OPERATIONALIZING THE COUNTER CYCLICAL CAPITAL BUFFER IN UKRAINE BASED ON EARLY WARNING MODELS

by

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Kyiv School of Economics

Abstract

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This paper is devoted to answering the question of which early warning indicator has the highest predictive power for systemic crisis, and what the optimal thresholds are to activate the countercyclical capital buffer (CCB) accumulation. Our dataset is an unbalanced panel of commercial bank balance sheets, macro, and credit-related variables for the period from 2009Q1 to 2019Q3. A classical early warning model (EWM) based on probit regression produced insignificant results for 50 different specifications, so we proposed an alternative approach in the form of a financial cycle indicator (FCI), which we then used to calibrate the CCB and discussed why our EWM models did not work.

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Chapter 1

INTRODUCTION

The economic and financial crisis of 2007-2008 strongly damaged the world's economy. Ukrainian financial and real sectors were influenced too. Besides hitting the exports, financial and capital accounts, the banking sector was also affected. Deposit outflows, increased amount of non-performing loans, obligation redemptions, and most of all "bubble" on the real estate market created illiquidity problems that drastically deepened the crisis (Burakovsky and Betliy 2009). Another crisis that occurred in Ukraine in 2014-2015 badly damaged banking sector once again. The war with Russia, Crimea peninsula annexation, market losses, and hryvnia devaluation were among the causes of the crisis.

The banks that the NBU liquidated during the crisis issued loans to the companies without operating activities because of the abuse of the owners.[1] Hence, in 2015 NBU started performing stress testing and slowly introduced new capital requirements, in particular, started implementing the Basel III, which is a package of the reforms including capital buffers developed by Basel Committee on Banking Supervision (BCBS), devoted to improving regulation, supervision and risk management in the banking system in response to the world crisis in 2007. Besides, the NBU introduced new liquidity ratios, loan-to-value ratio (LTV), debt-service-to-income ratio (DSTI), debt-to-income ratio (DTI) and capital buffers: countercyclical

1 According to the NBU, company Kroll performed an investigation for NBU which revealed the following: "PrivatBank, the largest bank in Ukraine, was subjected to a large scale and coordinated fraud over at least ten years ending December 2016, which resulted in the Bank suffering a loss of at least USD 5.5 billion" (NBU 2018).

capital buffer (CCB), capital buffer for systemically important banks (SIB) and Systemic risk buffer (SRB) and concentration buffer (NBU 2015). Besides, the world crisis in 2007 was the reason for revising Basel II and creating the Basel III framework by Bank for International Settlements (BIS).

According to the Basel Committee on Banking Supervision (2010), the main goal of setting CCB is to protect the banking sector from excessive aggregate credit growth associated with broad systemic risk. Activities aimed at protecting the banking sector mean that not just an individual bank accumulates minimum capital requirements but all banking system as a whole– building it up in a period of rapid growth and releasing it to be solvent in the period of stress. This is sometimes pointed out as the principle of "leaning against the wind" or"bad loans are provided in good times". For this purpose, the BCBS recommends accumulating additional cushion of risk-weighted assets in a range of 0% to 2.5% of capital adequacy ratio (CAR), namely CCB.

Identifying the periods of excessive growth of debt is not an easy task. According to the Basel III framework and its transposition to the Credit Requirements Directive (CRD) IV, counter-cyclical capital buffer should be built when the credit-to-GDP ratio deviates from its long-term trend, i.e. when the credit-to-GDP gap becomes positive[2].

2 BCBS stated that national authority could take credit-to-GDP ratio, calculate the trend with help of Hodrick-Prescott (HP) filter with lambda equals 400 000, find a credit-to-GDP gap taking the difference between the indicator and the trend and, finally, use gaps as a guide for buffer add-on. “The Hodrick-Prescott filter is a standard mathematical tool used in macroeconomics to establish the trend of a variable over time.” (BIS 2010)

Drehmann, Borio and Kostas (2011) analyzed different indicators and thresholds signaling when to activate CCB and concluded that the credit-to-GDP gap is the most accurate in signaling good or bad times for the banking system in the long-term, capturing excessive credit growth, which is, basically, the main vulnerability for the system. However, Plašil, et al. (2013) and Rychtárik (2014) analyzed this indicator and found that it does not apply to the Chech Republic and the Slovak Republic respectively. In these small open economies, the credit-to-GDP gap was mostly driven by changes in GDP but not lending activity. Moreover, there were structural breaks, for example, the Slovak banking system had a lot of write-offs before 2004 (Plašil, Seidler and Hlaváč 2016) and, basically, the active phase of credit lending, in particular, mortgages expanded in 2003. Structural changes to less than 10 years make it unsuitable for HP filter.

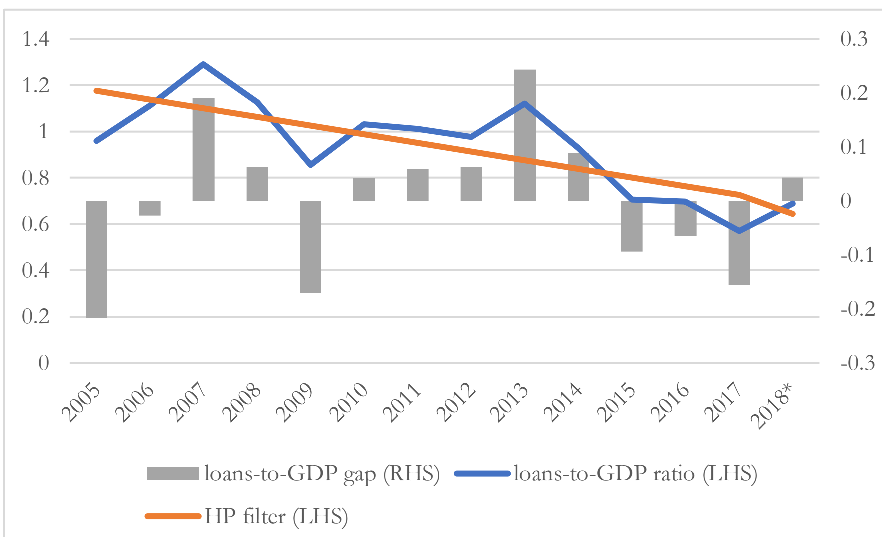

Figure 1. Loans-to-GDP gap in Ukraine

Indeed, this period is characterized by structural changes, in particular, banks were pressured to write a lot of non-performing loans off their balance sheets, which decreased lending significantly and resulted in a downward trend in the loans-to-GDP ratio. At the same time, this should hardly be taken as a signal to ease on bank capital requirements, suggesting that the credit-to-GDP ratio is giving a wrong signal due to noise and therefore it could not be taken as CCB signaling indicator.

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The main question is when to activate CCB. For this purpose, early warning models (EWM) could be a solution. They could help to build a system of indicators to signal about the accumulation of the cyclical systemic risk, in our case, excessive credit growth. Consequently, the research question of this thesis is: **which early warning indicator has the best predicting power for systemic crisis and what are the optimal thresholds to activate the CCB accumulation.**

This paper is devoted to investigating this question and to designing an early warning model for a specific country, in particular, Ukraine. The structure of the paper is the following: in the literature review, we will describe the contribution of the paper and the linkage between CCB and systemic crises in Ukraine. In the methodology section, we will show which models have been used before and the structure of our EWM. In the results section, we will describe the accuracy of the model and the effects of the significant variables. In the 5th chapter, we will describe the problems of our EWM and possible alternative.

C h a p t e r 2

LITERATURE REVIEW

As was mentioned above, the NBU is currently implementing the CCB framework according to its strategy. However, there is no universal recipe on how to calibrate it for all countries. That's why the NBU has to find its way of calibration suitable for the Ukrainian banking system. At the same time, a CCB is a relatively new concept. Earlier papers focused not so much on calibrating CCB, as on the use of early warning models for other purposes. As a result, early warning models were relatively simple when they were first introduced and became much more complex in the end.

