers, experts, media, and financial market participants. In the following, we describe the applied framework in more details.

The new risk map reflects risk assessments for the next 12 months based on quarterly data, as most macroeconomic and non-financial sector statistics are not available on a more frequent basis. Some of the indicators in the risk map show current distress, while some are able to provide an early signal of risk accumulation up to a year ahead.

3.1. Risk Categories

The set of risks was determined on the basis of the experience of other central banks, the significance of these risks for the financial system, and the impact of their materialization during previous crises. Since the Ukrainian financial sector is bank-centric and only banks bear systemic risks, the map is focused on risks to the banking sector.

We included the following categories in the map: macroeconomic risk, credit risk of households, credit risk of non-financial corporations, bank capital adequacy risk, bank profitability risk, bank liquidity risk, and foreign exchange risk.

We separated the credit risk of households and non-financial corporations, as these segments have different levels of indebtedness, loan quality, and sensitivity to crises. We also added a macroeconomic risk as a source of imbalances at the aggregate level. Even if the banking sector is healthy and resilient, risks can spill over into the financial system from the macroeconomic environment.

Risk assessments are presented in the heatmap both by risk categories and by indicators included in them, since proper macroprudential policy response requires clear understanding of the sources of risks. The overall risk level in the financial system is also calculated.

3.2. Selection of Risk Indicators

Each risk in the heatmap is measured by a set of indicators selected according to the following principles:

- There should not be too many indicators, while signals within risk categories should be effectively diversified.
- Indicators should be available at least on a quarterly basis and based on reliable statistics for a long enough time horizon.
- Indicators that can signal the accumulation and materialization of risks in advance should be included to ensure the forward-looking properties of the risk map.
- Risk indicators should be easy to interpret. We did not consider indicators with non-linear behavior relative to the level of risk.
- Highly correlated indicators should not be included, with the exception of indicators which clearly reflect different aspects of risk over the long term, even if they are correlated over a short horizon.

To start with, we compiled a list of indicators commonly used in risk dashboards and heatmaps by central banks, regulators and international financial organizations. These are primarily indicators of credit risk, bank solvency, profitability, and liquidity, which were supplemented by indicators used by the NBU to analyze the financial sector, and data from banking and economic activity surveys. We also added some macroeconomic and foreign exchange risk indicators that are of particular importance for Ukraine. For instance, indicators characterizing the foreign exchange rate dynamics were included, as FX rate volatility has a substantial effect on economic activity, inflation, the finances of households, and the corporate and public sectors.

As the next step, we excluded indicators related to areas that do not carry systemic risks for the Ukrainian financial sector. For example, non-banks currently do not bear systemic risks due to the small size of the sector, low interconnection with each other and with the banks, and their limited role in financial intermediation (NBU, 2020).[3] Given the weak development of the financial markets and financial instruments (derivatives, corporate shares and bonds, etc.) in Ukraine, the corresponding indicators were also discarded. Neither did we look at real estate market indicators, as mortgages are now at a low level, and the influence of banks on this sector is almost negligible. Nevertheless, the NBU constantly monitors and analyzes them, and also includes them in other analytical tools (for example, the Financial Cycle Index). Some indicators were withdrawn because of poor data quality or inconsistency. The final heatmap is to be used as a communication tool in the Financial Stability Report, showing the level of risks since 2015. Thus, we excluded indicators that contain missing data after Q1 2015, as well as those for which the calculation methodology has been fundamentally changed since then. Exceptions were made for the amount of overdue loans and the liquidity coverage ratio (LCR) as respective regulatory requirements emerged later.

At the next stage, we performed a visual and basic statistical analysis of the behavior of the indicators before

[3] Part 4. Non-Banking Sector Conditions and Risks.

and during crises. The crisis periods in Ukraine were set according to Filatov (2021). Some indicators signal the accumulation of risks in advance of the crisis, others – start signaling immediately the crisis occurs. We can use both to account for early warning signals and actual adverse events. At the same time, we omitted indicators that did not show any reaction before or during the crisis.

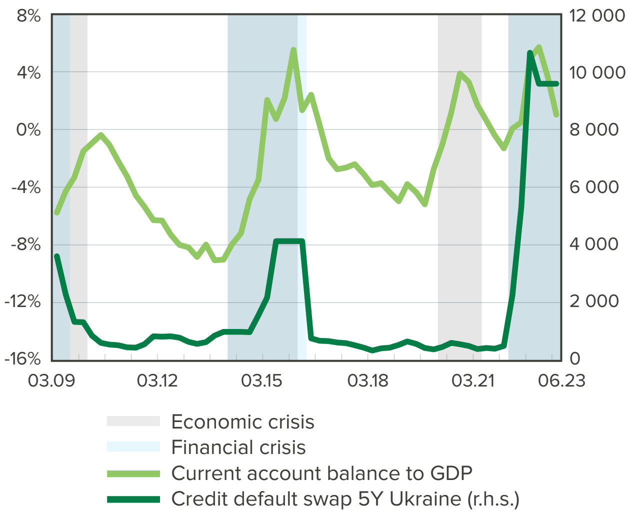


Figure 1. Dynamics while Current Account Balance to GDP Ratio and CDS 5Y Ukraine

For instance, both the current account balance to gross domestic product (GDP) ratio and the credit default swap (CDS) on 5-year Ukrainian sovereign debt reacted to previous crises (see Figure 1). The former indicator decreases robustly before the crises, then surges during the crisis and again declines after. Credit default swaps have spiked during all crises except the coronavirus crisis without prior reaction, thus we accept this indicator as coincident. Both can signal higher level of risks in the system either before or during the crisis.

Lastly, a correlation test was performed. Only one among highly correlated indicators within each of the risk categories was used. All of the others were omitted.

Ultimately, the final set of indicators encompasses 40 indicators grouped into seven risk categories. The number of indicators in each risk category varies from four to seven. A detailed description of the indicators is presented in Section 4 and Table 3 (Appendix A).

3.3. Color-Coding Scale and Threshold Selection

We retain the 1 to 10 color-coded scale used in the previous version of the risk map, where 1 is the lowest risk level, and 10 is the highest (see Figure 2). Thus, we had to set nine thresholds separating 10 intervals for each indicator to be able to assign a risk level for each observed value.

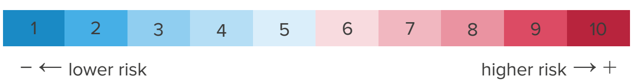


Figure 2. Color Bar Indicating Risk Score of Indicators

First, as a starting point, we created thresholds by dividing Ukraine's quarterly data from 2000, or since data became available, into deciles. Depending on the direction of the indicator – whether the higher values indicate higher or lower risk – we arranged the values either in descending or ascending order. Due to the short time series and several structural breaks in the data, we were unable to do this for every indicator. In such cases, we assumed that the values of the indicator should be more or less evenly distributed between its possible maximum and minimum. Thus, the historical data series were organized into 10 equally sized groups associated with the respective threshold and risk levels.

Setting the thresholds based on historical distribution or equally-sized intervals between potential minimum and maximum has advantages (high risk scores would reflect indicator values that are "historically high"), but it could also lead to a biased assessment if the time series is short and the observed values so far do not properly reflect the potential distribution of the indicator. In addition, for indicators where we created equally-sized intervals, the risk as captured by the indicator may change nonlinearly.

Second, we applied the decile-based method using data for other countries and analyzed their distribution.[4] This international dataset, which covers a large set of emerging markets, is available for a longer period and, at the same time, is more balanced, especially in terms of "good and bad times". We employed the same methodology to these data (percentile/decile distribution) and obtained another set of thresholds.

Finally, after analyzing the adequacy of the thresholds calculated for the Ukrainian data and for the relevant peer countries, we made final adjustments using expert judgments.

As an example of this three-step approach, we present here the calibration of the thresholds for the real GDP growth forecast (see Table 1). The NBU's real GDP growth forecast has been publicly available only since 2015, meaning it does not provide a data series long enough for there to be consistent thresholds. Hence, the historical distribution of data from peer countries is an important reference here.[5] We estimated thresholds based on both datasets separately. Some tail values of the peer countries data distribution were omitted as outliers. Then, we applied expert judgments to these estimates. For the higher risk intervals (8–10), we used an average between the Ukrainian and the peer countries' distribution threshold estimates. We adjusted the threshold for the 10th interval upward, so even a slight forecasted GDP decline is considered as high risk, as it usually is. For middle-risk intervals (4–7), we used the larger value of the two estimates. Usually, it leads to the selection of peer countries' values, as Ukrainian forecasts are highly concentrated closely to 2.5%, which is low, based on both comparative analyses and the expected potential GDP growth for Ukraine.[6] For lower risk intervals, we moved back to averaging. Additionally, for the lowest risk interval, we significantly decreased the value of the thresholds, considering that the probability of two-digit growth is relatively low in the observable future for Ukraine. It is also important that final threshold values were rounded to make the heatmap easily interpretable and more comprehensive.

