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Measuring the link between cyclical systemic risk and capital adequacy for Ukrainian banking sector

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Bilateral Assistance
& Capacity Building
for Central Banks

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Abstract

In this paper we investigate the impact of cyclical systemic risk on future bank profitability for a large representative panel of Ukrainian banks between 2001 and 2023. Our framework relies on two general methods. The first method is based on linear local projections which allows us to study the estimated negative impact of cyclical systemic risk on bank profitability. The second method is based on the original IMF's Growth-at-Risk approach, utilizing quantile local projections to assess the impact of cyclical systemic risk on the tails of the future bank-level profitability distribution. Additionally, we enhance the macroprudential toolkit with a novel approach to calibrating the countercyclical capital buffer (CCyB). Furthermore, we develop the "Bank Capital-at-Risk" and "Share of vulnerable banks" indicators. These indicators are valuable tools for monitoring the build-up of systemic risk in the banking sector.

Keywords: systemic risk, linear projections, quantile regressions, bank capital, macroprudential policy.

JEL: C3, C58, E58, G21, G32.

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Introduction

Financial crises come at a great cost and are difficult to anticipate. To minimize the probability of a new crisis, it is important to develop a preventive regulatory toolbox of indicators that enable systemic risk analysis. Given that banks are the largest financial intermediaries worldwide, systemic stress originating in the banking sector can trigger major crises with far-reaching adverse effects.

In this paper, we will develop instruments that allow us to measure the stability of the banking sector. They can also inform the regulators of the amount of additional bank capital needed if systemic risk materializes and imbalances unwind.

According to **World Bank (2020)**, higher levels of bank capital contribute to financial stability, as it forms a cushion for absorbing losses during financial distress. It also improves the monitoring and screening process of banks, as well as limits risk-taking, due to higher stake contributed by shareholders. During large economic downturns, such as the one Ukraine is currently experiencing, it is particularly important to be informed about downside risks to the solvency of banking system and have estimates of the extent of possible reductions in banks' equity.

Banks capital holdings can indicate the amount of resources the entity has to survive a stress period either caused by endogenous factors (i.e., the realization of risks the institutions take on as a part of its normal activity) or due to exogenous ones (importing the imbalances on national or global financial markets). Stress that banks endure is usually a mix of both endogenous and exogenous drivers since all banks deal with risk and there is a strong interconnectedness among the institutions in the sector. The latter is also a reason why the capital adequacy of every financial institution matters, regardless of its size: a solvency issue of one bank can be contagious for the whole financial sector. In that case, financial stress, under certain circumstances, can propagate to the global financial market.

Bank capital can be viewed from two perspectives when it comes to financial crises: it represents banks' own resources that help absorb losses and remain solvent during stress times; and as one of the indicators of banks financial strength. A reduction in capital in the sector can be seen as a warning signal of possible financial instability. Following the GFC, the Basel Committee on Banking Supervisions (BCBS) toughened requirements to regulatory capital of banks. Since then, banks must hold more and better-quality capital.[1] The rules formulated under Basel framework are the minimum requirements that the internationally active banks should follow. However, in practice many small jurisdictions and banks also follow them. According to Basel III, the regulatory capital consists of Tier1 and Tier 2 capital, which are the going and gone concern capital, respectively. Tier 1 capital, in turn, consists of two elements: Common equity tier 1 capital (CET1) and Additional Tier 1 capital (AT1). The CET1 capital has the highest capacity to absorb losses while the bank is still solvent and active. AT1 capital serves the same goal but consists of instruments that do not qualify for the CET1. In contrast, Tier 2 capital should absorb losses when the bank is insolvent, before the depositors and creditors do **(Bank for International Settlements, 2019)**. However, the bank's insolvency and capital adequacy ratio are not closely linked in every single case. A bank failure does not necessarily follow the breach of capital adequacy ratio. On top of that, even solvent banks can become gone concerns due to, for instance, liquidity shortages.

In this research we will develop a set of indicators that measure the downside risks for banks' capital adequacy, that arise due to cyclical systemic risk. There is a clear link between the cyclical systemic risk and bank revenues since excessive credit and asset price dynamics usually increase the probability of large bank losses in upcoming

[1] The capital of a bank can generally be viewed from two different perspectives, as discussed by **Avdjiev and Garralda (2020)**. Regulatory capital is related to the book value of assets and liabilities and reflects past profits and losses. While market capital is a function of the present discounted value of expected future dividends.

times. The bank profitability will be measured by the bank-level return on assets (ROA). ROA captures the pace of creation or loss of capital during the operational activity of a bank. To achieve the research objective, we will investigate a large representative panel of Ukrainian banks between 2001 and 2023. The rest of the paper is structured as follows.

We utilize linear local projections and quantile local projections to quantify the impact of the domestic financial cycle index on average bank profitability and tails of the profitability distribution over the chosen horizons of a few years into the future.

To transform the estimates built on the pre-tax ROA into effects on bank capital adequacy ratios, the results from the first stage are divided by the bank-level risk-weight density.[2]

Then we translate the obtained estimates on a bank-level to a country level "Bank capital at risk" by calculating a weighted average of the rescaled 5th percentiles of the conditional bank-level distributions, where the weights are given by the relative assets' size of each bank.

Additionally, the estimates obtained in the previous steps enable us to assess a "Share of vulnerable banks" that is a sum of asset shares of the banks, the conditional 5th pre-tax ROA quantile of which is below a certain threshold level.

Literature Review

The foundation for the "Bank capital-at-risk" framework is the "Growth-at-risk" concept, developed by **Adrian et al. (2016).** According to the original framework, the future distribution of real GDP growth is a function of current financial and economic conditions. They demonstrated that the lower quantiles of real GDP growth vary with financial conditions, while upper quantiles remain relatively stable. That allowed them to conclude that there is a correlation between the growth vulnerability and financial conditions. Moreover, the left tail of the GDP growth distribution demonstrates a positive correlation with a slack in financial conditions.

The "Bank capital-at-risk" framework developed as a separate evolutionary branch of the "at-risk" concept. Its methodology, outlined by **Lang and Forletta (2020)** in their working paper for the European Central Bank "Cyclical systemic risk and downside risks to bank profitability", will serve as a foundation for this research project. The main objective of the paper (*Lang & Forletta paper* hereafter) is investigation of the impact of cyclical systemic risk on future bank profitability. With the help of linear local projections, the authors proved that the high levels of cyclical systemic risk could predict large downfalls in bank profitability, as measured by bank-level ROA microdata, a few years in advance. The quantile local projections showed that the estimated effect of one-unit increase of domestic cyclical systemic risk indicator (d-SRI), as developed by **Lang et al. (2019),** on the fifth lower percentile of ROA distribution is in the range from -1.1 to -1.8 p.p. on horizons from three to five years. While the impact on median of the ROA distribution is within the range of -0.2 to -0.25, they managed to conclude that high cyclical systemic risk leads to significant left skewness of the bank revenue distribution. They also built a framework and calculated the "Bank Capital-at-Risk" and "Share of vulnerable banks" estimates, which are potentially important indicators of systemic risk build-up in the banking sectors that can contribute to the systemic risk analysis toolkit and communication of the financial sector regulators. Aside from this, they showed how their framework could contribute to the macroprudential policy toolkit, by enriching the methodology of countercyclical capital buffer calibration.

[2] A ratio of risk-weighted assets to assets.

According to the *Lang & Forletta paper*, "Bank Capital-at-risk" (BCAR) is the lower left tail (5th percentile) of the conditional bank-level pre-tax ROA distributions, (1) divided by bank-level average risk weights[3] and then (2) weighted by the relative size of each banks' assets and (3) aggregated in order to arrive at the system-wide level within one country. The "Share of vulnerable banks" (SVB) is estimated as the total asset share of banks with a conditional 5th percentile pre-tax bank-level ROA distribution of less than a certain threshold level.

The definition of systemic risk, according to **Kaufman and Scott (2003)** can have three different perspectives. The first perspective, expressed by **Mishkin (1995)**, envisages systemic risk as "the likelihood of a sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities". An example of the second approach to defining the systemic risk was outlined by the Bank for International Settlements **(BIS, 1994)** as "the risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default with a chain reaction leading to broader financial difficulties". The third definition, following **Kaufman and Scott (2003)** also includes the spillover effect from the initial exogenous external shock, but it does not include direct causation. Within the definition of systemic risk, authors described the pattern of a "common shock" or "reassessment shock" effect that represents correlation without direct causation. However, for the purposes of this research, we will use a later and broader definition: according to **ECB (2009),** systemic risk is the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially. This definition will allow us to link systemic risk with the real economy and its cycles.

The cyclical dimension of systemic risk, formulated by **Borio (2003)**, is the one that is concerned with the build-up of macro financial imbalances over time, throughout the financial cycle. The author also links the cyclical systemic risk and macroprudential toolkit, referring to it as to a reason the capital cushions are essential for financial institutions during economic upswings. In the *Lang & Forletta paper*, the cyclical dimension of systemic risk is measured by the d-SRI.