In this paper, we adopt rather than challenge the view that a CCB has a positive impact on the economy and society. This allows us to focus on issue of CCB calibration rather than its desirability or economic efficiency. As evidence of the positive impact of CCB, the literature suggests the theoretical framework on DSGE models that helps to analyze the impact of countercyclical buffer and capital adequacy on the real and financial sectors. For example, Clerc, et al. (2015) developed a model using three main participants: banks, entrepreneurs, and consumers, and all of them could default through probability functions (3-D model). The authors proved that the buffer is protecting the economy from shocks and reducing the costs when a crisis occurs.

Among the first authors who started to investigate event distress signaling was Frankel and Rose (1996). They looked at a large sample of developing countries that experienced currency crashes. The authors did not develop specific theories explaining the cause of the distress but examined a variety of vulnerabilities that could lead to potential financial crisis. They applied a probit model to a sample of 105 countries and a period from 1971 to 1992 and found that currency crashes tend to occur when FDI inflows decrease, reserves dry up, domestic credit growth is high, interest rates rise and the real exchange rate is overvalued. Besides using the multivariate probit model, they also developed a framework for identifying vulnerable periods. They were the first to apply sensitivity analysis for the robustness check of the model. On the other hand, they did not perform validation, the goodness of fit and policy application omits country-specific level meaning that while developing an analysis author focused only on the regional level.

Pazarbasioglu and Hardy (1998) built a more precise model as they were estimating the likelihood of bank distress events considering country-specific and regional peculiarities. They analyzed the banking crises in 38 countries during the 1980-1997 period using a multinominal logit model. Besides what has been found by Frankel and Rose (1996), they suggested that bank distress is associated with fall in real GDP growth, high inflation, declining capital-output ratio, and adverse trade shock, but most importantly banking sectors problems may occur without reaching the level of a crisis meaning that a single distress event does not mean a systemic crisis, but, most importantly, the authors suggested that severe banking difficulties are mainly domestic in origin and effect.

One of the first most methodologically complex research was performed by Demirgüç-Kunt and Detragiache (1999). They built an EWM with the help of a multinominal logit model using data on 65 countries during the 1980-1995 period. The novelty of their work lies in the choice of the threshold. In particular, they analyzed the probability of type I and type II errors, the unconditional probability of a crisis, and the decision maker's preferences parameter for taking a preventive action relative to the anticipated banking crisis. They also performed an in-sample and out-sample analysis estimating the predictive power of the model. As a result, two monitoring tools were developed: a particular threshold of the indicator and a bank rating system. At the same time, the authors cautioned that aggregated variables convey information about general economic conditions, while the individual banks or specific segments data might point out to weaknesses that could lead to contagion, but be invisible in the aggregated data.

Before the Basel III framework had been introduced from 2013 to 2015, most of the studies were tackling the same problem - vulnerable states identification from the ex-post perspective, but after its release, they were concentrating on the ex-ante perspective. Their motive has changed significantly because policymakers now considered CCB as an instrument for preventive actions.

Behn, et al. (2013) used univariate and multivariate models to forecast financial crises assessing credit and other macro-financial variables in a sample of 23 EU Member States during the period from 1982Q2 to 2012Q3. For validation purposes, they did an out-of-sample prediction of vulnerable states in Finland and Sweden in the early 1990s, and Italy and the U.K. in the mid-1990s preceding financial crisis in those countries. They found that the loans-to-GDP gap is the best domestic indicator among other credit-related indicators. Moreover, the results showed that more global indicators, i.e. aggregated on a regional level, are outperforming domestic indicators, i.e. aggregated on the local level. However, they also pointed out to the caveat that the evaluation period included the global financial crises but not the episodes of country-specific crises.

Relatively recently Detken, et al. (2014) developed a framework for modeling processes devoted to signaling the problems: a wide range of models analyzing the effects of different indicators The authors noted that in univariate[3] signaling, in the European Union as a whole, the credit-to-GDP gap is the best early warning indicator for the systemic banking crisis associated with excessive credit growth. Moreover, they found that while this indicator performed well for some of the countries, it could have mixed results for others because of their local peculiarities, which this indicator does not account for. Also, the European Systemic Risk Board (ESRB) set apart eastern European countries for which there is a significant lack of data.

The most recent work which I will use as guidance for modeling purposes is Lang and Peltonen (2018). Firstly, the authors created a framework advising how to build EWM that is most accurate in signaling vulnerable states depending on whether you build an explanatory or predictory model. Secondly, they developed a model that is aimed at predicting potential future crises at the micro (using aggregation method) and macro level. A large dataset of EU banks was used to build an EWM to predict bank distress. The model has good out-of-sample and in-sample signaling ability with 11 risk drivers and lead time of 1-8 quarters. For evaluation purposes, they used the loss function approach and cross-validation to find a model specification with optimal for the policymaker, real-time out-of-sample forecasting power. The authors also illustrated how the model's output could assist policymakers by providing EWM visualization.

3 Univariate models are models which have only one variable as an indicator.

The main contribution of this thesis is to develop an instrument for the activation of the CCB for Ukrainian banking system by developing EWM based on the Ukrainian quarterly bank-level data over the period which includes domestic crises, check whether the EWM is accurate enough in predicting a crisis in Ukraine and try an alternative way of calibration. While previous studies focused on the aggregated data mostly coming from the EU, according to Demirgüç-Kunt and Detragiache (1999) those models do not reflect country-specific nature of vulnerabilities due to the aggregation of various country-level crisis episodes The paper helps to distinguish variables and instruments that will help policymakers understand whether vulnerabilities are accumulating or not. Also, the paper describes problems which are occurring while working with data on the Ukrainian banking system. As you will see in the 5th section this thesis could help policymakers to understand not only when to activate CCB but how to calibrate it.

C h a p t e r 3

METHODOLOGY

3. 1. Premodeling

In general, early warning models are used for identifying vulnerable conditions before the distress events. As a result, we can view our problem as a two-class identification process, in particular, whether an object is in a vulnerable state or not. First, early warning models were based on the signaling approach using a simple univariate model as Drehmann, Borio and Kostas (2011). Even though those models were quite trivial, they were the first ones to propose the area under the receiver operator curve (AUROC) as the instrument to find the optimal threshold by calculating the trade-off between Type I error and Type II error. In our case we will take partial AUROC as we are more concerned about missing a crisis than issuing a false signal. This idea we will also use while estimating a loss function which is entierly different approach for valuating the performance of the model.

According to Lang and Peltonen (2018) EWM modeling includes three stages: pre-modeling (purpose, forecast horizon and event indicators), modeling (evaluation criterion, modeling technique, model selection, and evaluation exercise) and post-modeling (policy-relevant dimensions, visualization).

Articulating the purpose of the model is very important because depending on whether we do ex-ante or ex-post analysis, we may choose a very different objective function. In particular, for explaining the past, the focus should be on the in-sample analysis and for explaining the future – on the out-of-sample analysis. The purpose of our model is the triggering of the activation time on CCB by predicting the future crisis which will help policymakers to increase the banking system's resilience to imbalances.

The goal of an EWM is to signal the distressing event. However, we should consider the proper time horizon capturing vulnerable states before stress events. According to the literature, the choice of forecast-horizon can differ. For example, early studies by Kaminsky and Reinhart (1999) used an 8-quarters horizon and later studies by Behn, et al. (2013) and Detken, et al. (2014) included different time horizons for robustness check, which were varying in the range of 5-12 and 5-16 quarters respectively. There is no consensus about the time horizons in the literature (Lang and Peltonen 2018), and this issue needs to be examined further. In our case, we will evaluate the model with different time horizon scenarios.

For accurate signaling of the systemic crisis by the model, we will choose only those bank distress events that occurred in the periods of systemic crises, but not the tranquil period. In this way, we could capture the information about systemic vulnerabilities and not unnecessary noise. As it was mentioned before, bank distress events could also occur outside of the systemic crisis, for example, bank stakeholders want to invest money in another sector which they consider more profitable. Periods that we will be considered as a systemic crisis in Ukraine are from 2008 to 2009 and from 2014 to 2015 (NBU 2019). As a bank distressing event, we will consider three types of events – bank bankruptcy, default and refinance (Lang and Peltonen 2018). All information about these events could be found on the official website of NBU.