[4] As a peer countries dataset, we used statistics from the emerging economies, Ukraine's trade partners, and economies with similar structures. It includes data from Albania, Armenia, Bolivia, Bulgaria, Chile, Columbia, the Czech Republic, Estonia, Georgia, Hungary, Latvia, Lithuania, Moldova, Poland, Romania, Slovakia, and Turkey.
[5] Database of IMF WEO forecasts across 1990-2020 for emerging markets
[6] According to Grui and Vdovychenko (2019), potential GDP growth in the steady state was calibrated at the level of 4%.

Table 1. Calibration of Thresholds for the Real GDP Growth Forecast

Risk score	Ukrainian distribution threshold estimate (decile value)	Peer countries' distribution threshold estimate (decile value)	Final thresholds (expertly corrected)		Expert correction explanation
			Lower (including)	Upper (excluding)	
10	–	–	–	-2.0%	Average of Ukrainian and peer countries' values*
9	-0.9%	-5.8%	-2.0%	0.0%	
8	1.9%	-1.5%	0.0%	1.0%	
7	2.2%	0.3%	1.0%	2.0%	Higher of Ukrainian or peer countries' values
6	2.5%	2.1%	2.0%	3.0%	
5	2.7%	3.6%	3.0%	4.0%	
4	2.9%	5.0%	4.0%	5.0%	
3	2.9%	6.5%	5.0%	6.0%	Average of lower threshold and peer countries' value**
2	3.1%	8.1%	6.0%	7.0%	
1	3.5%	15.1%	7.0%	–	

* – 10th interval threshold additionally adjusted 1 p.p. upwards; ** – 1st interval threshold additionally adjusted 4 p.p. downwards.

Having decided on the thresholds, we assigned risk levels that correspond to the indicator values in each period of time. Comparing the actual value of an indicator at each time with the thresholds led to a unique assignment of the corresponding risk score, ranging from 1 to 10.

3.4. Risk Level

Further, we determined a risk level for each risk group by simple averaging. Using a simple average for aggregation is a standard approach for a number of heatmaps (Venditti et al., 2018; IMF, 2019; NBB, 2019; EBA, 2020). This method is straightforward for interpretation and analysis, which is an essential feature for a communicational and policy tool. More sophisticated methodologies, such as a principal component analysis, cannot be applied here due to short data series, different lengths of the time series across the indicators, and difficulties in interpretation.

Finally, we calculated a simple average across all risk categories to arrive at a single aggregated risk score.

4. RISK INDICATORS

In this section, we describe in detail the indicators of each risk category.

The ***macroeconomic risk*** category encompasses macroeconomic variables to monitor risks stemming from the real economy, and the fiscal and external sectors. Key financial risks tend to raise during economic downswings, when it is more difficult for economic agents to service their debts, whereas investors demand higher returns on capital and look for instruments with low risk and high liquidity.

We considered the real GDP growth rate as a general measure of economic activity, low values of which indicate poor performance by the economy and a potential subsequent increase in risks to the financial sector. As an early warning indicator of a downturn, we looked at the NBU's real GDP growth forecast.

Fiscal sector vulnerabilities such as high public debt and budget deficits are of particular concern when assessing systemic risks. Excessive gross external and state debt carries liquidity and solvency risks, which can lead to the crowding out of private investments, an increase in the tax burden, and so on. Market participants' perception of the government's financial position is reflected in the required rate of return on government debt and the level of credit default swaps on sovereign bonds. Thus, higher required returns worsen the conditions for public and private borrowing. In addition, the transmission of fiscal risks to the financial sector is exacerbated by the banks' significant exposures to the government. To monitor these fiscal sector vulnerabilities, we included the ratios of the state and state guaranteed debt, gross external debt, and state budget balance to GDP, as well as the CDS rate.

To track external imbalances, we examined the ratio of the current account balance to GDP. An excessive current account deficit is a signal of an imbalance in foreign trade and greater dependence on financial inflows, which can cause economic vulnerabilities and even a currency crisis.

Credit risk is the risk of credit loss by a bank due to the inability or unwillingness of borrowers to repay their loans. The nature of lending to households and non-financial corporations is different, so we considered their credit risk separately.

The ***credit risk of households*** is higher when the debt burden becomes higher. Thus, the first indicator to be included is the ratio of gross retail bank loans to GDP. Simultaneously, even if the relative debt burden, as measured by the loans stock to GDP ratio, is low, high loan servicing costs can lead to a deterioration in payment discipline, especially during periods of economic downturn. This is particularly relevant for Ukraine, as expensive short-term consumer loans currently account for nearly 85% of total household debt. From this perspective, the debt service-to-income ratio (DSTI) at the aggregate level was incorporated. To capture a forward-looking view from the lender's side, we added an indicator of banks' expectations regarding the quality of the loan portfolio taken from the NBU's Bank Lending Survey. When filling out the questionnaire, banks take into account the available microdata on borrowers' current and projected indebtedness and solvency. As another indicator of debt-servicing problems, we included an index of economic expectations of households derived from a third-party survey, which covers both changes in personal financial standing and macroeconomic developments. Worsening expectations could have a negative impact on the payment discipline of borrowers even before their solvency is undermined.

The ***credit risk of corporates*** depends on the indebtedness of the borrowers and their financial condition. As the debt burden indicator, the ratio of net bank corporate loans to GDP was employed. We also looked at the ability of borrowers to service their debts, which was proxied by the ratio of total corporate debt to earnings before interests and taxes (EBIT) and the interest expenses coverage ratio. To characterize borrowers' financial performance, we included the return on equity of non-financial corporations: companies with low profitability or losses are considered to be more risky. On the other hand, we monitor the quality of the banks' loan portfolio, as represented by the frequency of defaults. Even a moderate increase in this indicator signals a higher credit risk. Similarly to households, we incorporated the banks' expectations of the credit risk level of non-financial corporations from the lending survey. We also added a business outlook index from another NBU survey, which is an aggregate indicator of the expected development of enterprises over the next 12 months. A deterioration in business expectations, among other things, may precede a future slowdown in economic activity, lower demand for corporate loans and an increase in credit risk.

To capture the ***capital adequacy risk*** of the banking sector, we consider indicators that assess the sufficiency of banks' capital to absorb risks. A higher level of capital ensures the banks are able to absorb unexpected losses resulting from economic shocks, meet their obligations, and remain solvent. We included here both core and total regulatory capital ratios, as they complement each other. To capture risks for capital that may arise from high level of non-performing loans (NPLs), we used the ratio of non-performing loans net of provisions to capital. Credit risk for these loans has already materialized, but they can still have a negative impact on capital.

In Ukraine, the capital adequacy requirements currently fully cover only credit, foreign exchange and partially operational risks. Therefore, we took additionally into account the ratio of capital to total net assets – leverage. This indicator covers other risks, in particular market risk, such as the risk arising from investing in government securities. The growing leverage may signal an increase in risk appetite and a possible lack of capital to cover other risks that are not fully reflected in capital adequacy ratios.

We assess the ***profitability risk*** using the banks' return on assets, return on equity, net interest margin, cost of risk, and cost to income ratio. All of them reflect the ability of the banks to generate net profit, which is an internal source of capital. Loss-making banks or those with deteriorating indicators typically face higher funding costs, limited ability to grow, and a larger probability of a capital shortfall. Return on equity (ROE) measures the return a bank earns on its equity. Return on assets (ROA) shows how efficiently a bank uses assets to make a profit. Both of these indicators were included, because ROA can signal risks in the case of possible ROE distortions caused by capital distributions, rather than higher profitability. Net interest margin shows the ability of banks to earn income from their core operations. Higher values of these ratios indicate a lower risk. The other two indicators in this group have opposite dynamics – higher values indicate a higher risk. These are the cost of risk (measured as annual provisions for expected losses per unit of bank loans) and cost-to-income ratio (total operating costs divided by total operating income). An increase in the cost of risk or cost-to-income ratio reveals threats to profitability that come from the worsening of loan quality or excessive operational expenses.

Liquidity risk indicators demonstrate the ability of banks to meet their liabilities to depositors and creditors in full and in a timely manner. It includes the liquidity coverage ratio (LCR), which is defined as the ratio of available high-quality liquid assets (HQLA) to net cash outflow expected over a 30-day horizon under adverse conditions. LCR is a relatively new ratio, which was introduced in Ukraine in 2018. To complement the LCR retrospectively, we have included another indicator – share of HQLA in total assets. Its dynamics are similar to that of LCR, but data for it is available for a longer period. We also look at the loan-to-deposit ratio as an indicator of liquidity risk. The logic behind this indicator is as follows: a low value of the ratio signals the availability of free funds, and, consequently, high liquidity. On the contrary, a high loan-to-deposit ratio reflects a greater need to raise funds from the wholesale markets, and thus higher funding and liquidity risks. To add forward-looking component, we include banks' expectations of changes in liquidity risk, derived from the NBU lending survey.