The link between financial cycles and bank profitability or bank capital was previously investigated by **Albertazzi and Gambacorta (2009), Bolt et al. (2012), Kok, Móré and Pancaro (2015) and Kohlscheen, Pabón and Contreras (2018).**

In their work, **Albertazzi and Gambacorta (2009)**, with a help of a model that employs the GMM estimator, evaluate the impact of macroeconomic and financial conditions' shocks on the profitability of the banking sector for 10 countries and Euro area in general. They show that the bank profits are pro-cyclical with the GDP growth affecting both net interest income and loan loss provisions. Their results also suggest that pro-cyclicality was slightly greater in the United Kingdom and in the United States.

The paper by **Bolt et al. (2012)** investigated the link between bank profits and economic downtrend using a theoretical model that factored in the banks' lending portfolio and its quality on both aggregate and individual bank data. The authors estimate the pro-cyclicality using the data on net interest income, other income and net provisioning plus operational costs. They find that long-term interest rates on outstanding loans are among the most important determinants of current bank profitability, especially during the periods of relatively high economic growth. In addition, they prove that bank profits have pro-cyclical behavior with this link being the strongest during the severe recessions. This finding also contributes to the motivation of our research, since the

[3] In order to rescale results from bank profitability metrics into a bank capital indicator.

primary focus of this paper is the downside risks to bank profitability and bank capital, which usually coincide in time with the episodes of financial turmoil.

In their paper, **Kok, Móré and Pancaro (2015)** provide a long-term view of the developments in bank profitability in the Euro area and peer countries from the non-Euro area over 2003-2013. They argue that the diverging paths of the Euro area and US banks since 2009 are due to cyclical differences. The Euro area banks were enduring the pressure of weak macroeconomic environment that lasted longer than in the USA due to the sovereign debt crisis. They categorize the factors that influence bank profitability into three general groups: bank-specific factors, macroeconomic factors and structural factors. The cyclical patterns in bank performance and behavior are part of the macroeconomic factors, including real GDP growth, inflation rate, and credit extended by the banking system to the private sector relative to GDP. They adopted a dynamic modelling approach with the lagged dependent variable among the covariates. They found that from 2009 onwards, the macroeconomic factors that represented the cyclical component in this research drive the dynamics of bank profits.

Kohlscheen, Pabón and Contreras (2018) investigated the macro and microeconomic drivers of bank profitability based on the data on balance sheets of banks from 19 emerging market economies. They demonstrated that credit cycles might be a more important determinant of bank profitability than business cycles. Additionally, higher levels of long-term interest rates overall increase bank profitability due to higher net interest margins, while rising short-term rates tend to reduce bank profits. The authors also found that one of the most crucial drivers of bank profits in emerging economies is the sovereign risk premia that can reduce bank profitability significantly.

Motivation

The National Bank of Ukraine (hereafter – NBU) is responsible for maintaining price and financial stability with the goal of contributing to Ukraine's sustainable economic development. The financial stability is a qualitative (unquantifiable) objective and does not have universal indicators to evaluate its strength, like the consumer price index, which is a target for the monetary policy.

Assessing systemic risks is one of the key steps toward maintaining financial stability. This research will enhance the existing systemic risk assessment toolkit by adding a valuable mechanism for monitoring downside risks to the solvency of the banking system. Hence, this tool will allow us to estimate a direct link and the magnitude between the risks stemming from domestic credit, real estate markets, asset prices, external imbalances and future bank profitability, further translated into the estimates of bank capital that is at risk. Having such tool in place is especially important during large economic downturns, as the one Ukraine is going through right now. It provides information to the regulator about the depth of a possible fall in banks' solvency, which can amplify the severity of a crisis.

In addition to enhancing the systemic risk analysis toolkit, the framework for assessing the impact of cyclical systemic risk on the future bank-level ROA distribution will also contribute to the macroprudential policy calibration. Specifically, this tool is valuable for informing the calibration of the countercyclical capital buffer (CCyB), which is the key macroprudential policy instrument in the Basel III regulatory framework. It is designed to ensure resilience of banks over the financial cycle. For this research, we will use the estimated impact of the Financial Cycle Index (FCI) on future bank profitability, scaled by the inverse of the average risk-weight, as a conversion rate in the calibration process. The advantage of this methodology over a traditional CCyB calibration is its long lead-time ahead of the materialization of cyclical systemic risk. Sooner identification of risks gives banks enough time to smoothly accumulate the capital and adjust to changing capital requirements.

Another advantage of this framework is its ability to quantify the share of banks' equity that is at risk, given the past, current and expected level of cyclical systemic risk. Of interest for the NBU are the "Bank Capital-at-Risk" and "Share of vulnerable banks" estimates, which can be used as complex and advanced tools for monitoring solvency and stability of banking system. While stress testing of entire banking system is a long and costly process, the "Bank Capital-at-Risk" and "Share of vulnerable banks" estimates can provide the regulator with relatively high-frequency estimates that are quite similar in nature to those based on stress-tests. These estimates can be beneficial for the Financial Stability Department in its communication and can be used in the NBU's Financial Stability Report, to communicate the risks to the banks' solvency to the public more efficiently.

Background

Ukrainian financial sector is heavily dominated by banks. As of end 2022, the share of banks in total assets of the NBU-supervised financial sector amounted to 88.2%, which makes banking sector an object of heightened awareness from the regulator. As of January 2023, as depicted in *Figure 1*, there were 67 banks with total gross assets amounting to 2,354 UAH billion (hereafter – bn).

Since 2001, which marks the beginning of our period of observation, Ukraine went through four major economic crises: the economic crisis of 2008-2009 induced by the GFC; the social-economic crisis of 2014-2015, triggered by the Russian invasion of the eastern regions of Ukraine and annexation of Crimea; the economic crisis of 2020 caused by the Covid-19 pandemics; and the ongoing social-economic crisis, prompted by the full-scale Russian invasion of Ukraine in February 2022.

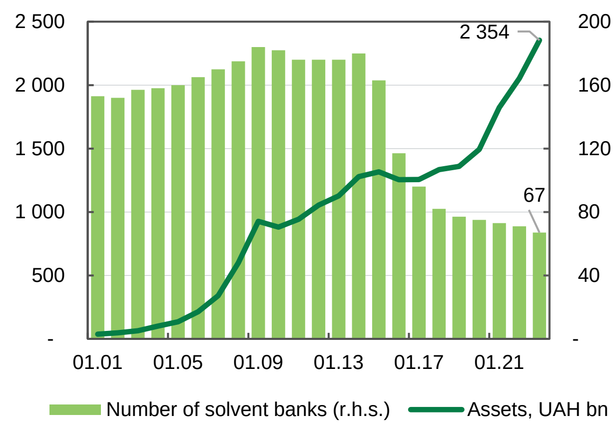


Figure 1. Size of the banking sector
Source: data from official website of the NBU.

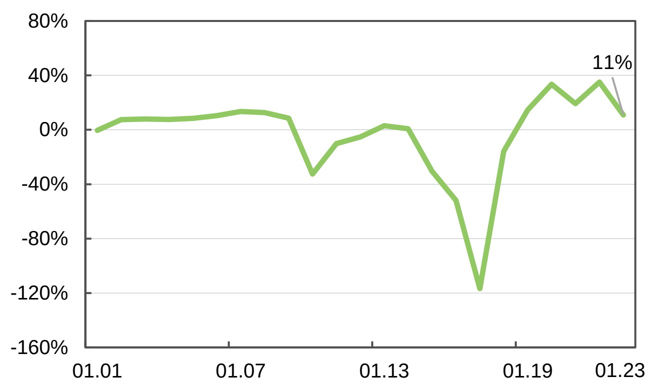


Figure 2. Return on capital
Source: data from official website of the NBU. The data on banks, solvent as of January 2023.

During the economic crises of 2014-2016, the NBU conducted the clean-up of the banking system. The regulator carried it out in order to increase the transparency and stability of the banking sector and avoid such crises in the future. Over three years more than 80 intermediaries were declared insolvent. They were holding about one-third of pre-crisis banking assets **(NBU, 2017a)**.

In 2015-2016, the NBU conducted a diagnostic study of banks with combined assets of over 98% of total sector's assets, which was performed in two stages. During stage one were examined the top-20 banks (88.5% of total bank assets) while during the second one – the following 40 banks (9.5% of total bank assets). The results of the study discovered inadequate bank reporting of the quality of the loan portfolio and failure to recognize credit risks **(NBU, 2016b)**.

According to the first round of diagnostic of top-20 banks (asset quality review and stress testing), the share of loans that fall into categories 4 and 5 (default loans and those with a probability of default exceeding 50%) went up from 27% as claimed by the banks before AQR, to 53% **(NBU, 2016a)**. The same exercise on the following 40 banks revealed that the real share of non-performing loans is 43% instead of 19% reported by the examined banks. The NBU forced banks to reflect the real quality of their portfolio uncovered during the diagnostic study and provision the toxic assets. That led to record losses of the banking sector that amounted to almost 160 UAH bn **(NBU, 2016b)**. The return on bank equity (ROE) in 2016 amounted to -116.7% *(Figure 2)*.

Additional provisioning and the related losses of the top-20 banks worsened the sector's capitalization in 2016 (*Figures 3 and 4*). It began to recover towards the end of the year, but in 2017 the sector's capital adequacy fell slightly again, as the next 40 banks brought their provisions in line with the diagnostic's findings. According to the **(NBU, 2017a)**, the total cost of banking crisis was estimated at 38% of GDP (with the cost of nationalization and subsequent recapitalization of Privatbank[4] equaling 4.8% of GDP).