3.2. Modeling

After defining the purpose of the model, strategy on the time horizon and bank distress event classification we should set up the modeling and evaluation approach. This involves stipulating the evaluation criterion, modeling technique, optimal model complexity and specification and setting up evaluation procedure.

A bank distress event can be described as a binary variable $I_{i,t} \in \{0,1\}$ which at time *t* signals about the vulnerable state of bank *i*. If $I_{i,t} = 0$, then it is a tranquil period, and if $I_{i,t} = 1$, then the bank is in a vulnerable state. A signal about the crisis that has already occurred does not give a policymaker enough reaction time to decrease the build-up of vulnerabilities and strengthen the financial system. Also, according to the BCBS banks have a year for CCB accumulation for better surveillance and resilience. Consequently, the time horizon for most scenarios should end 4 periods before the distressing event. Also, Bussiere and Fratzscher (2006) suggest eliminating all distress event observations plus 4 subsequent periods to account for possible crisis and post-crisis bias.

Taking into account that we need to find a probability of occurrence of vulnerable state, i.e distinguish between a tranquil period and vulnerable period, we suggested the following probit model:

$$p(I_{i,t} = 1 \mid X_{i,t}=x_{i,t})=\Phi\ (\beta' x_{i,t}), \qquad (1)$$

where, $p(Y_{i,t} = 1 \mid X_{i,t}=x_{i,t})$ denotes the probability that in period *t* bank *i* could be in a vulnerable state over some pre-specified time horizon. As independent variables, the vector $x_{i,t}$ includes credit, macro-financial, and balance sheet variables which will be described later in the data section and $\Phi(*)$ is cumulative normal distribution function. Once the model is estimated, we can use the estimated values of $p_{i,t}$ to construct a binary variable $P_{i,t}$ that mimics the behavior of $I_{i,t}$ In particular, when $p_{i,t}$ exceeds a certain threshold $\theta \in [0,1]$), then $P_{i,t}=1$ and $P_{i,t}=0$ otherwise. The relationship between $P_{i,t}$, and $I_{i,t}$ could be described in a contingency matrix (Table 1) estimating the goodness of fit or performance measure.

Most approaches on EWM in the literature focused on measuring the so-called Type I or Type II errors as explained below. This measurement is independent of the objective of whether the model is explanatory or predictory because it assesses its performance (Sarlin 2013). As central banks are concerned about missing a crisis at least as same as issuing a false signal i.e. they are more interested in getting true positive as same as true negative signals we used partial AUROC. Detken, et al. (2014) suggested that after the financial crisis, using AUROC as a performance indicator in EWM, the parameter theta (θ) should lie in the interval [0.5; 1] meaning that we are cutting off everything under θ=0.5.

Table 1. Contingency matrix

		Actual class $I_{i,t}$	
		Crisis	No crisis
Predicted class $P_{i,t}$	Signal	A Trues positive	B False positive
	No signal	C False negative	D True negative

where P_1 and P_2 are the estimated frequencies of the classes $P_1=(A+C)/(A+B+C+D)$ and $P_2=(B+D)/(A+B+C+D)$. Estimation is performed in-sample as the parameters are unknown ex-ante. With this definition of the loss function, we can not only compute the optimal threshold but also the usefulness of the signaling threshold. Policymakers could get a loss μP_1 when the model never signals about a crisis or $(1-\mu)P_2$ when the model always issues a signal, as a result, losses equal $\min[\mu P_1(1-\mu)P_2]$ if a policymaker does not apply early warning model. We can compute absolute usefulness U_a by substracting from the losses occurring from the model the losses incurred while ignoring the model or not using it:

$$U_a(\mu)=\min[\mu P_1,(1-\mu)P_2] - L(\mu) \quad , \tag{3}$$

We could also derive relative usefulness which will show $U_a(\mu)$ as a percentage of the usefulness that policymakers could gain.

$$U_r(\mu)=\frac{U_a(\mu)}{\min[\mu P_1,(1-\mu)P_2]} \,, \tag{4}$$

This means that if $L(\mu) = 0$, then $U_a(\mu)=\min[\mu P_1,(1-\mu)P_2]$ and $U_r(\mu)= 1$ signaling that model is working perfectly. For a given preference parameter we could obtain the optimal threshold by minimizing the loss function above. Moreover, it will be an evaluation criterion while using different preferences parameters and time horizons.

Also, it is important to mention that the optimal threshold we are estimating not by AUROC but the loss function. After model estimation we are fitting values for every observation and treat them as thresholds, then for every fitted value, we are estimating usefulness. A fitted value which gives us the highest level of the usefulness will be the optimal threshold. Thus, we consider a loss function as the main estimator of the goodness of the model.

3.3. Postmodeling

Once the model is estimated, and all evaluation exercise is passed, it is important to decide how the model output could be visualized and analyzed. For this purpose, aggregation is necessary. Taking into account that we have bank-level data, it is important to analyze the aggregated effect on the system. In this case, the properties of probit models are very important, in particular, marginal effects. In probit models, we can analyze the marginal effect only on the mean or average effect on every observation. However, it could create imbalances because Ukrainian banks are not homogeneous and it would be more correct to assess the average effect weighted on the share of the market, for instance, the share of each bank in total assets. This approach is intuitive and also recommended by Lang and Peltonen (2018).

Chapter 4

ESTIMATION RESULTS

4.1. Data description

Data consists of 207 banks and 88 distress events in a period of the 1st quarter of 2009 to the 3rd quarter of 2019 (5945 observations). According to the NBU website, the number of banks in Ukraine has dropped significantly from 175 in 2018 to 77 in 2019. Data was taken from the websites of State Statistics Service of Ukraine (SSSU) and National Bank of Ukraine. It is unbalanced panel bank-level quarterly data with gaps. If gaps were between the period, then such observations were eliminated. Data description you can find in Appendix A.

The series on Administrative and other operational costs/ Net revenue and Other operational income /Net revenue have a very high minimum and maximum, but it could be explained by the periods when net revenue was approximately zero. The same goes for lending and deposit growth for both corporate and household lending. It also can be explained, in particular, by the low amount of lending or funding for some banks in previous periods. In other words, some of the banks have indeed very high corporate and household, deposit and credit growth. As a result, we took the 99th percentile of each variable, excluded outliers. Also, we deleted missing observations and duplicates and were left with 4281 observations and 205 banks during the whole period.

We took 3 different types of variables, two of them – real-economy variables and credit-related variables were used by Drehmann, Borio and Kostas

(2011), Detken, et al. (2014) and Behn, et al. (2013) and third – bank balance sheet used by Lang and Peltonen (2018). We also added more variables in the balance sheet group as Lang and Peltonen (2018) did not specify all of them because they were using more than 100 variables and reported only those that were significant.

Our estimation strategy included both balanced and unbalanced panels, but estimating a balanced panel means that we have to take the same period for the same banks. However, as we can see from Table 2, only 24.8% of the data includes all periods. Moreover, from the same table, we can see that it is possible to take first or the last half of the data making the panel – balanced, however, resulting in the drop in the significant number of the bank distress events. It could be explained that most of the distress events are concentrated at the beginning of the period or the end. Also, in Ukraine, it is common for

Table 2. Pattern of the data

Freq.	Percent	Cum.	Pattern
50	24.15	24.15	1111111111111111111111111111111111111111111
12	5.80	29.95	11111111111111111111111....................
8	3.86	33.82	111111111111111111111......................
7	3.38	37.20	111111111111111111111111...................
7	3.38	40.58	111111111111111111111111111................
6	2.90	43.48	1111111111111111111111111111111............
5	2.42	45.89	11111111111111111111.......................
5	2.42	48.31	1111111111111111111111.....................
5	2.42	50.72	1111111111111111111111111..................
3	1.45	52.17	....11111111111111111111...................
3	1.45	53.62	.111111111111111111111111111111111111111111
3	1.45	55.07	11111111111111111..........................
3	1.45	56.52	1111111111111111111........................
3	1.45	57.97	11111111111111111111111111.................
3	1.45	59.42	11111111111111111111111111111111111........
2	0.97	60.39	11111111111111111111
2	0.97	61.35	...................1111111111..............
2	0.97	62.32	1111111111111111111111111
2	0.97	63.29	.................111111111111..............
2	0.97	64.25	1111111111111111111111111111111111
74	35.75	100.00	(other patterns)
207	100.00		XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX

Note: pattern of "1" represents available observations of 207 banks during the 1st quarter of 2009 to the 3rd quarter of 2019.

defaulted banks not to return to the market. As a result, preliminary experiments with the model showed that the model on any configuration of the balanced panel could not be estimated, because models based on the panel data included too little distress events. Thus, we decided to estimate the model based on different subsets trying to find different effects based on the banking system structure and, possibly, check the robustness of the model. According to the NBU classification methodology, until 2015 banks were grouped by the size of their assets, and after the concepts of systemically important banks[4] and ownership became the classification drivers.