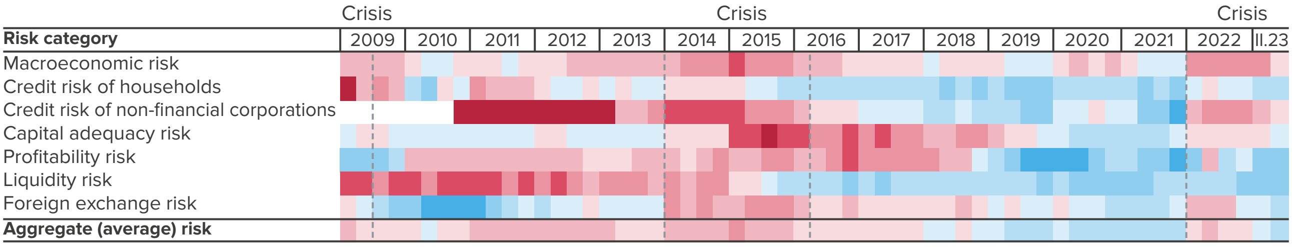
Foreign exchange risk shows to what extent adverse movements in exchange rates can affect financial stability. In fact, two aspects are captured here: the significance of the risk factors in the foreign exchange market and sensitivity of the financial system to those factors.

The first indicator in this category is exchange rate volatility. Higher volatility indicates higher risk. We have also included a leading indicator – the ratio of international reserves to imports. A higher level of this indicator shows a higher sufficiency of international reserves to mitigate possible adverse exchange rate fluctuations. Next, we have included the ratio of the banks' net open foreign currency position to regulatory capital. It reflects the exposure of banks to exchange rate fluctuations and their ability to cover foreign exchange risk by capital. Another indicator of the banks' vulnerability is their relative exposure to FX loans. Risk arises from a probable increase in the debt burden and the credit risk of borrowers who have loans in foreign currency but who do not have FX-linked income. We use the share of FX corporate loans in the total portfolio to capture this risk. FX-lending to households is not considered, as it has been prohibited since 2010. As a forward-looking indicator, we have added the banks' assessment of the foreign exchange risk level from the NBU lending survey. In addition, survey-based expectations of currency risks by corporates and households were added, as expectations may also determine their future behavior and influence risks.

5. RESULTS

In this section, we present the average risk level scores for all seven risk categories between Q1 2009 and Q4 2022.[7] The level of each risk category was calculated as a simple average across the indicators used in the risk category. This abbreviated format of our new heatmap is shown in Figure 3. We use colors to mark each risk level score. The color-coding scheme makes it easier to interpret the level of risk both

[7] In the Financial Stability Reports, the heatmap is shown since Q1 2015.



Notes: Financial crisis periods for Ukraine were derived following the methodology of Filatov (2021).

Figure 3. Heatmap for Risks Monitoring in Ukraine

for each indicator and for each risk category, as well as highlighting periods of higher and lower risk. The colors are the same as in the previous heatmap. The more detailed heatmap – presented with all risk indicators – is shown in Figure 12 (Appendix B).

The heatmap demonstrates a high level of risks in the crisis year of 2009. The following years, foreign exchange rate risk and capital adequacy risk eased, and macroeconomic conditions gradually improved. On the contrary, profitability risk increased. In 2012–2013, the situation worsened, signaling problems that materialized during the 2014–2016 crisis. At that time, most of the risks were at the highest level. A gradual improvement of all risk scores thereafter resulted in the lowest overall risk from 2019 to 2021, which was partially interrupted in 2020 due to the macroeconomic impact of the COVID-19 pandemic. Since the full-scale war began, the estimate of aggregate average risk has increased significantly. To sum up, we can conclude that risk scores calculated completely correspond to the actual situation during the illustrated period.

5.1. Testing the Explanatory Power of Risk Levels

To evaluate the explanatory power of our new heatmap, we employed the receiver operating curve (ROC). The ROC is a plot of the true positive rate against the false positive rate at various threshold settings. A summary measure of this curve – the area under the curve (AUC) measure – is a useful metric to assess predictive performance. An AUC of 0.5 indicates the predictive value of a coin toss. If the AUC is greater than 0.5, the respective factor (or combination of factors) has non-zero predictive power.

To test the ability of risk assessments to describe the current state, we estimated logit regression models for each risk category where explanatory variable is average risk score and dependent variable is the crisis event, which equals 1 if a crisis occurs, and 0 if one does not.[8] To test early warning capacity of heatmap, we built similar logit models for each risk category but dependent variables are crisis events one, two, three and four quarters ahead respectively. These regressions should indicate the ability of the heatmap to predict a crisis up to four quarters in advance. The higher the AUC value for each regression, the better the signaling and predictable power of the risk category scores.

To assess the predictive power of the heatmap more precisely, we employed additional accuracy metrics, which can be found in Table 4 (Appendix A).

In general, the results demonstrate that the heatmap can both show current and predict future crises (Figure 4). Aggregate, macroeconomic and foreign exchange risks explain and predict banking crises well. Profitability risk provides reliable advance signals of financial crises. The weaker performance of other risk categories could be a result of structural changes in the banking sector over the past decades, which have affected the overall risk profile of

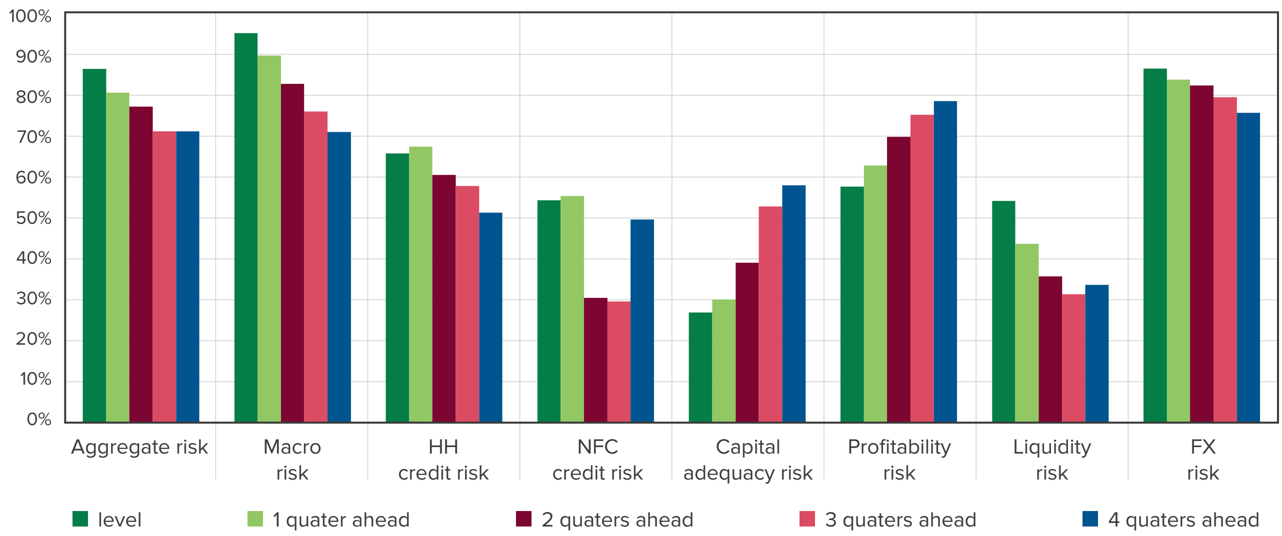


Figure 4. Cross-Validated AUC by Risks

[8] Financial crisis periods for Ukraine were derived following the methodology of Filatov (2021).

the financial sector, and limitations in data for certain periods. In particular, the liquidity risk and credit risk of non-financial corporations have the worst signaling power, mainly due to short time series available. Only two of the four liquidity risk indicators are available for the full time period, and none of the non-financial corporation credit risk indicators are available before 2012. Hence, we do not have enough crisis events in the sample to properly assess the predictive power of the risk estimates of these two risks. At the same time, we believe that these risks have been properly measured in recent periods: the heatmap reflects improved corporate credit risk up to 2022 and low liquidity risk.

Giving the proper signaling power of the heatmap, we discuss risk dynamics in more detail further in this section.

5.2. Dynamics of Average Risk Scores

Based on the dynamics of each risk category scores, we can also explain the key threats to the resilience of the financial system during the analyzed period.

The ***macroeconomic risk*** was building up prior to the 2014–2016 crisis (Figure 5). The imbalances in fiscal and monetary policy led to an increase in the budget and current account deficits in 2012–2013, which were reflected in a gradual increase in the level of risk. Along with a decline in real GDP growth and its forecast, this led to the highest level of macroeconomic risk during the 2014–2016 crisis. At the same time, the macroeconomic risk score was moderate prior to the COVID-19 pandemic and full-scale invasion in 2022. This is well explained by the unexpected and non-economic drivers of these crisis events. Risk scores were growing in response to adverse events of a non-economic nature.