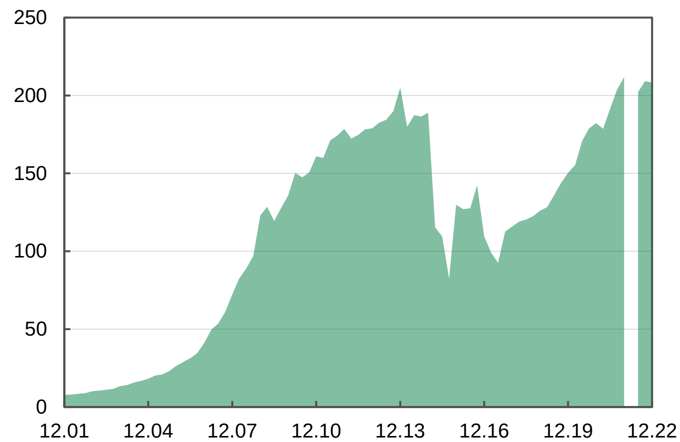


Figure 3. Total regulatory capital, UAH bn

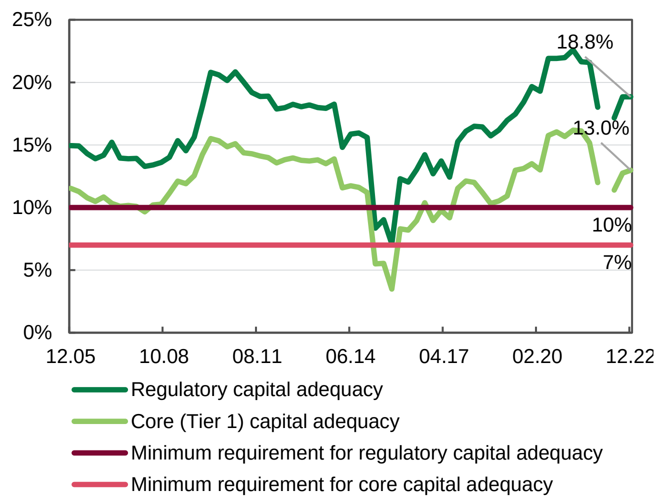


Figure 4. Regulatory and Core (Tier 1) capital adequacy

The data on banks, solvent as of January 2023. No data available in the 1st quarter of 2022.
Source: data from official website of the NBU.

Another episode of stress for the banking system is the crisis, provoked by the Russia's full-scale war on Ukraine. In 2021, on the eve of the full-scale invasion, the capital adequacy of the banking system exceeded the minimum requirements. However, the level of capitalization started falling towards the end of year due to rising risk weights, increased as a part of restrictive macroprudential policy of the regulator. This, in turn increased the risk-weighted assets. The capital adequacy of Ukrainian banks was sufficient to withstand stricter capital requirements that were planned to be introduced in 2022-2024. Specifically, the NBU planned to oblige banks to cover 100% of the estimated operational risk with capital rather than 50% required previously. Also, the risk weight for FX domestic government debt securities was expected to increase from 50% to 100%. Additionally, the NBU planned to fully phase-in the capital conservation buffers and systemic importance buffers by January 2024. **(NBU, 2021b)**. All those plans were postponed due to the war.

As of December 2022, most Ukrainian banks maintained sufficient capital adequacy with several banks having increased their capital during the year of full-scale war. This can be explained by significant capital cushions prior

[4] The shareholders of the biggest private-owned bank, Privatbank, following the findings of the asset quality review and stress testing of the bank failed to increase the bank's capital and restructure related party loans. It was decided to nationalise and recapitalise the bank to protect financial stability.

to the invasion and high profitability of the banking sector helped by the environment of high interest rates. **(NBU, 2022b)**.

Methodology

The research is based on the methodology described in the *Lang & Forletta paper*. The framework relies on two general methods.

The first method is to use linear local projections that will let us study the average impact of the cyclical systemic risk on the bank profitability. This method relies on a model that projects the bank-level ROA on the chosen dataset, which includes bank-specific factors, fixed effects, and a measure of cyclical systemic risk, as follows:

$$\pi_{i,t+h} = \rho^h \pi_{i,t} + \theta^h CSRI_t + \alpha^h X'_{i,t} + \beta^h Y'_t + \gamma_i^h + \varepsilon_{i,t+h} \,, \tag{1}$$

$\pi_{i,t+h}$ is a dependent variable, a bank-level ROA, for bank *i*, in time *t+h*. $CSRI_t$ is a cyclical systemic risk indicator. $X'_{i,t}$ and Y'_t are the bank and macro-level control variables, respectively. γ_i^h is for bank-level individual fixed effects. The dependent variable in this model is employed with a lead of $t + h$, while all right-hand-side variables are in period t to capture the forward-looking nature of this research. Within this method we use the standard fixed effects estimator to control for individual fixed effects with FCI as a shock variable and groups of control variables, described in the following section.

The second method is based on the original Growth-at-Risk approach, which is based on quantile local projections that assess the impact of cyclical systemic risk on the tails of the future bank-level profitability distribution. It is employed based on the same dataset, as depicted in the equation (1):

$$Q\pi_{i,t+h}|\Omega_{i,t}(\tau|\Omega_{i,t}) = \rho^{h,\tau}\pi_{i,t} + \theta^{h,\tau}CSRI_t + \alpha^{h,\tau}X'_{i,t} + \beta^{h,\tau}Y'_t + \gamma_i^{h,\tau} \text{, where} \tag{2}$$

τ stands for the conditional quantile of the ROA distribution. Within this method we utilize quantile local projections on panel data, controlling for individual fixed effects.

The estimates obtained in the previous steps will enable us to assess the “Bank capital-at-risk” indicator. To achieve this, the following equation will be used:

$$BCAR_{t+h} = \sum_{i=1}^{N} Q_{\pi_{i,t+h}|\Omega_{i,t}}(5\%|\Omega_{i,t}) \frac{1}{rw_{i,t}} \frac{a_{i,t}}{\sum_{k=1}^{N} a_{k,t}} \text{, where} \tag{3}$$

$rw_{i,t}$ is the average risk-weight of bank *i* at time *t* and $a_{i,t}$ are the total assets of a given bank.

Additionally, we estimate “Share of vulnerable banks” using the following equation:

$$SVB_{t+h}^{\bar{l}} = \sum_{i=1}^{N} \frac{a_{i,t}}{\sum_{k=1}^{N} a_{k,t}} 1_{Q_{\pi_{i,t+h}|\Omega_{i,t}}(5\%|\Omega_{i,t})<\bar{l}} \text{, where} \tag{4}$$

$1_{Q_{\pi_{i,t+h}|\Omega_{i,t}}(5\%|\Omega_{i,t})<\bar{l}}$ is an indicator function that can take value of 1 when the conditional 5-th percentile value of h-quarters ahead conditional ROA distribution is less than the threshold $\bar{l}$ and zero otherwise.

Data

Unlike the original “at-risk” framework, which estimates the impact of financial conditions on the tails of the future economic growth, using macro data, this research is based on bank-level microdata. This should considerably enhance the ability to identify the impact of cyclical systemic risk on bank profitability, due to the availability of a large cross-section of banks. All microdata used in this research is available on a quarterly basis from Q1 2001. Table 1 below lists the preliminary set of variables employed in this research, which is consistent with the dataset proposed by **Lang and Forletta (2020)**.

Table 1. The preliminary set of variables

Category	Variable	Start from
Dependent variable	Pre-tax return on assets ratio for Ukrainian banks (bank-level microdata)	Q1 2001
Main covariate	Financial Cycle Index for Ukraine	Q1 2001
Bank-specific variables	Loan loss provisions / Total gross assets (%)	Q1 2001
	Cost-to-Income (%)	Q1 2001
	Net Interest Margin (%)	Q1 2001
	Capital Adequacy Ratio (N2) (%)	Q1 2001
Banking sector variables	Bank loans to private sector to GDP ratio (%)	Q1 2001
	Herfindahl–Hirschman index for market based on total assets	Q1 2001
Macro-financial variables	House price growth on the secondary residential real estate market, y-o-y (%)	Q1 2001
	Price-to-rent ratio for housing market in Kyiv city	Q1 2003
	Real GDP growth, y-o-y (%)	Q1 2001
	Inflation y-o-y (%)	Q1 2001
	Change in UAH/USD exchange rate (%)	Q1 2001
	Current account balance (inversed sign) to GDP ratio (%)	Q1 2001
	Interest rate on non-collaterized loans to households (%)	Q1 2003
	Interest rate on loans to corporates (%)	Q1 2003

Source: developed by authors, based on Lang and Forletta (2020).

We obtained the necessary microdata for all Ukrainian banks that operated during the period of observation from 2001 to 2023, on a quarterly basis. However, the number of banks, as shown in *Figure 1*, is not a constant number: within a given period, some banks can enter the market, while others may exit it. This produces two problems that one must deal with when working with the full sample. Firstly, the panel data will be unbalanced and working with some statistical packages may be complicated, due to the NA's produced by the changes in number of active banks. Secondly, newly established banks, as well as banks, approaching the gone concern state are likely to produce outliers, as demonstrated in *Figure 5*.