The structure of the Ukrainian banking system by ownership in 2016 and 2020 is the following: most of the banks have Ukrainian ownership and this structure has not changed significantly. As you can see from Figure 2, the share of the total number of foreign banks increased and the share of the private banks decreased during the 2016-2020 period.

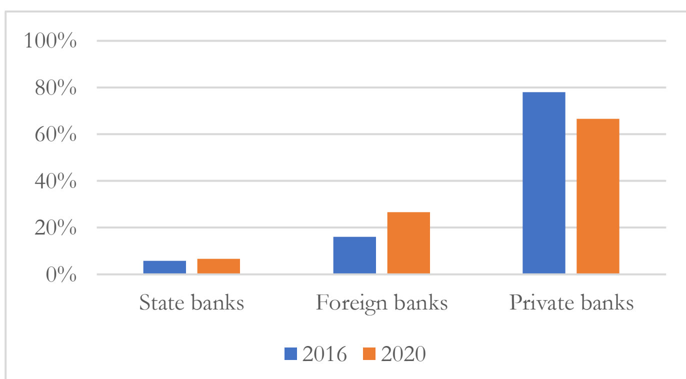

Figure 2. Classification by ownership (shares of the total number)

4 There are 14 systemically important banks in Ukraine classified in the 2019 year. This group was not estimated as the only Privatbank had a distress event.

It can be explained by the fact that the private banks had the highest default rate during the 2008-2009 and 2014-2015 periods[5]. That is why it is meaningless to divide data into ownership subsets because most of the distress events are concentrated in the private ownership group.

As it was mentioned before, the NBU was dividing banks according to the size of the assets into 4 groups, where the 1st group include banks with the highest amount of the assets[6] and the 4th – the smallest. Some of the banks were floating from one group to another but the structure did not change significantly (Figure 3) as same as ownership structure.

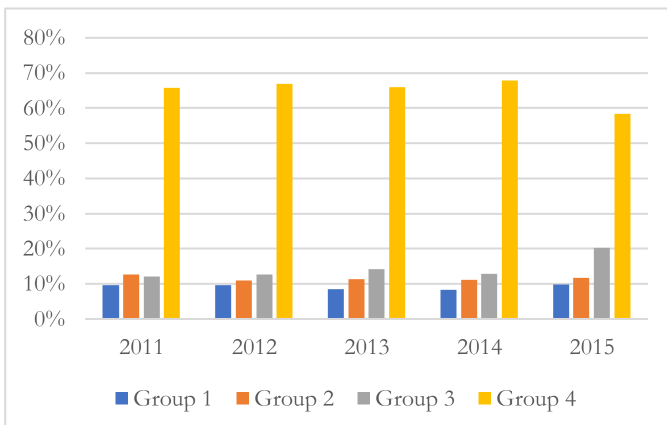

Figure 3. Classification by the size of the assets (shares of the total number)

According to our data in the last quarter of 2013, there were 171 banks and it was the largest number of the existing banks in the sample. As a result, we took this structure assuming that banks did not change it which helps us to estimate the model based on 4 subsets.

5 More details about the Ukrainian banking system are enclosed in the Discussion section.
6 NBU classification methodology until 2015: 1 group – the largest (>15 bln UAH), 2 group – large (>5 bln UAH), 3 group – medium (>3 bln UAH) 4 froup – small (<3 bln UAH)

4.2. Estimation results

For the bank distress events, we first gathered all banks that exited from the market from 2008 to 2019, and then excluded those that exited because of the war in the east of Ukraine or territory occupation by Russia and those that were shut down by the NBU because of unclear stakeholders structure or money laundering. Finally, we excluded those exits from the market that occurred because of the merge with other banks. As a result, we were left with 88 bank distress events in 85 banks. Then, the data points containing distress events and 4 subsequent periods were also excluded from the sample due to the noise in the data caused by a crisis.

We estimate the model on five sample variations: on the whole data sample and separately on four sample subsets corresponding to different bank groups (based on size of their assets). We also took 2 time horizons (5 or 9 periods before the crisis event) for every sample that we used. Also, in each model we included from 0 to 4 lags of each variable. As a result, we ended up with 50 models including models with different lags, estimated subsamples and time horizons (Table 3).

Evaluating the best model out of 50 is not a trivial exercise. That's why after estimating each model, we also calculated AUROC, which showed that models have good predictive power as for all of them. The AUROC indicator was more than 0.8 but taking into account that we have a relatively small number of crisis events, it is not unexpected that the models are good at predicting true negatives.

However, our results demonstrated that all these models are not good for predicting true positives, as partial AUROC is less than 0.4 for most of them

(Table 3). Nevertheless, the loss function is the main indicator for choosing the best model.

Table 3. P-AUROC results

	Time horizon = 5 periods					Time horizon = 9 periods				
	4 lags	3 lags	2 lags	1 lags	no lags	4 lags	3 lags	2 lags	1 lags	no lags
P-AUROC (0.5) group 1	0.24	0.25	0.25	0.2	0.2	0.23	0.19	0.22	0.22	0.14
P-AUROC (0.5) group 2	0.28	0.18	0.3	0.3	0.33	0.29	0.1	0.29	0.28	0.32
P-AUROC (0.5) group 3	0.21	0.29	0.36	0.37	0.36	0.23	0.23	0.33	0.35	0.35
P-AUROC (0.5) group 4	0.38	0.39	0.38	0.38	0.37	0.39	0.38	0.38	0.37	0.36
P-AUROC (0.5)[7]	0.42	0.41	0.4	0.39	0.37	0.39	0.39	0.39	0.38	0.37

While capturing all the true positives they also have a high amount of false positives. While all models exhibit very similar behavior, the best predicting power belongs to a model based on the whole sample with 4 lags and short time horizon (its partial AUROC is 0.42). The models that were based on the separate groups of banks have low predictive power because the number of distress events in each group was relatively small. Also, the fact that group 1 has the lowest partial AUROC and group 4 has the highest could be explained by the simple fact that the number of distress events is the highest in group 4

[7] Model based on the whole sample.

This is also confirmed while estimating absolute usefulness U_a (μ) for every preference parameter μ={0.6;07;08;0.9}. In the best case, this measure was approximately 11.6% for μ=0.8 for the model with 4 lags estimated on the whole sample and long horizon (Table 7). The threshold (θ) is 0.997 (Table 8 contains all optimal thresholds). This means that the model is not accurate but, at least, it is better than the absence of the model. Thresholds are the same for every preference parameter and we are explaining this by the absence of the sensitivity as most fitted values i. e. thresholds are concentrated around 1 and 0.

Nevertheless, some of the variables are significant, meaning that if a model doesn't issue a sufficient signal about a distress event we still can use those variables as indicators for vulnerability accumulation. In particular, Table 9 contains full results of the model, and in Table 4 we picked only those that were significant. We also took marginal effects at means and average marginal effects but they were either insignificant or very low and did not reveal any useful information. Besides, we estimated the linear probability model (LPM) model because of the easier way of extracting marginal effects (Table 9). However, they are also marginally too low. Our results replicate the signs of the coefficients of the model based on the whole sample with 4 lags and a long time horizon approving the robustness.