The credit risk of households was among main triggers for financial stability distress in 2009 (Figure 6). At that time the highest level of this risk was observed, being associated with the excessive growth of FX mortgages and a further significant devaluation of the national currency, leading to the insolvency of borrowers. The share of non-performing FX mortgages surged. As a consequence, lending to households in foreign currency was prohibited.

Significant deleveraging followed, lending slowed due to the lower risk appetite of the banks and weak demand from households. Since then, the loan stock of households has remained low, as has lending penetration.

This explains the absence of strong signals from household credit risk prior to all subse-quent crises. During the crisis in 2020 and 2022, the total debt burden and the loan quality remained at appropriate levels, and this risk increased moderately.

The credit risk of non-financial corporations was driving financial system risks for some time before the 2014–2016 crisis (Figure 7). Indeed, that crisis for banks was caused by excessive lending to financially weak borrowers, a significant part of which were related parties. For example, Privatbank, the largest Ukrainian bank, provided more than 97% of corporate loans to companies related to shareholders. Besides that, there were a substantial number of captive banks that served business groups or were used to redistribute cash flows between them.

Crisis led to inability of some corporate borrowers to service their debts. The assets quality review revealed these hidden problems and forced banks to recognize the true quality of loans, leading to higher default rates. The regulatory reforms and measures introduced since 2016 have had a

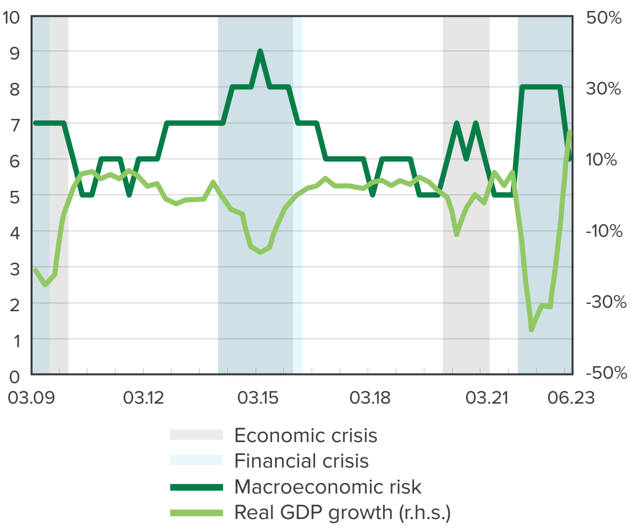


Figure 5. Macroeconomic Risk

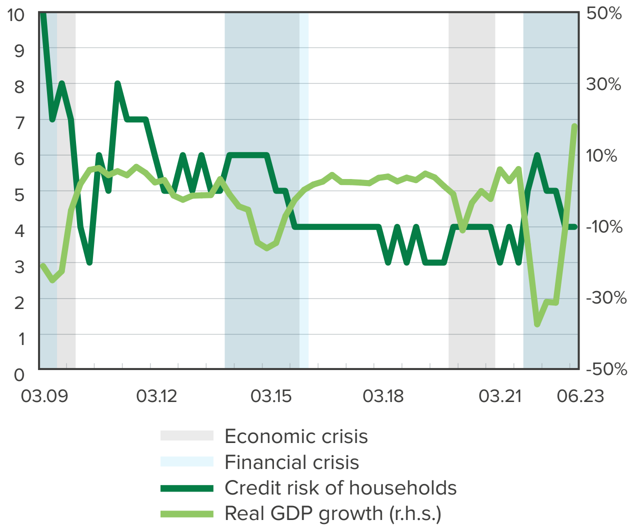


Figure 6. Credit Risk of Households

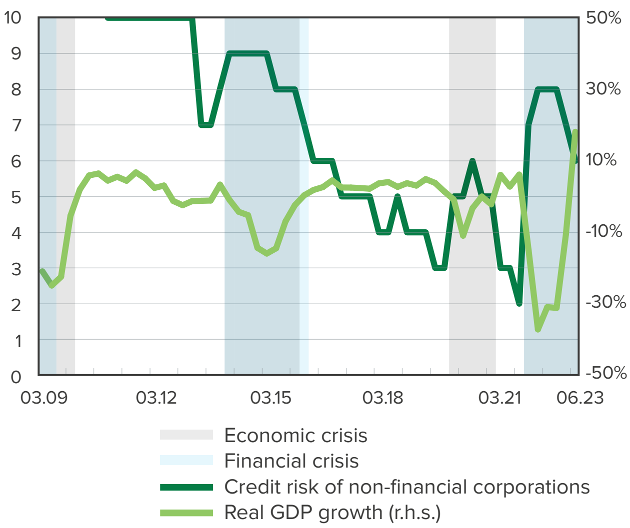


Figure 7. Credit Risk of Non-Financial Corporations

significant positive impact on the quality of the loan portfolio and the transparency of the banking sector. In particular, default rates have gradually decreased, and indicators of the financial state of borrowers have improved. This is fully reflected in the improvement in the corporate credit risk scores in recent years. The sudden surge in the level of credit risk in 2020 was primarily driven by adverse expectations of banks and enterprises, while the actual deterioration of the loan portfolio was moderate. Despite the high quality of the corporate loan portfolio prior to the invasion, the huge economic decline and damage to the real sector made credit risk one the key threats to the financial system in 2022.

Technically, ***capital adequacy risk*** revealed itself as a key risk to the financial system only in 2014 (Figure 8). This is explained by the fact that until then, banks rarely showed the true quality of loans and, accordingly, loan loss provisions. As a result, capital was inflated. Following an assets quality review, the banks were forced to reflect the real situation, and the risk increased sharply. Thus, the highest level of risk was observed in 2015, with gradual improvement seen since then. The banking sector passed through the COVID-19 crisis without significant capital losses. In 2022, capital ratios slightly deteriorated, leaving capital adequacy risk at a moderate level.

Low operating efficiency and a high share of poor-quality assets in the banks' portfolios were sources of high ***profitability risk*** in the financial system for many years (Figure 9). The crisis of 2014–2016 worsened the situation. After the crisis, operational costs surged, and increased default rates forced banks to recognize provisions, reducing profits significantly. After the regulatory reforms and the banking sector cleanup, the system was reborn from the ashes, like a phoenix. In particular, 2021 was the most profitable year in the last 30, despite the COVID-19 crisis. The system continued to generate high profits even in 2022. Hence, the risk scores remain in the "blue" low-risk zone.

Liquidity risk was high prior to 2015: most of the liquidity shortage occurred during the 2014–2016 crisis in small banks, which then left the market (Figure 10). After that crisis, the banks became much more prudent in funds allocation, keeping a high level of liquid assets. This was enhanced by the implementation of new liquidity requirements. Since then, liquidity risk has been low, even during the COVID-19 and war-related crises.

The ***foreign exchange risk*** was one of the triggers for the 2014–2016 crises (Figure 11). Maintaining a fixed exchange rate prior to the crisis required an enormous overdrawing