Additionally, financial data for banks that left the market over the period are not reliable. Most of them misrepresented their financial statements, underestimated credit loss provisions and inflated the value of their assets. These malpractices were identified during the asset quality review in 2015-16 and those banks were forced to leave the market. Inclusion of those banks in the sample would make modelling results highly unreliable. In addition, many banks left the market due to AML/CFT issues, non-transparent ownership structures, so they left the market for reasons not related to their financial strength.

Furthermore, the primary focus of this research is placed on the investigation of system-wide effects that the cyclical systemic risk has on bank profitability and level of capital adequacy. Thus, the episodes of realization of idiosyncratic risk do not fall under the scope of this research. Therefore, for the purpose of this research we decided to proceed with the sample of banks that operated throughout the complete observational period. While the whole sample consisted of microdata from 239 banks (21510 observations in the long format, respectively), the sample of banks contains 43 banks (3526 observations). We also decided to shorten the period of observation for the survivors' sample to 20 years (from Q1 2003 to Q1 2023), in order to include more control variables into regression that do not start before Q1 2003.

Dependent variable. The bank profits affect bank capital via retained earnings / accumulated loss. Thus, significant losses may completely erase the bank's capital. Profitability is the main factor that contributes to changes in bank capital. It is also highly elastic to changes in macro financial environment and thus serves as a link between the stage of financial cycle and solvency of the banking sector. For the purposes of this research, as a measure of banks' profitability we will use the pre-tax return on assets ratio (ROA) for Ukrainian banks. It is convenient to use ROA since it is normalized relatively to the size of a bank, while absolute loss or profit are not informative because sizes of banks differ. ROA[5] time series of the survivors' sample of banks is much less volatile compared to the whole sample and does not exhibit large outliers (*Figure 5*).

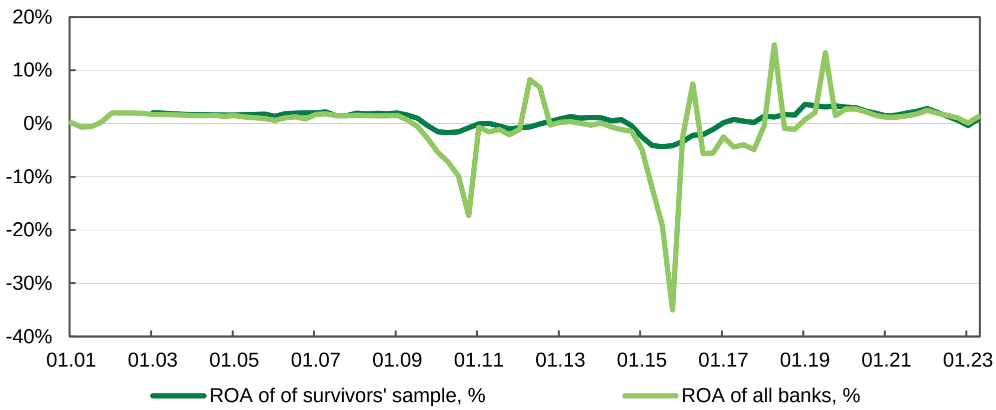


Figure 5. Simple average of return on assets ratio for all banks and for the survivors' sample of banks, %

Given that Ukraine is a small open economy that went through a few episodes of large local currency depreciation during the crises in 2009[6] and 2015[7], it is important to factor in the role of exchange rate movements into the banks' balance sheets dynamics. Moreover, the long-term average share of FX-denominated assets in Ukrainian banks during the period of observation exceeds 40%, which makes the ER-adjustment an important step in data processing. Therefore, we applied the FX-adjustment on the data series on bank assets (including loans), denominated in foreign currency. The adjustment provided us an updated data that exhibits the true movements of banks' assets outstanding and is devoid of any effects due to ER movements only.

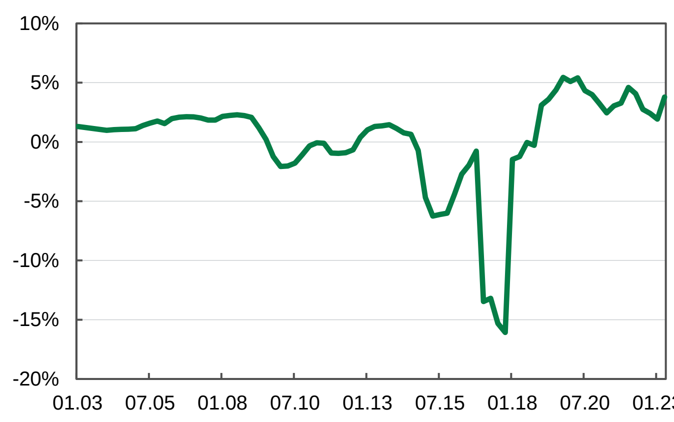


Figure 6. Weighted average of return on assets ratio for banks, included into the survivor' sample, %

Source: the NBU.

Note that the difference between the ROA in this figure and in Figure 5 is due to the difference in the method of averaging: simple average vs the weighted average.

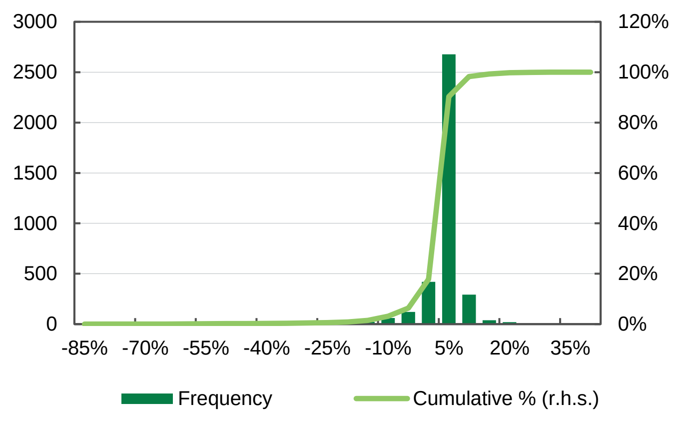


Figure 7. Histogram of return on assets ratio for banks from the survivors' sample

Source: the NBU.

[5] ROA is calculated as follows: Pre-tax rolling sum of the latest 4 quarters of net income of a bank / Rolling average of a bank's net assets over the latest 4 quarters.

6 From 4.85 to 7.70 UAH/USD over Q3:2008-Q1:2009.

7 From 12.58 to 21.12 UAH/USD over Q3:2014-Q1:2015.

Main Covariate. We will use the domestic Financial Cycle Index (FCI) for Ukraine as a time-varying risk measure. It is an integral indicator of a phase of financial cycle, which aims at early warning on the accumulation and materialization of systemic risks. It consists of four sub-indices, which can inform on the build-up of systemic risk, namely: material increase of debt burden in the economy; easing of credit conditions and acceleration of credit growth, ahead of the economic growth; house price bubble build-up; and macroeconomic imbalances. Since the FCI is the arithmetic mean of four sub-indices, the normalized values of which are mostly in the range between minus two and two, its values are mostly within these limits. However, the volatility of the FCI is lower due to the averaging and smoothing of its components and the index itself. The highest historical value of the index observed before the GFC is around one.

The Ukrainian Financial Cycle Index, as demonstrated on *Figure 8*, reached its peak in late 2007 – early 2008, on the eve of GFC and stabilized around 0 since 2018, even during the full-scale war. In 2022-2023, tighter financial conditions, and lower credit demand, as well as a relatively stable and controlled macro financial environment neutralized the growing misbalances on the housing market.

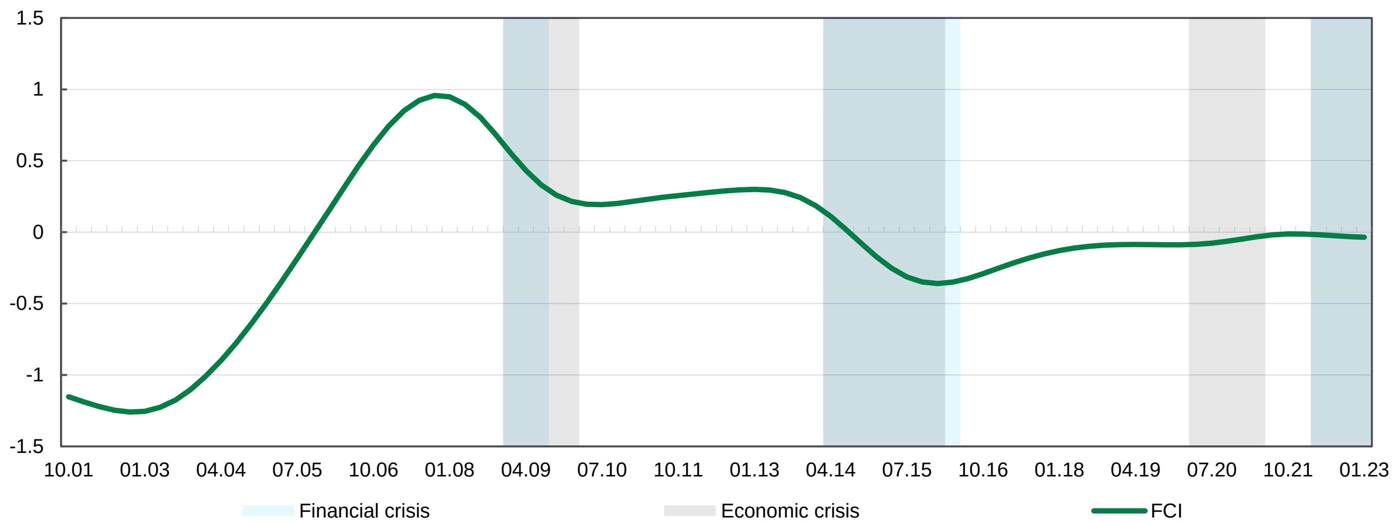


Figure 8. Financial Cycle Index for Ukraine
Source: the NBU.