By analyzing the results of the model we can distinguish only the direction of the vulnerabilities accumulation. In particular, Net interest income/total assets and interest expenses/total liabilities are indicating the efficiency of the assets and liabilities[8], respectively as these ratios show income per asset and expenses per liability. Increasing income per asset reduces the probability of issuing signal and increasing expenses per liability increases this probability. As a result, according to the model, the effective managing of the balance sheet is a key indicator of bank solvency.

Household deposit growth has a negative sign in the 1st lag which could be explained by the fact that with increasing deposits, banks will also have higher interest expenses which in the future (in our case in the 1sr period) will harm the bank's solvency.

Explaining the significance of capital adequacy ratio is relatively straightforward as this indicator shows the amount of capital in the bank which will be the cushion in the time of recession. As it is expected, this indicator is showing a decreasing probability of issuing a signal while increasing.

Table 4. Results of the model based on the whole sample with 4 lags and 5 periods of time horizon

Variable	
Net interest income/Total assets	-14.85***
	(-4.28)
Net interest income/Total assets(-1)	-7.451*
	(-2.16)
Net interest income /Total assets (-3)	-8.429*
	(-2.44)
Households deposit growth(-1)	0.566*
	(2.29)
Interest expenses/Total liabilities	-10.02***
	(-3.67)
Interest expenses/Total liabilities(-1)	-6.988*
	(-2.49)
Interest expenses/Total liabilities(-3)	-5.582*
	(-2.21)

8 There is a negative sign, as in the original data expenses have also negative sign meaning that increasing expenses will increase the probability of signaling.

TABLE 4 — Continued

Variable	
Provisions/Total assets	-2.237*
	(-2.14)
ROE(-3)	0.827*
	(1.99)
Real GDP YoY(-2)	0.158**
	(2.62)
Inflation	-0.0593**
	(-2.64)
Money Supply M3 growth(-3)	16.87*
	(2.30)
Corporate lending growth	0.509*
	(1.98)
Corporate lending growth(-1)	0.527*
	(2.03)
Corporate lending growth(-4)	0.581*
	(2.40)
Nominal public debt/GDP	1.418*
	(2.29)
Capital adequacy ratio(-1)	-0.243*
	(-2.17)
Capital adequacy ratio(-2)	-0.295**
	(-2.75)
Unemployment rate(-4)	1.242*
	(2.02)
N	3559

* p<0.05, ** p<0.01, *** p<0.001
t-statistics in the parentheses

The indicator of the return on equity (ROE) is showing an increasing probability of the signal being issued which is, on the one hand, a misleading signal because ROE is showing the profitability of the equity. Nevertheless, it could also be a signal that a bank has very low equity but high profits which is a case of a bank with a high-risk appetite which is issuing loans with high-risk premium to risky clients.

Rapid corporate lending growth also results in a higher probability of signal being issued as it could be a threat to banks' solvency. It is logical because usually bad loans are provided in good times meaning that non-performing loans are issued in times of rapid credit growth. Moreover, as practice shows most of the non-performing loans were corporate loans (NBU 2019).

The higher ratio of provisions to total assets decreases the probability of a signal being issued: if banks have a higher level of provisions, they are more protected as these provisions are created to back up non-performing loans.

The coefficient on Nominal public debt/GDP also has the expected sign. High public debt creates a material risk to the whole financial sector. That's why growing ratio of Nominal public debt/GDP will lead to the increasing probability of issuing a signal to the banking sector.

Real economy variables are significant but a sign of inflation and GDP growth are not as expected and are misleading. In the case of the money supply growth, it has positive sign, meaning that an increase in the money supply will lead to an increase in the probability of a signal issuance. This could be explained by the fact that an increase in the money supply in Ukraine will influence inflation with a lag, and as a result will harm the banking system by, for example, devaluation of hryvnya. An increase in unemployment will lead to an increase in the probability to issue a signal.

Chapter 4

ALTERNATIVE WAY OF CCB CALIBRATION

5.1. Data issues disrupting early warning models

The main problem occurring while estimating the early warning model in Ukraine is that the data is very noisy, meaning that it contains variation which could not be explained by the model and disrupts the results. The noise in the data could be explained by the peculiarities of the banking system of Ukraine. For example, the banking system started to be profitable only for the last two years. Before, its profit from Figure 4 is almost zero during the whole period. It could be a sign that owners of the banks are not interested in profits but opportunistic behavior which creates noize in the data.

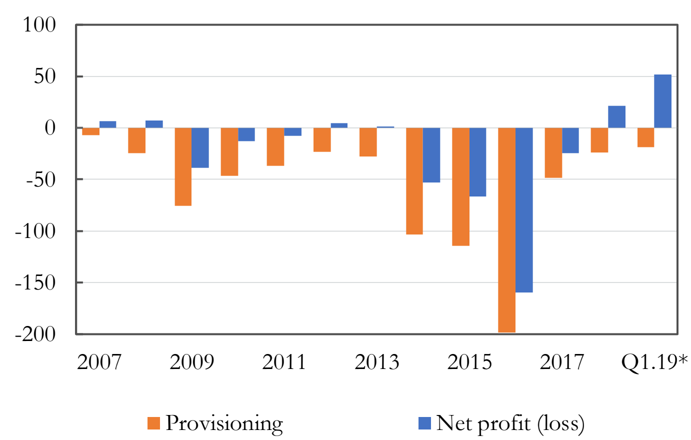

Figure 4. Profit or loss of the banking sector, UAH billion
Source: NBU, financial stability report, June 2019

As was mentioned before banks exited from the market not only because of the weak financials but unclear stakeholders' structure or money laundering.

This makes it difficult to set a threshold for a bank distress event that occurred due to systemic risk creating more noise in the model.

Non-performing loans (NPL) recognition could be evidence of opportunistic behavior, too. NPLs started to grow from the middle of 2014 (Figure 5). There was a nominal increase in 2017 as a result of the transition to international standards for defining non-performing assets. Banks recognized their real quality of loans with a delay as you can see from Figure 5 overdue loans that turned into NPLs started to grow from the end of 2015. In this way, banks tried to win time by capitalizing on interest and small restructurings.

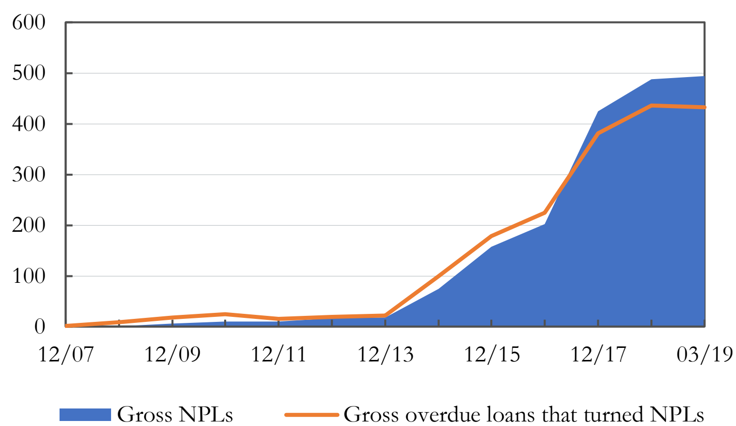

Figure 5. Defaulted loans recognition and overdue loans accumulation for loans that turned NPLs, mln UAH

Source: NBU, financial stability report, June 2019

According to the NBU, only 17% of NPL stock is the result of the territory occupation, market loss or decrease of the domestic demand. However. accumulated disbalances were the most significant factors, in particular, the absence of the operational activity of the lender. Moreover, those lenders did not provide collateral for the loans which mostly where issued before the crisis in 2014. The majority of those lending companies were part of the unclear business groups. As a result, 96% of the NPLs are loans more than 100 mln UAH and 128 legal entities pose 3 quarters of NPL stock.