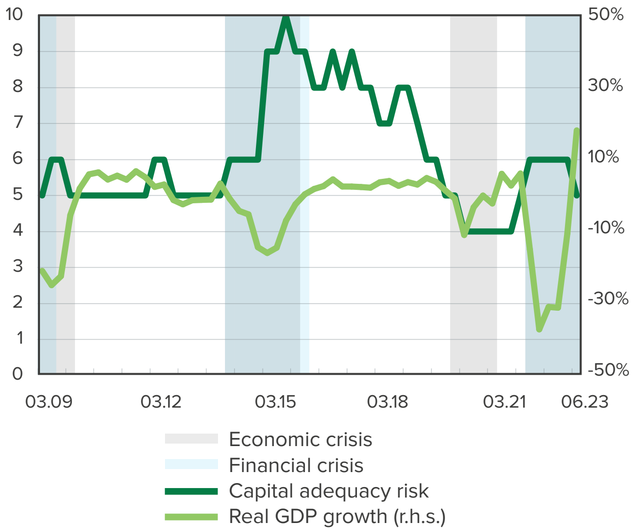


Figure 8. Capital Adequacy Risk

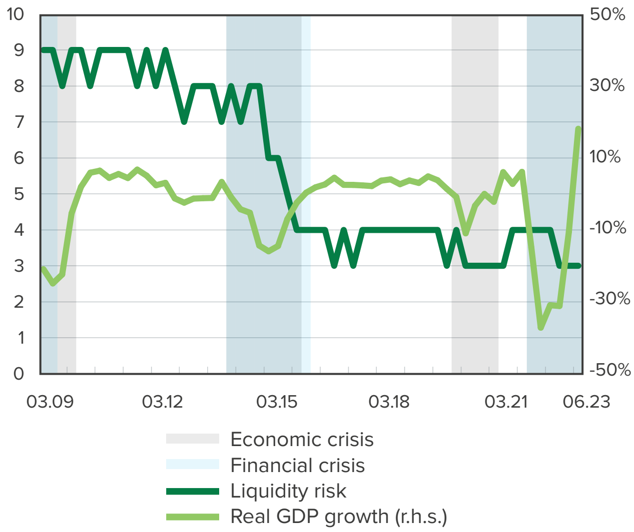


Figure 10. Liquidity Risk

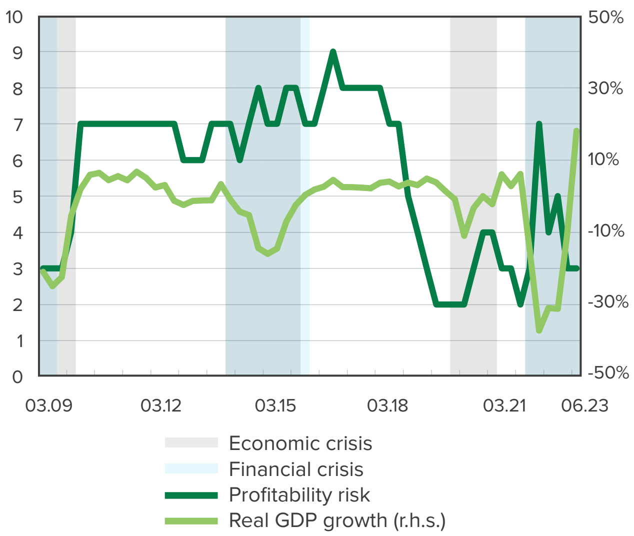


Figure 9. Profitability Risk

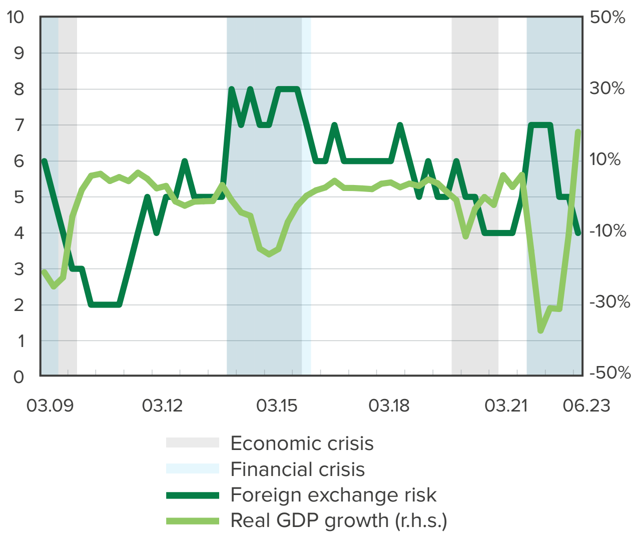


Figure 11. Foreign Exchange Risk

of international reserves. Their exhaustion pointed to an inevitable sharp devaluation, which created stress for the system. Since then, foreign exchange risk scores have improved on average. Currently the highest negative impact for the system can come from still high share of FX loans.

6. CONCLUSIONS

In this study, we present a refined risk map for monitoring systemic risks in Ukraine. The risk map is built on quantitative indicators rather than expert judgments. We identify 40 indicators capturing a wide range of economic and financial vulnerabilities and aggregate them into seven key risks: macroeconomic risk, credit risk of households, credit risk of non-financial corporations, capital adequacy risk, profitability risk, liquidity risk, and foreign exchange risk. The selection of indicators is based on international experience, data availability, and their ability to reflect risks to the financial system or the economy.

The values of the indicators used in the heatmap are assigned risk scores on a 1–10 scale with respective color-coding, with a set of threshold values being constructed for each indicator, using a combination of the historical data distribution in Ukraine, the historical data distribution in a pre-defined set of peer countries, and expert judgments. The color scheme makes it easier to visualize the risk assessment results for each indicator, highlighting periods of higher and lower risk. Finally, indicator risk scores in each risk category are averaged to obtain a score for each type of risk. The aggregate risk level is derived as an average score of all risks.

According to the results, which are also supported by a formal statistical analysis of the early warning properties, the new heatmap efficiently captures the vulnerabilities of the financial system and predicts financial crises up to a one-year horizon. Macroeconomic risk and foreign exchange risk have the best explanatory and predictive power. The weaker results from other risks are mainly due to structural changes in the banking sector and the short time series of data for the indicators.

The heatmap is a useful tool for macroprudential monitoring and will underpin regular risk surveillance and decision-making at the NBU. The forward-looking analysis could help predict crises; simultaneously, the backward-looking analysis could help better understand the causes of previous crises and market reactions to policy initiatives. We also regard the heatmap as a valuable communication tool to raise the awareness of stakeholders and the public about the nature of the risks that threaten financial stability in Ukraine. In addition, the risk map can be used together with indicators to calibrate macroprudential policy instruments.

REFERENCES

Aikman, D., Bridges, J., Burgess, S., Galletly, R., Levina, I., O'Neil,l C., Varadi, A. (2018). Measuring risks to UK financial stability. Staff Working Paper, 738. London: Bank of England. Retrieved from https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2018/measuring-risks-to-uk-financial-stability

Arbatli, E. C., Johansen, R. M. (2017). A heatmap for monitoring systemic risk in Norway. Staff Memo, 10. Oslo: Norges Bank. Retrieved from https://www.norges-bank.no/contentassets/c934013b17fc46259fa27c5da390236e/staffmemo_10_2017.pdf

Arena, M., Bouza, S., Dabla-Norris, E., Gerling, K., Njie, L. (2015). Credit booms and macroeconomic dynamics; stylized facts and lessons for low-income countries. IMF Working Paper, 2015/011. Washington: International Monetary Fund. Retrieved from https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Credit-Booms-and-Macroeconomic-Dynamics-Stylized-Facts-and-Lessons-for-Low-Income-Countries-42615

Borio, C., Lowe, P. (2002). Asset prices, financial and monetary stability: exploring the nexus. BIS Working Papers, 114. Basel: Bank for International Settlements Communications. Retrieved from https://www.bis.org/publ/work114.pdf

Central Bank of Ireland (2020). Systemic Risk Pack, December 2020. Dublin: Central Bank of Ireland. Retrieved from https://www.centralbank.ie/docs/default-source/publications/systemic-risk-pack/systemic-risk-pack---december-2020.pdf

Dell'Ariccia, G., Igan, D., Laeven, L., Tong, H., Bakker, B., Vandenbussche, J. (2012). Policies for macrofinancial stability; How to deal with credit booms. Staff Discussion Notes, 12/06. Washington: International Monetary Fund. https://doi.org/10.5089/9781475504743.006

Demirgüç-Kunt, A., Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. IMF Staff Papers, 45(1). Washington: International Monetary Fund. Retrieved from https://www.imf.org/external/pubs/ft/staffp/1998/03-98/pdf/demirguc.pdf

Demirgüç-Kunt, A., Detragiache, E. (1999). Monitoring banking sector fragility: A multivariate logit approach. IMF Working Paper, 99/147. Washington: International Monetary Fund. https://doi.org/10.5089/9781451856712.001

Drehmann, M., Borio, C., Gambacorta, G. J., Trucharte, C. (2010). Countercyclical capital buffers: exploring options. BIS Working Papers, 317. Basel: Bank for International Settlements Communications. Retrieved from https://www.bis.org/publ/work317.pdf

Drehmann, M., Borio, C., Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: the role of credit aggregates. BIS Working Paper, 355. Basel: Bank for International Settlements Communications. Retrieved from https://www.bis.org/publ/work355.pdf

Drehmann, M., Tsatsaronis, K. (2014). The credit-to-GDP gap and countercyclical capital buffers: questions and answers. BIS Quarterly Review, March 2014. Basel: Bank for International Settlements Communications. Retrieved from https://www.bis.org/publ/qtrpdf/r_qt1403g.pdf

EBA (2020). Risk Dashboard Data as of Q4 2020. Paris: European Banking Authority. Retrieved from https://www.eba.europa.eu/sites/default/documents/files/document_library/Risk%20Analysis%20and%20Data/Risk%20dashboard/

Q4%202020/972092/EBA%20Dashboard%20-%20Q4%20 2020%20-%20footnote%20%281%29.pdf

ESRB (2013). Recommendation of the European Systemic Risk Board of 4 April 2013 on intermediate objectives and instruments of macro-prudential policy (ESRB/2013/1). Official Journal of the European Union, C 170, 1-19. Retrieved from https://www.esrb.europa.eu/pub/pdf/recommendations/2013/ESRB_2013_1.en.pdf

Filatov, V. (2021). A new financial stress index for Ukraine. Visnyk of the National Bank of Ukraine, 251, 37-54. https://doi.org/10.26531/vnbu2021.251.03