Another important group of control variables is the banking sector indicators. We use Herfindahl-Hirschman Index based on the assets of banks to measure the sector's concentration and Loans, issued to private sector to GDP ratio (ER-adjusted), as according to the *Lang & Forletta paper*. Both variables are derived from the data on the survivors' sample of banks. The dynamics of the Herfindahl-Hirschman Index (*Figure 9*) shows that the banking sector in Ukraine was never concentrated, with a value 1500 being a cut-off point for the moderate concentration. The ratio of portfolio of loans, issued to private sector GDP (*Figure 10*) grew at a fast pace during the onset of economic crisis of 2008-2009, but returned to its initial values as of Q1 2023. Among the reasons for that – mortgage portfolios that are less than 1% of GDP as of December 2021 **(NBU, 2021b)**.

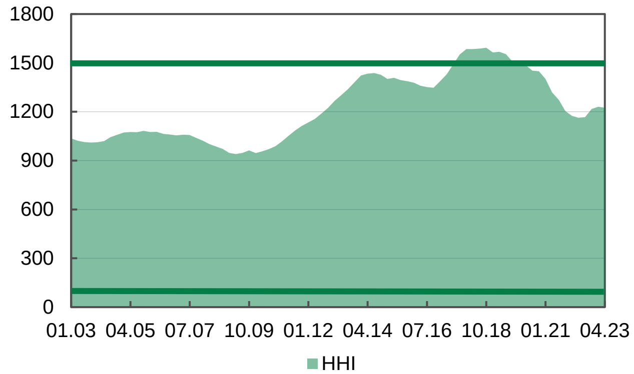


Figure 9. Herfindahl-Hirschman Index for the survivors' sample of banks
Dark green lines on the graph represent the boundaries of the ranges that indicate the highly competitive industry (below 100) and unconcentrated industry (between 100 and 1500).
Source: the NBU.

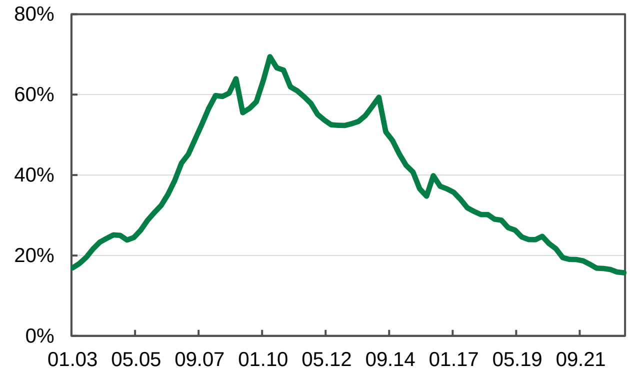


Figure 10. Net loans, issued to private sector to GDP ratio (ER-adjusted) for the survivors' sample of banks

In order to transform the profit-based indicator into a measure of bank capital we employ the method proposed in the *Lang & Forletta paper*. Thus, we divide the 5th percentiles of the conditional bank level ROA distributions by the asset-weighted risk weights as of 1Q 2023 for banks from the survivors' sample. This is done in order to rescale results into units of bank capital adequacy. According to *Figure 11*, most of the observations of the weighted average of risk weights lie around the 40% basket.

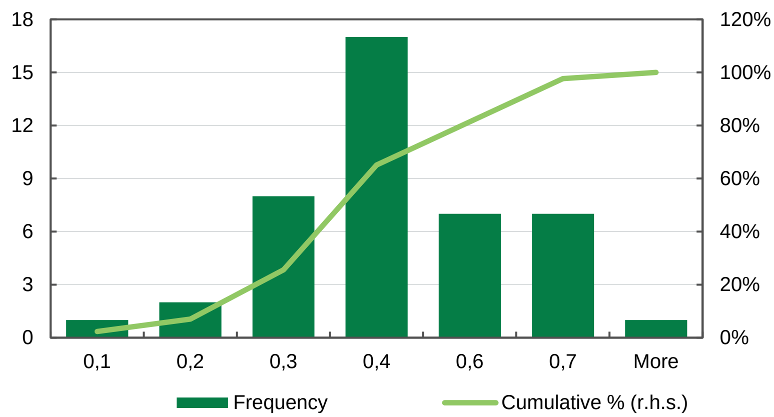


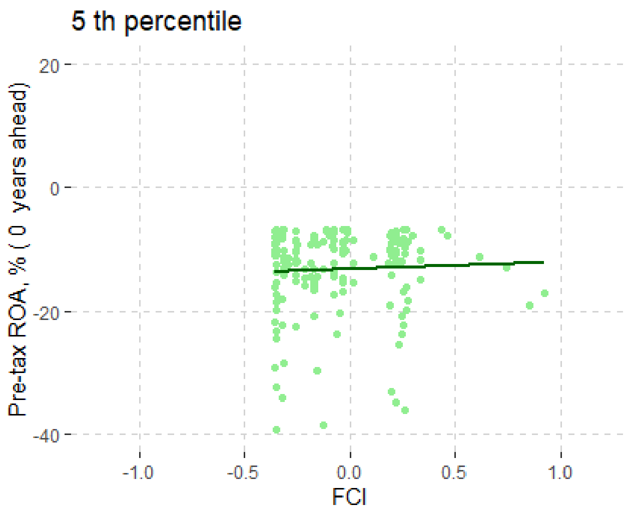
Figure 11. Histogram of asset-weighted risk weights as of 1Q 2023 for banks from the survivors' sample
Source: the NBU.

Results

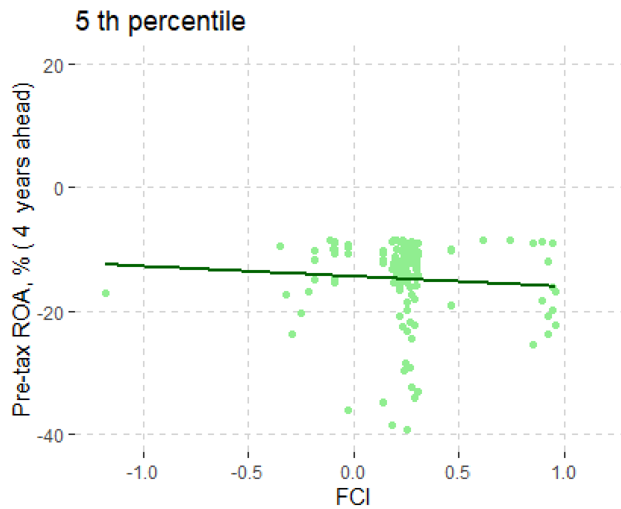
Linear local projections.

We start our investigation by checking whether our FCI can explain movements in the future ROA on different horizons and for different percentiles of ROA. According to *Figure 12*, the relation between the bank profitability and FCI highly depends on the number of lags and percentile of the pre-tax ROA. The relations between ROA and FCI for the lowest percentiles even change the sign when going from a no-lag (both ROA and FCI at time t) to a 4-year lag (ROA at time $t+4$ years and FCI at time t).

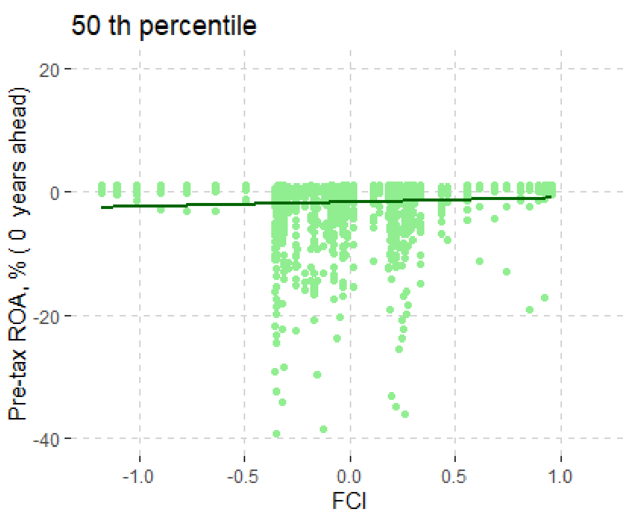
The same conclusion applies for other percentiles of interest: 50th and 95th. However, on this stage of research we can already notice that the magnitude of the relations between bank profitability and indicator of cyclical systemic risk significantly depend on the part of distribution. Thus, the relation between these two variables of interest is the strongest for the lower left tail of the distribution (the lowest values of bank profitability), and relatively weaker for the median and the right tail of the distribution (the highest values of bank profitability). This conclusion affirms the choice of the main method (quantile local projections), which investigates the relations between our variables of interest for different quantiles and multiple horizons.