5.2. Financial cycle index

Taking into account the facts of the opportunistic behavior of the banks it became more clear why our model did not issue a sufficient signal for macroprudential purposes. However, we could calibrate CCB based on a simpler approach. One of the possible ways to do it is to construct a composite indicator of systemic risk, in particular, the financial cycle indicator (FCI). This simple for understanding indicator describes the financial cycle that would be easy to construct and interpreted by a general audience. As our model could give only a direction of several variables, it is important to analyze other possible indicators. FCI is used by the Central bank of Czech Republic for capturing financial cycles and is described by Plašil, Seidler and Hlaváč (2016).

FCI has several advantages in comparison with factor models as it also accounts for co-movements of the variables. FCI is also useful in the case of the short time series which are usually common for transforming economies as it is difficult to verify the validity of the statistical assumptions used in the factor models. Moreover, factor models are designed to reproduce the variability of the original data but FCI includes weights that allow decreasing or increasing the importance of those factors which have lower or higher probability and magnitude of risk materialization. Finally, basic factor models assume a constant cross-correlation across the variables and time but the design of the FCI allows researchers to account for the changes in the cross-correlation and analyze individual phases of the financial cycle (Plašil, Seidler and Hlaváč 2016).

These authors constructed FCI in two steps: firstly, they chose variables that capture the financial cycle across different segments of the economy and, secondly, they combined those variables into one using the aggregation algorithm. The main focus of their work was placed on the timely identification of the build-up phase of the systemic risk and its materialization. It is essential as this period is necessary for macroprudential policy implementation. The intuition behind the FCI is to analyze particular segments of the economy and then make an aggregation of the composite indicator. As a result, it gives a possibility for identification of the common movements in the selected variable because an important part of the indicator is a correlation between variables.

The main criterion for variables is that they should be capturing the build-up of the systemic risk and its materialization. Due to limited data availability for Ukraine, our model contains a shorter list of variable that that of Plašil, Seidler and Hlaváč (2016)[9]. We took monthly growth of new loans to households and corporates (annual moving sum of monthly new loans), spread between rate on new loans to households and 3 months interbank lending interest rate and spread between the rate on new loans to non-financial corporations (NFC) and 3 months interbank lending interest rate.

[9] Plašil, Seidler and Hlaváč (2016) used the following variables: New bank loans to households, new bank loans to nonfinancial corporations, property prices (inflation), household debt/gross disposable income, nonfinancial corporations' debt/gross operating surplus, spread between rate on new loans to households and 3 M PRIBOR, spread between rate on new loans to NFCs and 3 M PRIBOR, PX stock index Adjusted current account deficit/GDP

We also included monthly growth of new loans households and corporates as many studies have shown that credit growth could be considered as one of the most reliable variables for future problems in the financial sector (Drehmann, Borio and Kostas 2011). This fact is linked to the procyclicality of the financial sector because economic agents could lose the ability to recognize risks in the time of economic growth.

Intuitively, if lending accelerates, decreasing interest rates (spreads) would suggest that it is caused by the supply side while increasing rates (spreads) would be a sign of a demand-driven growth. According to Hájek, Frait and Plašil (2017) the spreads indicate lending conditions that characterize financial risk as, for example, in the expansion phase of the cycle, banks may underestimate the credit risk by offering low interest rates for less creditworthy clients. However, this could not be the case for Ukraine, as banks could increase their rates due to the high risk premium.

We took the data for the period from January 2007 to December 2019. All variables were standardized to a unit interval (0,1) using Kernel estimate of the cumulative distribution function (Figure 6). This transformation allows us to represent variables in the standardized form and make them mutually comparable. Transformation is based on the historical distribution, meaning that when new data arrives historical quantiles may change. It is important to outline that initially Plašil, Seidler and Hlaváč (2016) excluded the period of structural break and took a shorter time horizon which allowed them to make data cleaner. Unlike the authors, we could not afford data elimination as our time horizon has already been relatively short.

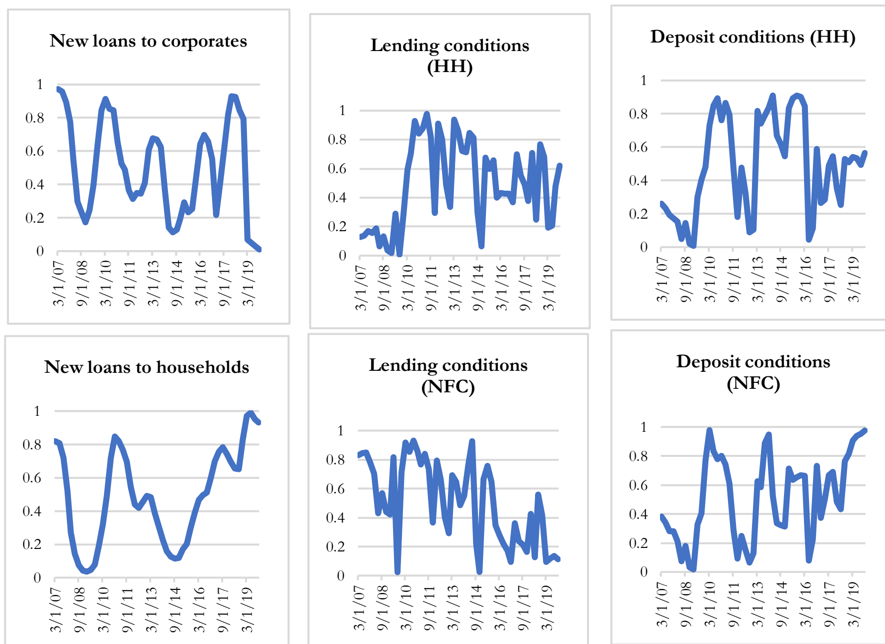

Figure 6. Input variables for FCI

The aggregation algorithm could be expressed in the following formula:

$$FCI_t = (w^\circ s_t)'C_t(w^\circ s_t), \qquad (5)$$

where w is a vector of weights indicating the relative importance or preferences of each variable s_t represents a vector of sub-indicators and matrix $w^\circ s_t$ is a multiplication of these vectors. Matrix C_t is a pairwise correlation of the sub-indicators, where $\rho_{t,ij}$ is determining how strong the correlation between sub-indicators i and j is. The higher the indicator is, the higher the aggregated risk appetite is in the economy.

One of the most important features of the indicator is that it accounts for a time-varying cross-correlation structure unlike the HP filter recommended by the BCBS. Meaning that a stronger correlation across the sub-indicators will make higher FCI making it very useful for macroprudential policy decision as a signal over cycle sentiment will be stronger. In addition to the cross-sectional point of view which is represented by the cross-correlation between individual segments, the time dimension of the risk is represented by the magnitude of the sub-indicators.

As it as mentioned before lending condition sub-indicator could be not representative in Ukraine. That's why we took lower weights for these sub-indicators. In particular, lending conditions for both categories have weights of w=0.3 and the other 2 sub-indicators have weights of w=0.2.

Time-varying correlations coefficients $\rho_{t,ij}$ are estimated using the exponentially weighted moving average method (EWMA) with smoothing factor $\lambda = 0.94$. Covariances $\sigma_{t,ij}$ and variances $\sigma_{t,i}^2$ between sub-indicators and are known at t=0 as we can estimate them then calculate approximated correlation $\rho_{t,ij}$ using the following formulas: (Plašil, Seidler and Hlaváč 2016).

$$\sigma_{t,ij} = \lambda\sigma_{t-1,ij} + (1-\lambda)\bar{s}_{t,i}\bar{s}_{t,j}, \tag{6}$$

$$\sigma_{t,i}^2 = \lambda\sigma_{t-1,i}^2 + (1-\lambda)\bar{s}_{t,i}\bar{s}_{t,j}, \tag{7}$$

$$\rho_{t,ij} = \frac{\sigma_{t,ij}}{\sigma_{t,i}\sigma_{t,j}} \quad , \tag{8}$$

where $\bar{s}_{t,i} = (s_{t,i} - 0.5)$ represents the values of the sub-indicators after subtracting their theoretical mean. It helps sub-indicator to enter the FCI calculation corresponding the to "equilibrium" situation where the financial cycle is neither on expansion, nor recission stage (Hájek, Frait and Plašil 2017).