Geršl, A., Seidler, J. (2015). Countercyclical capital buffers and credit-to-GDP caps: Simulation for Central, Eastern and Southeastern Europe. Eastern European Economics, 53(6), 439-465. https://doi.org/10.1080/00128775.2015.1102602

Grui, A., Vdovychenko, A. (2019). Quarterly projection model for Ukraine. NBU Working Papers, 3/2019. Kyiv: National Bank of Ukraine. Retrieved from https://bank.gov.ua/admin_uploads/article/WP_2019-03_Grui_Vdovychenko_ua.pdf

IMF (2011). World Economic Outlook, September 2011: Slowing Growth, Rising Risks. Washington: International Monetary Fund. https://doi.org/10.5089/9781616351199.081

IMF (2019). Global Financial Stability Report, April 2019. Washington: International Monetary Fund. https://doi.org/10.5089/9781498302104.082

Kaminsky, G. (1999). Currency and banking crises: the early warnings of distress. Working Paper, 99/178. Washington: International Monetary Fund. https://doi.org/10.5089/9781451858938.001

Kaminsky, G., Lizondo, S., Reinhart, C. (1998). Leading indicators of currency crisis. IMF Staff Papers, 45(1). Washington: International Monetary Fund. Retrieved from https://www.imf.org/external/pubs/ft/staffp/1998/03-98/pdf/kaminsky.pdf

Kaminsky, G., Reinhart, C. (1999). The twin crises: The causes of banking and balance-of-payments problems. American Economic Review, 89(3), 473–500. https://doi.org/10.1257/aer.89.3.473

Latvijas Banka (2018). Financial Stability Report, 2018. Rīga: Latvijas Banka. Retrieved from https://www.bank.lv/images/stories/pielikumi/publikacijas/FSR_2018_en.pdf

Lepers, E., Sánchez Serrano, A. (2017). Decomposing financial (in)stability in emerging economies. Working Paper Series, 39. Frankfurt am Main: European Systemic Risk Board. Retrieved from https://www.esrb.europa.eu/pub/pdf/wp/esrbwp39.en.pdf

Mencía, J., Saurina, J. (2016). Macroprudential policy: objectives, instruments and indicators. Documentos Ocasionales, 1601. Madrid: Banco de España. Retrieved from https://repositorio.bde.es/bitstream/123456789/6354/1/do1601e.pdf

Mendoza, E. G., Terrones, M. E. (2008). An anatomy of credit booms: evidence from macro aggregates and micro data. Working Papers, 14049. Cambridge: National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w14049

Mitra, S., Beneš, J., Iorgova, S., Lund-Jensen K., Schmieder Ch., Severo T. (2011). Toward operationalizing macroprudential policies: When to act? Chapter 3 in Global Financial Stability Report, September 2011. Washington: International Monetary Fund. Retrieved from https://www.imf.org/-/media/Websites/IMF/imported-flagship-issues/external/pubs/ft/GFSR/2011/02/pdf/_ch3pdf.ashx

NBB (2019) Financial Stability Report, 2019. Bruxelles: National Bank of Belgium. Retrieved from https://www.nbb.be/doc/ts/publications/fsr/fsr_2019.pdf

NBU (2020). Financial Stability Report, December 2020. Kyiv: National Bank of Ukraine. Retrieved from https://bank.gov.ua/admin_uploads/article/FSR_2020-H2_eng.pdf

RBI (2013). Report of the Internal Working Group on Implementation of Counter-Cyclical Capital Buffer, Draft, December 2013. Kolkata: Reserve Bank of India.

Schularick, M., Taylor, A. M. (2012). Credit booms gone bust: monetary policy, leverage cycles and financial crises, 1870-2008. American Economic Review, 102(2), 1029-1061. https://doi.org10.1257/aer.102.2.1029

Venditti, F., Columba, F., Sorrentino, A. M. (2018). A risk dashboard for the Italian economy. Occasional Paper, 425. Rome: Bank of Italy. Retrieved from https://www.bancaditalia.it/pubblicazioni/qef/2018-0425/QEF_425_18.pdf

World Bank (2010). Comments on the Consultative Document Countercyclical Capital Buffer Proposal. Retrieved from https://www.bis.org/publ/bcbs172/worldbank.pdf

APPENDIX A. TABLES

Table 2. Tools for Monitoring Financial Stability Risks across Countries

Countries	Name	Risk categories	Aggregation method	Threshold setting and color coding	Source
22 advanced and 7 emerging countries	Matrix of financial vulnerability indices	Nonfinancial Corporates Households Banks Sovereigns Insurers Other financial institutions	Normalization by a pooled z-score, aggregation by an unweighted/ weighted arithmetic average of the z-scores	Percentiles of historical data	IMF (2019)
30 European countries	Risk indicators heatmap	Solvency Credit risk and assets quality Earnings and balance sheet structure	Weighted average	Percentiles of historical data	EBA (2020)
11 emerging countries	Heatmap of vulnerabilities	Valuation pressures and risk appetite Non-financial sector imbalances Financial sector vulnerabilities Global vulnerabilities	Aggregation of standardized series within each component to end up with an aggregated score for that component	By standardized risk score (from 0 to 1)	Lepers and Sánchez Serrano (2017)
Belgium	A risk dashboard for detecting and monitoring systemic risk	Indicators are grouped according to the ESRB's first four intermediate objectives[9]	A simple average of colors associated with all indicators in the sub-category	Mixed approach: early warning methodologies, international level, legislation or guidelines level, cross-country/ historical distribution, expert judgments	NBB (2019)
Ireland	Systemic risk heatmap	Indicators are grouped according to the ESRB's first four intermediate objectives	–	Historical or European average, guidelines level	Central Bank of Ireland (2020)
Italy	Risk dashboard	Interlinkages Credit markets Macroeconomic environment Funding conditions Financial markets Banking and insurance sectors	Standardized series are aggregated by simple and weighted average	Expert judgments or historical distributions	Venditti et al. (2018)
Latvia	Heatmap	External macrofinancial and domestic macroeconomic risks Credit risk of borrowers Liquidity and funding risks Solvency and profitability risks	–	Expert judgments, percentiles of historical observations	Latvijas Banka (2018)

[9] According to ESRB (2013) the intermediate objectives of macroprudential policy should be to: (a) mitigate and prevent excessive credit growth and leverage, (b) mitigate and prevent excessive maturity mismatch and market liquidity, (c) limit direct and indirect exposure concentration, (d) limit the systemic impact of misaligned incentives with a view to reducing moral hazard, and (e) strengthen the resilience of financial infrastructures.

Table 2 (continued). Tools for Monitoring Financial Stability Risks across Countries

Countries	Name	Risk categories	Aggregation method	Threshold setting and color coding	Source
Norway	Heatmap	Risk appetite and asset valuations Non-financial sector imbalances Financial sector vulnerabilities	Each indicator is normalized based on its empirical cumulative distribution function	Shading according to indicator changes from 0 to 1	Arbatli et al. (2017)
Spain	Aggregate heatmap	Potential risks: first four of the ESRB's intermediate objectives and macroeconomic imbalances. Materialized risks: real economy, as well as NPLs and dependence on central bank	Linear aggregation, weighted by adjustment factors: the capacity of indicators to anticipate future crises, the correlation between different indicators	Historical percentiles of the distribution	Mencía and Saurina (2016)
United Kingdom	Heatmap of the individual risk indicators	Private non-financial sector leverage (households, private non-financial corporations, external leverage) Asset valuations (financial and property) Terms of credit (residential and commercial property)	Aikman et al. (2017) approach: unweighted average of z-scores of individual series PCA-based weights "Intensity score" measure according to Kaminsky (1999)	Historical distributions	Aikman et al. (2018)