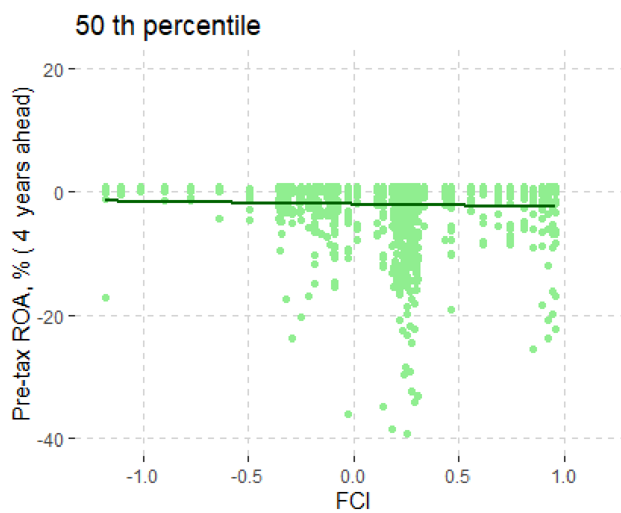
Panel A



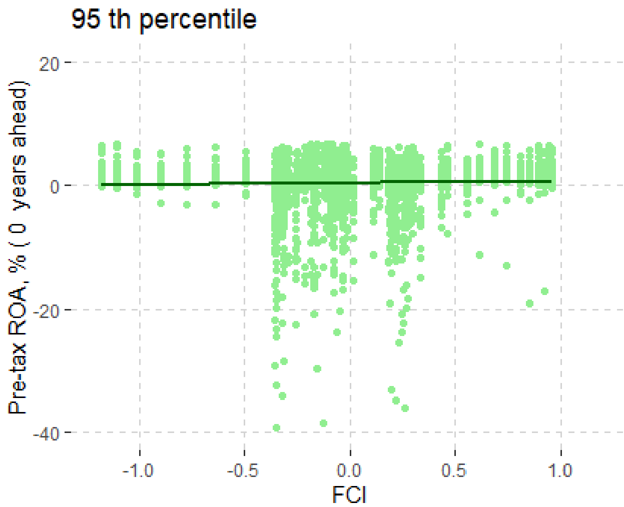
Panel B



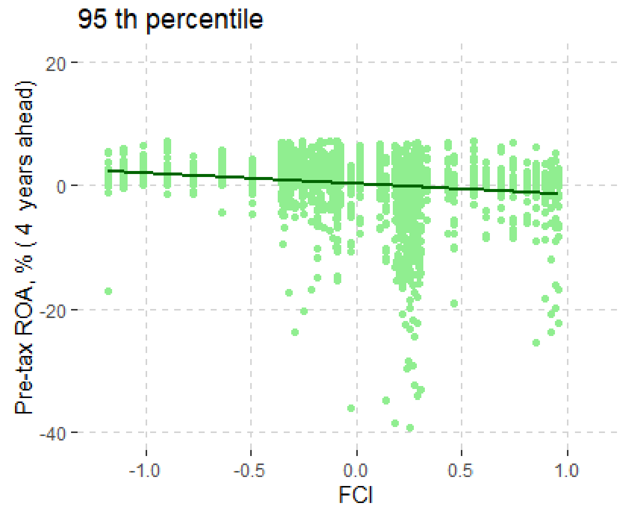
Panel C



Panel D



Panel E



Panel F

Figure 12. Histogram of asset-weighted risk weights as of 1Q 2023 for banks from the survivors' sample

Source: the NBU, authors' calculations.

The charts, displayed on panels A-F, show the relation between the FCI at time *t* and bank-level pre-tax ROA at time t = 0 and 4 (no lag and 4 years ahead, respectively) for different percentiles of ROA: 5th, 50th and 95th. The dark-green lines are the fitted linear regression lines for ROA ~ FCI.

When dealing with a large number of variables, one of the biggest problems that can create obstacles or unreliable results is multicollinearity. Therefore, prior to moving to the main stage of this research, which is the estimation of linear and quantile local projections, we decided to work with our control macro-level variables and reduce the dimensionality of this partition. To achieve this, we employed the principal component analysis. We created a new variable, which contains around one third of the variation of the entire original set of macro financial variables. The biggest contribution to the dimensions according to *Figure 13* stems from exchange rate growth, real GDP growth and inflation.

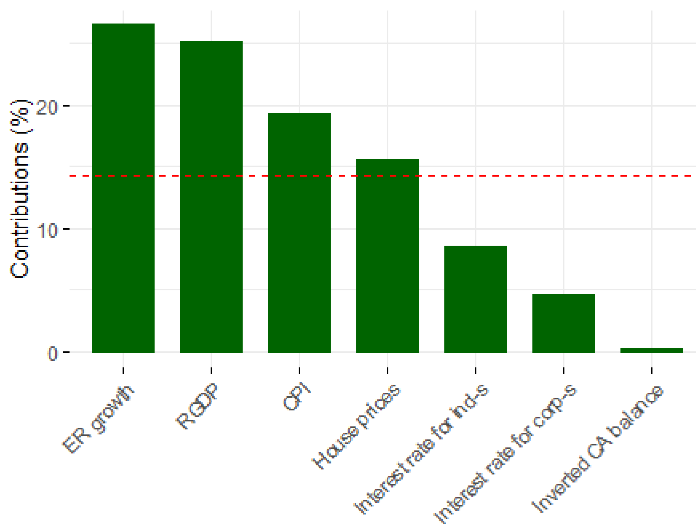


Figure 13. Contribution of macro financial variables to new dimension using the PCA method

Source: authors' calculations.

After tests for multicollinearity and linear codependence issues using both the linear and quantile local projections, the best fit turned out to be the baseline specification of the following form:

$$ROA_{t+h,i} = FCI_t + \text{LLP to gross assets}_{t,i} + NIM_{t,i} + CIR_{t,i} + CAR_{t,i} + Loans\ to\ GDP_t + HHI_t + Macro1_t \qquad (5)$$

Now we proceed to the estimation of the impulse responses of ROA with a shock placed on the FCI variable using the linear local projections.

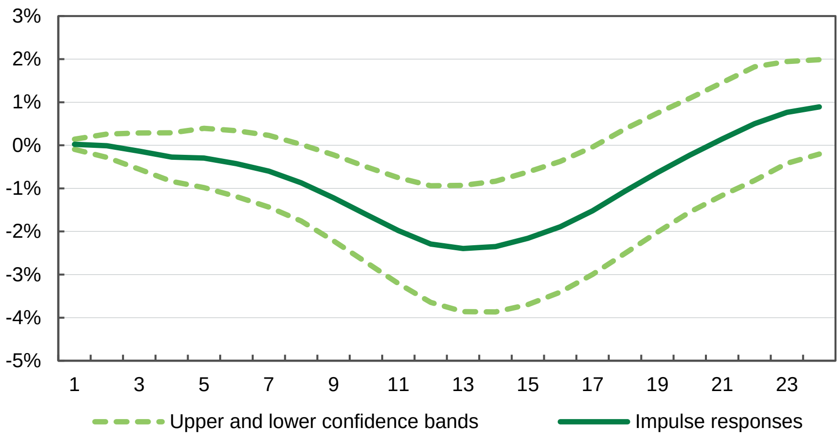


Figure 14. Impulse responses of ROA to a unit shock in FCI controlling for macro financial, banking sector and bank specific variables

Source: developed by authors.

The confidence bands of the responses are based on robust standard errors, clustered on the individual level. On the horizontal axis are depicted quarters after the shock.

According to *Figure 14*, rising values of accumulated cyclical systemic risk lead on average to a large and long-lasting drop in the pre-tax ROA of banks between two to five years ahead. A one-unit increase in FCI leads to an average drop of 0.9%, 2.3%, 1.9%, 0.2%, and 0.9% increase in pre-tax ROA two to six years ahead. This proves that bank profitability is greatly dependent on the cyclical systemic risk given that the average value of pre-tax ROA in a sample is 0.8%. The regression output shows us that the shock variable, which is an indicator of cyclical systemic risk, is highly significant (p-value lower than 5%) on horizons from nine to sixteen quarters ahead. The highest level of significance is recorded for the 12th quarter, while the highest value (biggest drop) of impulse response is recorded for the 13th quarter.

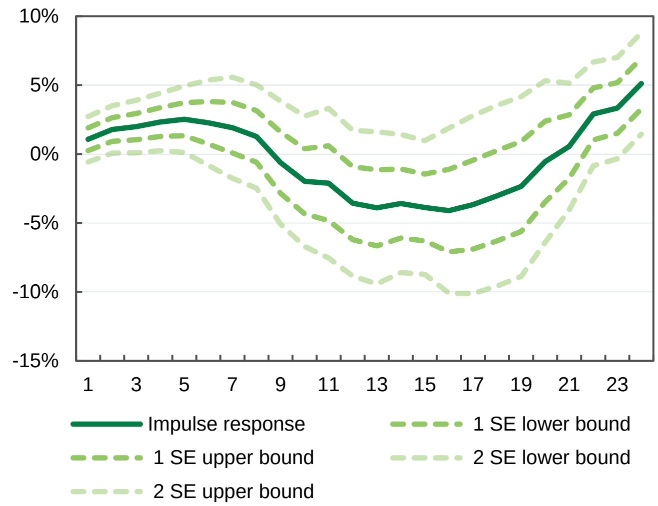
Table 2. Summary statistics for the shock variable (FCI) estimated using local linear projections on different horizons