Results of the calculated FCI you can find on Figure 7. According to the Hájek, Frait and Plašil (2017) calibration of the CCB is performed in the following way: the start of the FCI build-up corresponds to 0% of the CCB and the peak of the indicator corresponds to the maximum of the CCB i.e. 2.5%.

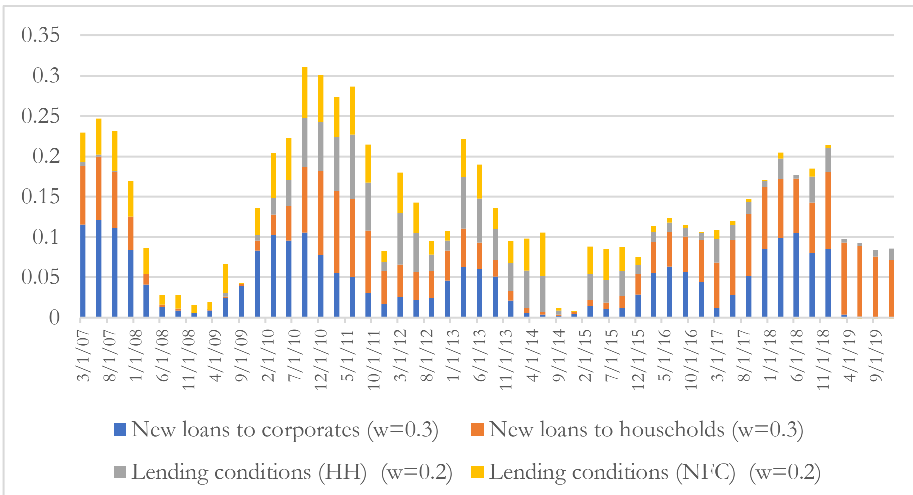

Figure 7. FCI results

Ideally for CCB calibration, we should take the period before the crisis in 2008. However, taking into account data availability we considered the next peak which occurs during 2008-2010. This period is a phase of economic recovery after the crisis in 2007-08 followed by credit growth or expansionary phase of the financial cycle. The build-up period consists of 8 observations. Thus, CCB in the 1 period is 0%, it will end up in 2.5% in the last period with the step of 0.3571%.

The FCI is constructed using a quadratic system of weights (Hájek, Frait and Plašil 2017). As the nature of the FCI is not linear, the increase in the FCI is not proportional to the width of the step of CCB change meaning that it should replicate the exponential behavior of the FCI during the build-up period. To do it we considered to build a quadratic regression:

$$FCI_t = \beta_0 + \beta_1 b_t + \beta_2 b_t^2 + \varepsilon \quad (9)$$

Where FCI_t is a FCI in the period t, b_t is a buffer in the period t, where t ∈ [1;8] as we stated before we have 8 periods and ε is an error term. β_0 is a constant, β_1 and β_2 are the weights of the quadratic regression. After estimation of the weights, we fitted the values of the buffer with step 0.25 into the equation (9) to get the values of FCI and construct the interval of the indicator which is corresponding to a certain level of a buffer (Table 5).

Table 5. Relationship between FCI and CCB rate

FCI		
from	**to**	**CCB rate**
0	0.01	0
0.01	0.02	0.25
0.02	0.03	0.5
0.03	0.05	0.75
0.05	0.07	1
0.07	0.10	1.25
0.10	0.13	1.5
0.13	0.17	1.75
0.17	0.21	2
0.21	0.26	2.25
0.26	1	2.5

Results are replicating the nonlinear behavior of the FCI. However, they are quite conservative because even a low FCI will be corresponding to a certain level of the buffer. Such results are explained by the fact that FCI is very volatile meaning that the Ukrainian economy had not been recovered from one recession and then immediately entered another expansionary phase of the financial cycle accumulating vulnerabilities. As FCI shows 2011 follows by high volatility. From this perspective, conservative estimation of the CCB for the Ukrainian banking system will have a positive impact.

Most of the literature devoted to CCB calibration suggests that the process of decision making regarding CCB calibration involves different models and most importantly expert judgment. The main purpose of the FCI is capturing the financial cycle, meaning that FCI is one of the compasses that central banks are using while operationalizing the CCB.

Nevertheless, our results could be also used in CCB decision making. FCI is the lowest during the time of the recession capturing two crises that occurred in 2008-2009 and 2014-2015 as Figure 7 shows. Before the first crisis in 2007, FCI is approximately 0.25 indicating already high-risk appetite. According to our estimation CCB on that period should have been set at a rate of 2.25%. Meaning that banks would have entered the crisis with additional capital reducing the negative impact of the crisis.

Before the second crisis in 2014-2015, FCI in the second quarter of 2013 was approximately 0.22 indicating about CCB at the level of 2.25% giving a certain signal about holding additional capital for better solvency of the banking system. However, taking into account that the crisis started in 2014, it is very difficult to say whether banks would have accumulated the CCB taking into account the conditions of the banking system in Ukraine at that time.

At the end of 2018 according to the results, the buffer should have been 2.25% as an indicator was approximately again 2.2. If we assume that the buffer had been set at 2.25% level then the banking system at the beginning of 2020 would have been better prepared for the idiosyncratic shock caused by the coronavirus outbreak.

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Chapter 6

CONCLUSION

The main goal of setting CCB is to protect the banking sector from the excessive aggregate credit growth associated with broad systemic risk. The goal is to build it up in a period of rapid growth and to release it to be solvent in a period of stress. Different economists analyzed a wide range of indicators and thresholds signaling when to activate CCB and concluded that the credit-to-GDP gap is one of the most accurate indicators for many countries. However, this is not a case for East European countries as these countries have structural changes and a relatively short observation period and Ukraine is in the list of these countries.

Besides these problems even more advanced models such as EWM models could be not sufficient if they are built on the data containing a lot of noise. This is a particular case for Ukraine because the banking system was characterized by massive opportunistic behavior and produced a lot of noisy data for a long time. NPL analysis is good evidence showing that 96% of the NPLs are loans more than 100 mln UAH and 128 legal entities pose 3 quarters of NPL stock. As a result, EWM in the form of a probit does not issue a sufficient signal meaning that there is no difference between any estimated model and preference of the central bank always issue a signal.

Nevertheless, we can distinguish a direction of the vulnerabilities accumulation in the best of the estimated model estimated on the whole sample with a time horizon of 9 periods, 4 lags for each variable. According to the model, the effective managing of the balance sheet is one of the key indicators of bank solvency. Rapid corporate lending growth could be a threat to banks' solvency which is not trivial as usually lending growth increases income. Besides, provisions are absorbing the losses from non-performing loans, and the model shows that indeed provisions reduce vulnerabilities. As expected, the capital adequacy ratio shows that if banks have a higher amount of equity, then they will have a lower probability of distress event, thus, the model has a lower probability of issuing a signal. ROE, on the one hand, has a wrong sign: being positive, it adds to the probability of issuing a signal, though higher ROE could also be a sign of high profits from risky assets and low equity. Most of the credit-related and macro variables are not significant. Two out of three significant macro variables produce a misleading signal. Money supply growth is significant and has a positive sign meaning that a high increase in the money supply growth in Ukraine will influence inflation and harm the banking system. Also, unemployment is significant and indicates an increasing probability of issuance of a signal while increasing and last but not least public debt shows a potential threat to the financial sector in case of increasing.

Taking into account the finding that the EWM has weak signaling ability, we calibrated CCB based on the simpler approach, in particular FCI. This simple for understanding indicator describes the financial cycle that would be easy to construct and interpreted by a wide audience. FCI is also useful in the case of the short time series. Moreover, FCI allows researchers to account for the changes in the cross-correlation, analyze individual phases of the financial cycle. FCI account not only for the magnitudes of the sub-indicators bit its weights that allow decreasing or increasing the importance of them.