Table 3. Indicators Selected for Risk Assessment

Risk	Indicator	Description	Threshold	Start date
Macroeconomic risk	Real GDP growth	Is a measure of real economic performance, but is a lagging indicator of risk.	Historical and peer countries data	Q4 2002
	Real GDP growth forecast	Reflects the NBU's expectations regarding the growth or recession of the economy and is one of the main guidelines of economic policy; is an early warning indicator of crises at the macro level.	Countries data	Q1 2015
	Gross external debt to GDP	Indicates the level of debt burden of state residents to non-residents.	Historical and peer countries data	Q4 2003
	Current account balance to GDP ratio	Reflects the trade position of a country. An analysis of the indicator and its dynamics makes it possible to identify imbalances in the foreign economic relations of the state, which appear in a deficit or surplus of the current account of the balance of payments.	Expert judgments	Q4 2001
	External state and state guaranteed debt to GDP ratio	Is used to assess the level of the government's debt burden - a significant level of external debt denominated in foreign currency carries liquidity and solvency risks for the fiscal sector, can lead to the crowding out of private investment, an increase in the tax burden, etc.	Historical and peer countries data	Q4 2001
	State budget surplus/deficit to GDP ratio	Is used as a tool to measure the government's ability to meet its financial needs and ensure efficient public financial management.	Expert judgments	Q4 2005
	Credit default swap 5Y Ukraine	Reflects the probability of Ukraine's default on its obligations, should reflect in advance changes in the expectations of economic agents of the level of fiscal and financial stability of the country.	Historical and peer countries data	Q1 2007
Credit risk of households	Gross bank loans to GDP ratio	Allows the debt burden of households to be estimated.	Historical and peer countries data	Q1 2006
	Gross bank loans to disposable income ratio	Reflects the debt burden of households relative to their real income.	Expert judgments	Q1 2006
	Debt service ratio[10]	Measures the share of household disposable income spent on loan payments relative to total sector liabilities.	Historical and peer countries data	Q1 2012
	Loans at risk	The share of 30 days past due loans in gross performing loans to households.	Expert judgments	Q4 2016
	Index of economic expectations	Shows the expectations of households regarding changes in their financial situation and the development of the country's economy. Lower expectations lead to an increase in savings and a decrease in the purchasing power of consumers, which will ultimately slow down economic activity, and, accordingly, will lead to an increase in credit risk and a decrease in demand for loans in the future.	Expert judgments	Q1 2009
	Expected change in the loan portfolio quality over the next 12 months	Reflects the banks' expectations of changes in the credit risk of households (source – Bank Lending Survey, NBU).	Historical and peer countries data	Q1 2015
Credit risk of non-financial corporations	Net bank loans as a percentage of GDP	Gives an estimate of the debt burden of non-financial corporations at the macro level.	Historical and peer countries data	Q1 2012

[10] The inclusion of the indicators *Gross bank loans to GDP ratio* and *Debt service ratio* simultaneously in the category *Credit risk of households* is due to the following. The amount of debt can be small, so the debt to GDP ratio will not signal high credit risk. At the same time, the high cost of loans can lead to a deterioration in the debt service ratio.

Table 3 (continued). Indicators Selected for Risk Assessment

Risk	Indicator	Description	Threshold	Start date
	Gross corporate debt to EBITDA ratio	Reflects the ability of the corporate sector to meet its debt obligations from operating income; calculated at the level of individual companies and then averaged.	Historical and peer countries data	Q4 2013
	Return on equity (ROE)	Demonstrates how effectively non-financial corporations use capital to generate profits.	Historical and peer countries data	Q4 2013
	Interest coverage ratio	Shows the ability of non-financial corporations to cover interest costs from operating profit.	Historical and peer countries data	Q4 2013
	Default rate	Means the share of non-financial corporations with loans defaulted. This indicator reflects the quality of the corporate loan portfolio.	Expert judgments	Q4 2010
	Business outlook index for the next 12 months	The expectations of enterprises for their development over the next 12 months.	Expert judgments	Q2 2013
	Expected change in the loan portfolio quality over the next 12 months	Reflects banks' expectations regarding changes in the credit risk of non-financial corporations (source – Bank Lending Survey, NBU).	Historical and peer countries data	Q1 2015
Capital adequacy risk	Regulatory capital adequacy ratio	Reflects the banks' ability to pay their liabilities in a timely manner and in full.	Percentiles of historical data	Q4 2005
	Core (Tier 1) capital[11] adequacy ratio	Assesses the banks' ability to fully meet their obligations and remain solvent (going concern).	Percentiles of historical data	Q4 2005
	Net non-performing loans to capital ratio	Reflects the potential level of losses that may arise from the non-performing portfolio of banks, compared to their capital, and hence the banks' ability to absorb these risks and maintain solvency.	Expert judgments	Q1 2009
	Capital to total net assets ratio	Determines the financial leverage of banks, that is, the proportion of assets financed by borrowing. The indicator takes into account risks other than credit, in particular the risks that may arise from investing in government securities. A negative trend in the ratio may signal an increase in risk appetite and possible problems with capital adequacy, which are not fully reflected in the indicators of capital adequacy ratios.	Historical and peer countries data	Q1 2009
Profitability risk	Return on equity (ROE)	Shows how efficiently a bank uses capital to make a profit.	Historical and peer countries data	Q1 2010
	Return on assets (ROA)	Shows how effectively a bank manages its assets to make a profit. The indicator is related to the previous one, however, it should compensate for possible distortions in ROE by reducing capital, rather than increasing profits.	Historical and peer countries data	Q1 2010
	Net interest margin (NIM)	Gives an estimate of the profitability of the main operations carried out by banks.	Historical and peer countries data	Q1 2010
	Cost of risk (CoR)	Shows the level of losses from credit risk per unit of bank loans.	Historical and peer countries data	Q1 2010
	Cost-to-income ratio (CIR)	Is used to measure a bank's performance by comparing a bank's operating expenses with its operating income. Together with the NIM and CoR indicators, it provides a complete picture of the banks' ability to generate profits from core operations and possible risk factors for profitability.	Historical and peer countries data	Q1 2009

[11] Core capital in Ukraine is inherently analogue of Tier 1, but it does not include retained earnings.

Table 3 (continued). Indicators Selected for Risk Assessment

Risk	Indicator	Description	Threshold	Start date
Liquidity risk	Liquidity coverage ratio (LCR)	Is used to assess the state of banks' liquidity over a 30-day horizon. It sets the minimum required liquidity level to cover the net expected cash outflow within 30 calendar days, taking into account the stress scenario.	Expert judgments	Q4 2018
	High-quality liquid assets to total assets ratio	Reflects the volume of highly liquid assets available to banks in case of emergencies associated with a lack of liquidity. The indicator has similar dynamics to the LCR, but is available over a longer period, therefore, it is intended to complement the LCR retrospectively.	Expert judgments	Q1 2009
	Loan to deposit ratio	Indicates the activity of banks in lending, the level of direction of funds into lending operations. A low value indicates the availability of free funds, and therefore high liquidity, a high indicator indicates a greater need to raise funds and higher risks.	Historical and peer countries data	Q1 2009
	Expected change in the liquidity risk for banks over the next quarter	Reflects the dynamics of the liquidity risk during the next quarter according to the banks' assessment (source – Bank Lending Survey, NBU).	Expert judgments	Q4 2013
FX risk	US Dollar exchange rate volatility	Reflects the variability and frequency of changes in the official exchange rate of the Ukrainian national currency against the US dollar over time.	Percentiles of historical data	Q4 2000
	International reserves to import ratio	Shows the sufficiency of international reserves to reduce potential adverse exchange rate fluctuations and maintain the required level of international transactions.	Expert judgments	Q1 2006
	FX corporate loans to total corporate loans	Assesses the volume of credit claims on non-financial corporations that are vulnerable to currency fluctuations. For these loans, fluctuations in the exchange rate can lead to the materialization of both market risk and credit risk due to a negative impact on the solvency of borrowers.	Expert judgments	Q4 2005
	Net open FX position to regulatory capital ratio	Reflects the level of coverage by the capital of potential foreign exchange risks, taking into account the net open foreign exchange position of the bank.	Expert judgments	Q2 2014
	Corporate expectations of UAH/USD exchange rate for next 12 months	Deviation of expectations from the actual values of the exchange rate of the national currency against the US dollar.	Historical and peer countries data	Q2 2013
	Index of devaluation expectations of households	Reflects the expectations of households regarding the devaluation of the national currency against the US dollar.	Historical and peer countries data	Q1 2012
	Change in the currency risk for banks within the past quarter	Demonstrates the dynamics of the foreign exchange risk over the last three months according to the banks' assessment (source – Bank Lending Survey, NBU).	Historical and peer countries data	Q4 2013

Table 4. Predictive Power Performance of a Risk Measures

Metrics	Economic crisis dummy				
	level	1Q ahead	2Q ahead	3Q ahead	4Q ahead
	Aggregate (average) risk				
Accuracy	0.8933	0.8667	0.8267	0.8000	0.7467
Precision average	0.9394	0.9254	0.9058	0.8929	0.8699
Recall average	0.7647	0.7222	0.6579	0.6250	0.5476
F1 average	0.8139	0.7674	0.6880	0.6400	0.5122
Kappa	0.6350	0.5487	0.4080	0.3284	0.1316
AUC ROC	0.8631	0.8104	0.7650	0.7136	0.6680
AUC ROC cross-validated	0.8643	0.8061	0.7719	0.7116	0.7116
Observations	75	75	75	75	75
	Macroeconomic risk				
Accuracy	0.9067	0.8533	0.8400	0.7600	0.7467
Precision average	0.8876	0.8201	0.8310	0.6923	0.7101
Recall average	0.8357	0.7515	0.7190	0.6136	0.5767
F1 average	0.8577	0.7764	0.7500	0.6250	0.5709
Kappa	0.7161	0.5557	0.5087	0.2703	0.1963
AUC ROC	0.9615	0.9016	0.8412	0.7695	0.7152
AUC ROC cross-validated	0.9515	0.8966	0.8275	0.7597	0.7105
Observations	75	75	75	75	75
	Credit risk of households				
Accuracy	0.7069	0.7241	0.7069	0.6724	0.6552
Precision average	0.6250	0.6750	0.6646	0.6697	0.8246
Recall average	0.5861	0.6167	0.6066	0.5368	0.5238
F1 average	0.5897	0.6234	0.6092	0.4848	0.4391
Kappa	0.1958	0.2658	0.2427	0.0923	0.0600
AUC ROC	0.6793	0.6549	0.6269	0.5914	0.5515
AUC ROC cross-validated	0.6582	0.6748	0.6053	0.5781	0.5137
Observations	58	58	58	58	58
	Credit risk of non-financial corporations				
Accuracy	0.7179	0.6923	0.6667	0.6410	0.6154
Precision average	NaN	NaN	NaN	NaN	NaN
Recall average	0.5000	0.5000	0.5000	0.5000	0.5000
F1 average	NaN	NaN	NaN	NaN	NaN
Kappa	0.0000	0.0000	0.0000	0.0000	0.0000
AUC ROC	0.5828	0.5278	0.4660	0.5886	0.6097
AUC ROC cross-validated	0.5438	0.5540	0.3054	0.2969	0.4966
Observations	39	39	39	39	39