Horizon	Estimate	Std. error	t-statistic	p-value
1	0,000	0,00	0,34	0,73
2	0,000	0,00	-0,06	0,95
3	-0,001	0,00	-0,54	0,59
4	-0,003	0,00	-0,81	0,42
5	-0,003	0,00	-0,72	0,47
6	-0,004	0,00	-0,93	0,35
7	-0,006	0,00	-1,21	0,23
8	-0,009	0,01	-1,63	0,10
9	**-0,012**	**0,01**	**-2,04**	**0,04**
10	**-0,016**	**0,01**	**-2,41**	**0,02**

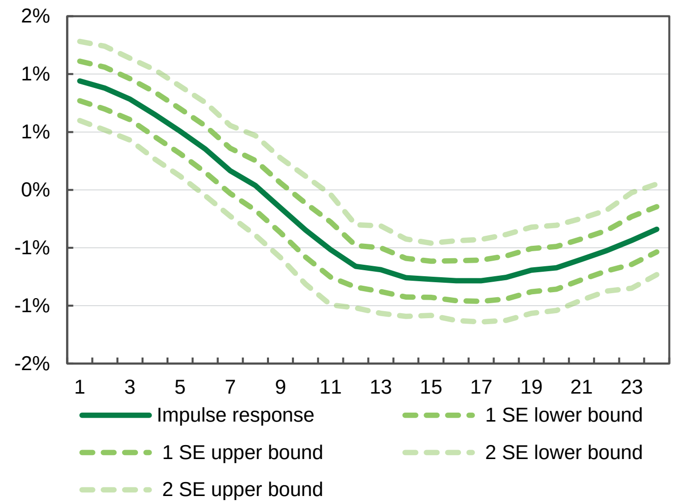
11	**-0,020**	**0,01**	**-2,70**	**0,01**
12	**-0,023**	**0,01**	**-2,83**	**0,00**
13	**-0,024**	**0,01**	**-2,73**	**0,01**
14	**-0,023**	**0,01**	**-2,59**	**0,01**
15	**-0,022**	**0,01**	**-2,34**	**0,02**
16	**-0,019**	**0,01**	**-2,08**	**0,04**
17	-0,015	0,01	-1,72	0,09
18	-0,011	0,01	-1,23	0,22
19	-0,006	0,01	-0,77	0,44
20	-0,002	0,01	-0,29	0,77
21	0,001	0,01	0,19	0,85
22	0,005	0,01	0,64	0,52
23	0,008	0,01	1,08	0,28
24	0,009	0,01	1,36	0,17

Quantile local projections.

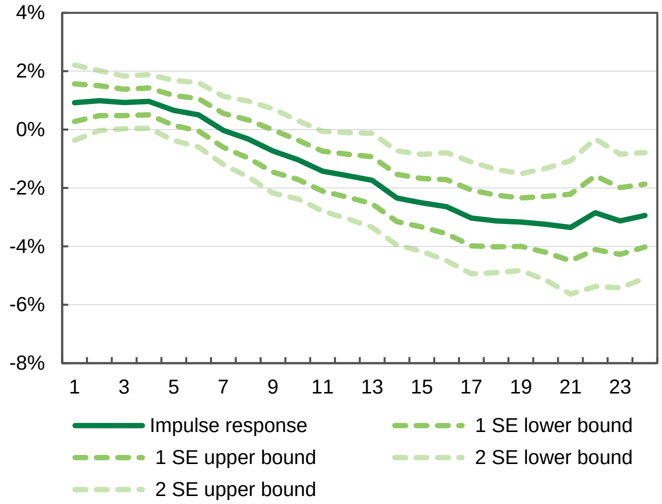
As a next step of this research, we estimated the impulse responses of the bank-level pre-tax ROA to a one unit increase in the FCI using the quantile local projections method. According to *Figure 15*, bank profitability responds to increased cyclical systemic stress with a shift downwards across all parts of the distribution. However, the magnitude is the largest for the lower left tail of the distribution (5^{th} percentile), especially when compared to the impact on the median (50^{th} percentile). Thus, the impact of a one-unit increase in the FCI on the median pre-tax ROA is negative from the 9^{th} quarter onwards and ranges from -0.2 to -0.8 percentage points. Meanwhile, the impulse responses for the 5^{th}-percentile ROA are of much larger magnitude (-0.5 to -4.1 percentage points). In addition, it leaves and enters the negative zone more abruptly. This proves the considerable heterogeneity in the impact of cyclical systemic risk on future bank profitability quantiles, which reaffirms us that there is an added value of running the quantile local projections compared to the linear ones.



Panel A. 5^{th} percentile



Panel B. 50^{th} percentile



Panel C. 95th percentile

Figure 15. Impulse responses of ROA to a unit shock in FCI controlling for macro financial, banking sector and bank specific variables estimated using the quantile local projections
Source: developed by authors.

The standard errors are estimated using the generalized bootstrap of **Bose and Chatterjee (2003)** with unit exponential weights sampled for each individual rather than each observation.

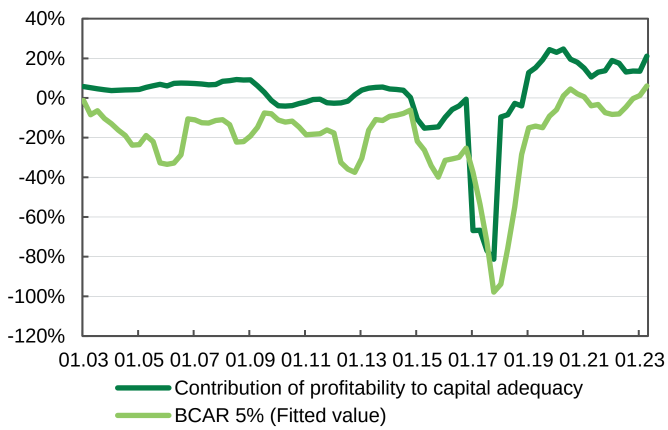
Application of the framework for the macroprudential policy.

The results obtained within the course of this research can enhance the macroprudential toolkit on two levels. The first one allows us to complement the toolkit of systemic risk analysis and can benefit the communication cycle of the NBU. The second level suggests an improvement to the process of calibration of the countercyclical capital buffer due to the forward-looking perspective of this framework.

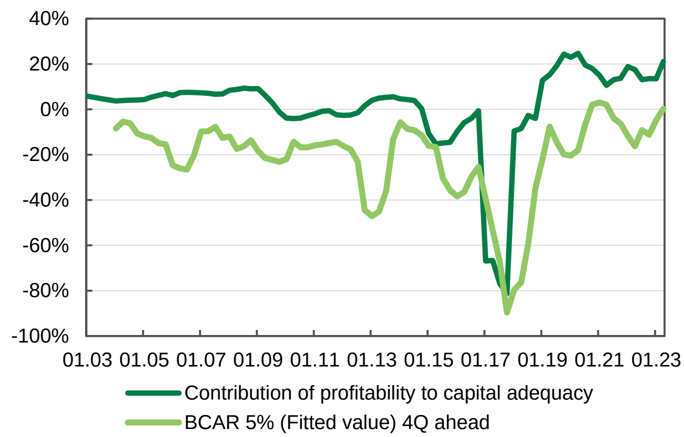
Complementing the systemic risk analysis toolkit.

Using the empirical results of this research, we can develop two indicators of stability of banking sector, namely the "Bank Capital-at-Risk" and "Share of vulnerable banks", the methodology of calculation of which is described in the previous sections.

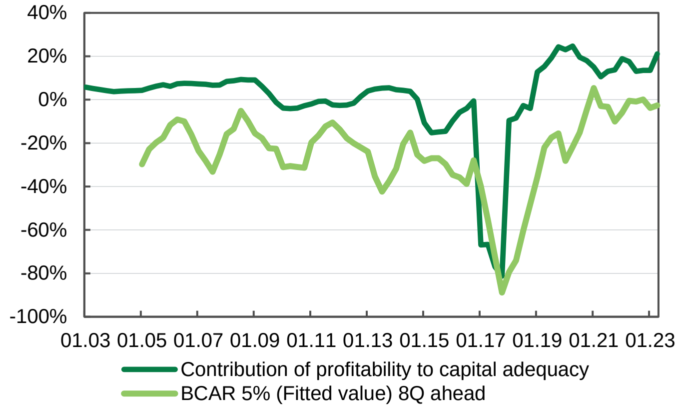
On the *Figure 16*, we show the "Bank Capital-at-Risk" (BCAR) indicator, constructed for different lags of $ROA_{t+h,i}$.



Panel A. 0 quarters ahead



Panel B. 4 quarters ahead



Panel C. 8 quarters ahead

Figure 16. Aggregate "Bank Capital-at-Risk" with a different lead horizons of ROA

Source: developed by authors.

The light green line is the fitted bank-level ROA quantiles with a lead-time of $ROA_{t+0,i}$, $ROA_{t+4,i}$ and $ROA_{t+8,i}$. To obtain the BCAR we first divided the fitted 5th percentile ROA values by the average risk weight and then weighed them by the bank-level asset share.
The dark green line is contribution of profitability to capital adequacy for the banks, calculated on the original data.

Figure 16 shows that the values of BCAR, calculated on the fitted fifth percentile values are overall significantly lower than the level of contribution of profitability to capital adequacy, calculated on the original data. As the forecasting horizon of BCAR increase (lead time of the $ROA_{t+h,i}$expands), the fitted line start showing more adverse (in terms of negative and falling profitability) results as compared to shorter horizons. Therefore, as the horizon increases, the magnitude of the predicted downfall goes down. However, the predicted results become more accurate for the actual episodes of stress in the banking sector. For example, the minimum value of BCAR on panel A is -98%, recorded for the end of Q3 2017, on panel B is -90% and on panel C is -89%. The obtained values are accurate in timing and scale compared to the actual level of contribution of profitability to capital adequacy, which was a bit over 80% at the time.

This figure also demonstrates the way that the forward-looking property of this indicator works. For instance, on panel C, the minimum value of BCAR plotted for the end of Q3 2017 is the predicted value for Q3 2017, conditional on the dataset as of end Q3 2015.

On the *Figure 17*, we demonstrate the estimated "Share of vulnerable banks" indicator (SVB) for different thresholds with a two-year lead (fitted values of $ROA_{t+8,i}$).

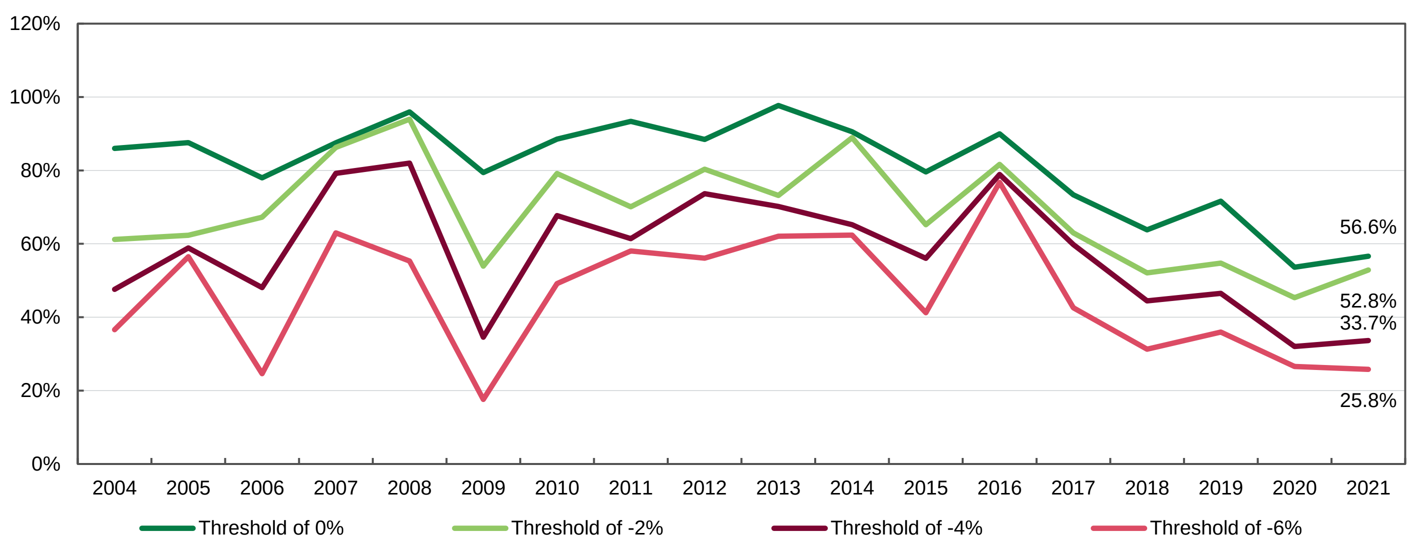


Figure 17. "Share of vulnerable banks" for different thresholds

Source: developed by authors.

The lines represent the shares of banks whose estimated conditional 5th percentile ROA over the next 8 quarters will fall below a threshold of 0%, 2%, 4% and 6%. The values plotted for 2021 are the predicted SVBs for year 2023, conditional on information available in 2021.

We decided to set the thresholds based on the level of consequences that the respective downfall of profitability will trigger. In order to do this, we need to account for the current level of capital adequacy in the banking system, its minimum required level and the current value of risk-weight density. As of September 2023, the system-wide level of bank capital adequacy for Ukraine amounted to 24.9% with the minimum required level set to be 10%. The risk-weight density as of April 2023 was 41%. Considering the method, we previously used to transform the bank profitability into units of bank capital adequacy, we set the following four thresholds: 0%, -2%, -4% and -6% of the pre-tax ROA downfall. 0% downfall simply indicates the risk of the bank experiencing losses. -2% converts to nearly 5% loss of capital adequacy, which is not critical, given the current level of capitalization of the system; however, is a reason to start monitoring the bank more closely. In turn, -4% converts to approximately -10% loss of capital adequacy, which makes the average bank more vulnerable, but still fully capitalized. However, a 6% fall of the pre-tax ROA would make an average bank in the current state of the system breach the capital adequacy requirements.

According to the figure, the highest values of SVB recorded for the years 2008 and 2013, which, considering the horizon, are estimated values for years 2010 and 2015. The predicted values for 2023 were among the historical lows; however, they increased somehow on a yearly basis. The values for the thresholds of 0%, -2%, -4% and -6% were the following: 56.6%, 52.8%, 33.7% and 25.8%, respectively. Thus, the share of the vulnerable banks that could breach the capital adequacy requirements and risk becoming insolvent in 2023, estimated on the 2021 data, amounted to 25.8%. It is worth nothing that the SVB is highly non-linear in its response to the thresholds set. Even though the thresholds are set in equal steps (meaning that each subsequent is 2% less than previous), the SVB for the 4% and 6% thresholds are significantly lower than the values obtained for 0% and 2% thresholds. One explanation can be that when experiencing losses of 4 to 6% of its assets, the bank reaches the vulnerability zone, that can be distinguished from other cases of underperformance, being at risk of becoming undercapitalized and, in subsequent periods, insolvent.

Enhancing the calibration of CCyB.

The current approach to calibrate the buffer is based on the level of FCI. We believe that the approach proposed in the *Lang & Forletta paper* will give the regulator a longer lead-time, compared to the calibration guidance based on the credit-to-GDP gap and thus allow the financial institutions that are to form this buffer more time to introduce necessary changes and smoothly adapt to new capital requirements.

The linear calibration rule as proposed in *the Lang & Forletta* paper is as follows:

$$CCyB_t = \max\left\{\frac{\sum_{h=2}^{4} -\theta^h}{\overline{rw}} * FCI_t, 0\right\}, \textit{where} \tag{6}$$

in the numerator of the expression, by which the level of FCI at time t is multiplied, we feature the sum of the linear local projection coefficients, produced for the 12th and 16th quarter (3rd and 4th years, respectively). The reasoning for choosing these horizons is the following. The largest impact of FCI on ROA was recorded for the third year. It makes it the year when the cyclical systemic risk accumulated at point t_0 leads to the largest revenue and capital adequacy losses for the banking system. However, this will not be a short-lived shock, on the contrary, it will last for another year, causing further depletion of solvency of the banks. Thus, it is reasonable to calculate the level of cumulative depletion of capital adequacy of the banks, adding up the largest impulse responses, which are also statistically significant. In our case, these are the coefficients for the 12th and 16th quarter, the cumulative effect of which is -4.2%, according to *Table 2*. This is of large value compared to the results obtained by *Lang & Forletta*. However, our results are justified by the historically very low values of bank profitability during the quite frequent stress episodes and crises in Ukraine.

In the denominator of this expression, we use the average risk-weight $\overline{rw}$ to translate the impact measured in units of bank profitability into the impact measured in units of bank capital. The value of average risk weights as of end of first quarter of 2023 is 41%. Thus, the rule implies that the buffer should increase by around 10 percentage points for each unit increase in FCI. According to *Figure 8*, the FCI in Ukraine was never even close to one since the GFC. On contrary, it was negative since late 2014.

Conclusions

In this research, we managed to estimate the impact of cyclical systemic risk on bank profitability for the Ukrainian banking sector. To achieve this goal, we singled out a sample of 43 banks that operated throughout the period of observation, which amounts to 21 years: 2003 to 2023. We estimated both the median impact and on both right and left tails of the profitability distribution using the linear and quantile local projections.

The obtained results suggest that elevated cyclical systemic risk leads on average to a large and long-lasting drop in the pre-tax ROA of banks between two to five years ahead. A one-unit increase in FCI leads to an average drop of between 0.2% – 2.3% in pre-tax ROA two to five years ahead. Meanwhile, the impulse responses for the lower left tail of ROA distribution (5^{th} percentile) are of much larger magnitude (-0.5 to -4.1 percentage points). In addition, it leaves and enters the negative zone more abruptly. Thus, we managed to prove the considerable heterogeneity in the impact of cyclical systemic risk on future bank profitability quantiles. Additionally, this reaffirms to us that there is a benefit of running the quantile local projections compared to the linear ones.

Additionally, this work can be applied in a few ways: by enhancing the macroprudential toolkit for calibration of capital buffers and by complementing the set of systemic risk indicators. Thus, we constructed a rule for calibration of CCyB that allows the regulator to have a forward-looking perspective and implement the buffers with a longer lead-time. We also constructed two new indicators of stability of banking sector, namely “Bank Capital-at-Risk” and “Share of vulnerable banks”. These two indicators can benefit the NBU by providing relatively high-frequent estimates that are quite similar in nature to the ones provided by stress-test results. These estimates can be potentially used in the communicational cycle, particularly in the NBU's Financial Stability Report, to communicate the risks to the banks’ solvency to the public more efficiently.

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