Table 4 (continued). Predictive Power Performance of a Risk Measures

Metrics	Economic crisis dummy				
	level	1Q ahead	2Q ahead	3Q ahead	4Q ahead
	Capital adequacy risk				
Accuracy	0.7119	0.6949	0.6780	0.6610	0.6441
Precision average	NaN	NaN	NaN	NaN	NaN
Recall average	0.5000	0.5000	0.5000	0.5000	0.5000
F1 average	NaN	NaN	NaN	NaN	NaN
Kappa	0.0000	0.0000	0.0000	0.0000	0.0000
AUC ROC	0.5056	0.5230	0.5342	0.5622	0.5934
AUC ROC cross-validated	0.2703	0.3019	0.3912	0.5286	0.5803
Observations	59	59	59	59	59
	Profitability risk				
Accuracy	0.6957	0.7391	0.7174	0.7174	0.7174
Precision average	0.6678	0.7250	0.6896	0.6896	0.6896
Recall average	0.6063	0.6688	0.6521	0.6521	0.6521
F1 average	0.6054	0.6783	0.6593	0.6593	0.6593
Kappa	0.2406	0.3699	0.3281	0.3281	0.3281
AUC ROC	0.5917	0.6271	0.7010	0.7542	0.7906
AUC ROC cross-validated	0.5771	0.6287	0.6985	0.7523	0.7855
Observations	46	46	46	46	46
	Liquidity risk				
Accuracy	0.6522	0.6522	0.6522	0.6522	0.6522
Precision average	NaN	NaN	NaN	NaN	NaN
Recall average	0.5000	0.5000	0.5000	0.5000	0.5000
F1 average	NaN	NaN	NaN	NaN	NaN
Kappa	0.0000	0.0000	0.0000	0.0000	0.0000
AUC ROC	0.6063	0.5396	0.4958	0.4688	0.5823
AUC ROC cross-validated	0.5421	0.4371	0.3582	0.3144	0.3376
Observations	46	46	46	46	46
	Foreign exchange risk				
Accuracy	0.9114	0.8667	0.8481	0.8101	0.7595
Precision average	0.9136	0.8532	0.8356	0.7754	0.6913
Recall average	0.8155	0.7602	0.7202	0.6746	0.6084
F1 average	0.8522	0.7917	0.7531	0.6990	0.6187
Kappa	0.7063	0.5875	0.5143	0.4102	0.2602
AUC ROC	0.8695	0.8392	0.8307	0.7975	0.7562
AUC ROC cross-validated	0.8648	0.8377	0.8235	0.7949	0.7566
Observations	79	79	79	79	79

The confusion matrix

		Actual: Yes	Actual: No
Predicted	Yes	True Positives (TP)	False Positives (FP)
	No	False Negatives (FN)	True Negatives (TN)
Total		P	N

The precision metric indicates how many predictions that we made were correct:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

The recall metric shows for the events that occurred, how many we predicted:

$$Recall = \frac{TP}{P} \tag{2}$$

The accuracy specifies how often the classifier is correct.

$$Accuracy = \frac{TP + TN}{P + N} \tag{3}$$

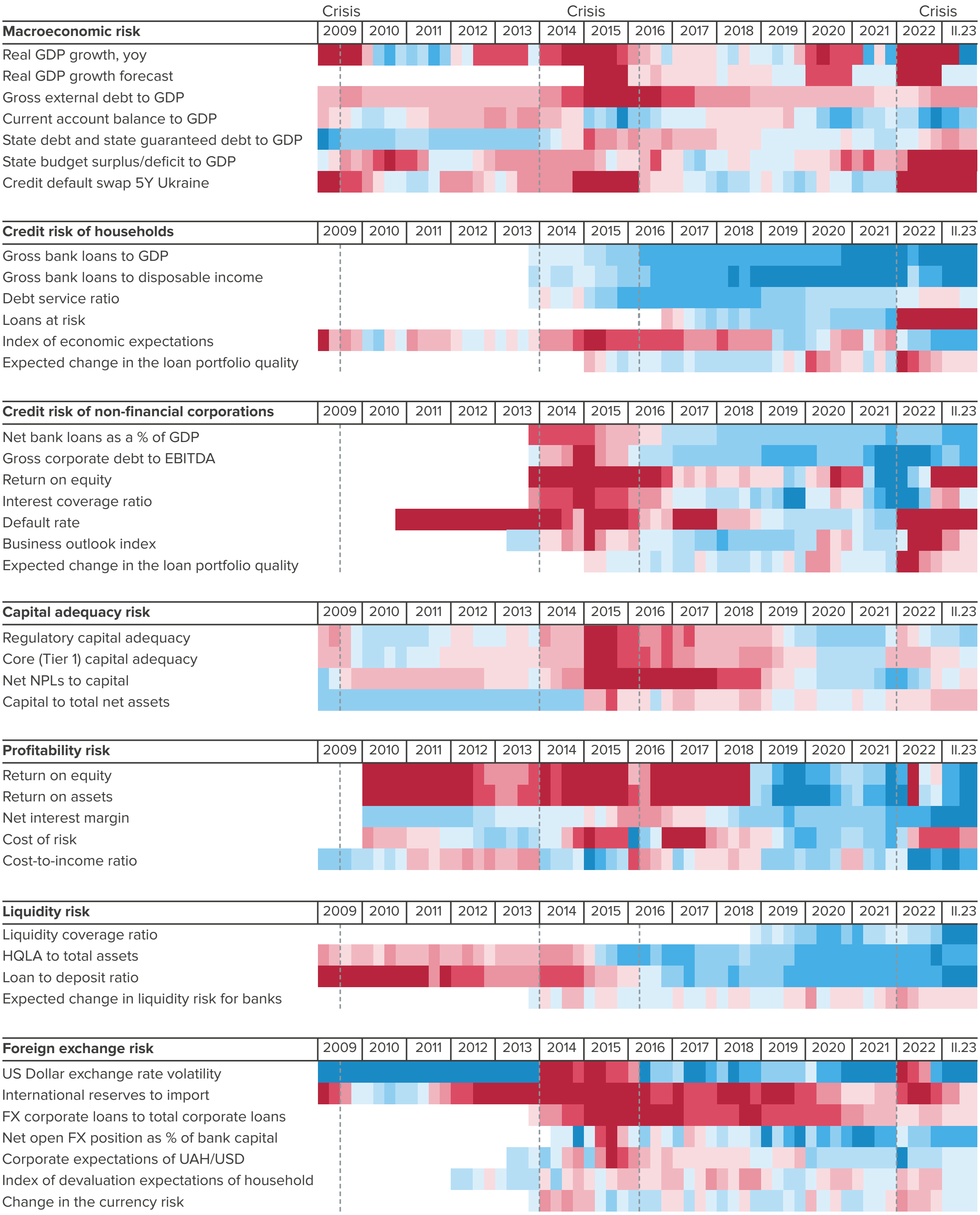
The F1 metric is defined as the harmonic mean (or a weighted average) of precision and recall.

$$F1 = \frac{2}{1 / Precision + 1 / Recall} \tag{4}$$

In addition, we calculated the kappa coefficient, which evaluates how well the classification performs compared to a map in which all values are just randomly assigned. The kappa coefficient can range from -1 to 1. A value of 0 indicates that the classification is as good as random values. A value below 0 indicates the classification is significantly worse than random. A value greater than 0 indicates that the classification is significantly better than random.

The receiver operating curve (ROC) is a plot of the true positive rate ($TP\,rate = TP / P$) against the false positive rate ($FP\,rate = FP / N$) at various threshold settings.

APPENDIX B. FIGURES



Notes: Financial crisis periods for Ukraine were derived following the methodology of Filatov (2021).

Figure 12. Heatmap Visualization by Indicators Risk Score