We can conclude that FCI has the potential to be a leading instrument in the decision process while calibrating CCB. As our analysis suggested buffer could have reduced the negative impact of shocks in 2008-2009, 2014-2015 and potentially in 2020 if it would have been set at a level of 2.25% before the crises giving the banking system time to accumulate the buffer. Further calibration may be required as the buffer is very conservative. However, we should also take into account that this is the first estimation of the FCI and further investigation is required because we did not analyze the cost and benefits of the indictor as there is no certain proxy for FCI which is initially designed only exactly for replication of the financial cycle.

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APPENDIX A

DESCRIPTION STATISTICS

Table 6. Description statistics

	mean	sd	max	min
Bank balance sheet variables:				
Net interest income/total assets	0.03	0.03	0.15	-0.11
Net commission income/total asset	0.01	0.01	0.10	-0.07
Corporate deposits growth	0.08	0.44	3.87	-1.00
Households deposits growth	0.05	0.23	1.70	-1.00
Consumer lending growth	0.03	0.47	5.58	-1.21
Corporate lending growth	0.03	0.18	1.00	-1.00
Assets in other banks/total asset	0.07	0.08	0.44	-0.00
interest expenses	-0.05	0.03	-0.01	-0.42
Provisions /total assets	-0.09	0.17	0.01	-7.66
Total equity /total assets	0.22	0.19	0.82	-6.42
Common equity/total assets	0.21	0.18	1.43	0.00
ROE	-0.07	1.09	1.31	-47.82
ROA	-0.01	0.12	0.07	-7.40
Credit-related variables:				
Nominal public debt/GDP	1.50	0.63	3.13	0.69
Capital Adequacy Ratio	16.80	3.04	20.83	7.09
Loans/GDP	2.27	0.57	3.35	0.93
Real-economy variables:				
Real GDP growth	-0.87	6.67	6.70	-17.30
Inflation	10.89	12.34	58.93	-0.48
Money Supply M3 growth	0.03	0.03	0.08	-0.05
REER	0.90	0.10	1.01	0.66
Unemployment	8.49	0.76	10.10	7.00
N	4281			

Note: Data in the table is after the cleaning. Before the cleaning the number of observations qual to 5945.

APPENDIX B

ESTIMATION RESULTS

Table 7. Relative usefulness results

		short time horizon				long time horison			
group 1		μ=	μ=	μ=	μ=	μ=	μ=	μ=	μ=
		0.6	0.7	0.8	0.9	0.6	0.7	0.8	0.9
	lag 0	0	0	0	0.015	0	0.003	0.025	0.025
	lag 1	0	0.007	0.021	0.039	0	0.011	0.033	0.029
	lag 2	0.002	0.013	0.027	0.044	0.009	0.026	0.046	0.036
	lag 3	0.02	0.03	0.042	0.055	0.037	0.053	0.071	0.053
	lag 4	0	0.005	0.021	0.04	0.036	0.052	0.07	0.049
group 2									
	lag 0	0.04	0.047	0.055	0.063	0.075	0.088	0.1	0.087
	lag 1	0	0	0	0.005	0.05	0.064	0.08	0.067
	lag 2	0	0	0	0.006	0	0	0	0
	lag 3	0	0	0	0.007	0	0	0	0
	lag 4	0	0	0	0.007	0	0	0.004	0
group 3									
	lag 0	0.042	0.05	0.057	0.065	0.074	0.087	0.1	0.086
	lag 1	0.041	0.049	0.057	0.065	0.07	0.083	0.097	0.08
	lag 2	0.02	0.03	0.041	0.054	0.037	0.052	0.07	0.055
	lag 3	0	0	0	0	0	0	0	0
	lag 4	0	0	0	0	0	0	0	0
group 4									
	lag 0	0.042	0.05	0.0571	0.065	0.076	0.089	0.101	0.087
	lag 1	0.045	0.052	0.06	0.067	0.078	0.091	0.104	0.087
	lag 2	0.046	0.054	0.061	0.069	0.08	0.094	0.107	0.087
	lag 3	0.047	0.055	0.063	0.07	0.084	0.097	0.112	0.086
	lag 4	0.043	0.052	0.06	0.07	0.0857	0.1	0.115	0.085
whole sample									
	lag 0	0.043	0.05	0.057	0.065	0.077	0.09	0.1	0.087
	lag 1	0.044	0.052	0.059	0.067	0.079	0.092	0.1	0.086
	lag 2	0.045	0.053	0.06	0.067	0.081	0.095	0.109	0.086
	lag 3	0.047	0.054	0.063	0.07	0.084	0.098	0.112	0.086
	lag 4	0.048	0.056	0.064	0.073	0.087	0.101	0.116	0.085

Table 8. Optimal Thresholds

		short time horizon				long time horison			
group 1		μ= 0.6	μ= 0.7	μ= 0.8	μ= 0.9	μ= 0.6	μ= 0.7	μ= 0.8	μ= 0.9
	lag 4	1	1	1	1	1	1	1	1
	lag 3	1	1	1	1	1	1	1	1
	lag 2	1	1	1	1	1	1	1	1
	lag 1	1	1	1	1	1	1	1	1
	lag 0	1	1	1	1	1	1	1	1
group 2									
	lag 4	1	1	1	1	1	1	1	1
	lag 3	1	1	1	1	1	1	1	1
	lag 2	1	1	1	1	1	1	1	1
	lag 1	1	1	1	1	1	1	1	1
	lag 0	1	1	1	1	1	1	1	1
group 3									
	lag 4	1	1	1	1	1	1	1	1
	lag 3	1	1	1	1	1	1	1	1
	lag 2	1	1	1	1	1	1	1	1
	lag 1	1	1	1	1	1	1	1	1
	lag 0	1	1	1	1	1	1	1	1
group 4									
	lag 0	0.868	0.868	0.868	0.868	0.957	0.957	0.957	0.957
	lag 1	1.000	1.000	1.000	1.000	0.981	0.981	0.981	0.981
	lag 2	1.000	1.000	1.000	1.000	0.997	0.997	0.997	0.997
	lag 3	1.000	1.000	1.000	1.000	0.999	1.000	0.999	0.999
	lag 4	1.000	1.000	1.000	1.000	0.998	0.998	0.998	0.998
whole sample									
	lag 0	0.770	0.770	0.770	0.770	0.936	0.936	0.936	0.936
	lag 1	0.954	0.954	0.954	0.954	0.981	0.981	0.981	0.981
	lag 2	0.975	0.975	0.975	0.975	0.993	0.993	0.993	0.993
	lag 3	0.989	0.989	0.989	0.989	0.986	0.986	0.986	0.986
	lag 4	0.999	0.999	0.999	0.999	0.997	0.997	0.997	0.997

Table 9. Results on the whole sample with 4 lags and time horizon of 9 periods.

Variable	Probit	LPM
Assets in other banks/Total asset	0.574	0.0412
	(0.72)	(0.33)
Assets in other banks/Total asset(-1)	0.753	0.0578
	(0.77)	(0.38)
Assets in other banks/Total asset (-2)	-0.356	-0.0266
	(-0.36)	(-0.18)
Assets in other banks/Total asset (-3)	-1.288	-0.137
	(-1.30)	(-0.93)
Assets in other banks/Total asset (-4)	-0.699	-0.115
	(-0.91)	(-0.96)
Net commission income/Total asset	-3.214	-0.563
	(-0.55)	(-0.86)
Net commission income/Total asset(-1)	-5.847	-0.462
	(-0.90)	(-0.68)
Net commission income/Total asset(-2)	-1.979	-0.526
	(-0.30)	(-0.79)
Net commission income/Total asset(-3)	-11.43	-0.554
	(-1.67)	(-0.81)
Net commission income/Total asset(-4)	-7.475	-0.594
	(-1.22)	(-0.88)
Net interest income/Total assets	-14.85***	-1.722***
	(-4.28)	(-4.55)
Net interest income/Total assets(-1)	-7.451*	-1.134**
	(-2.16)	(-2.99)
Net interest income /Total assets (-2)	-5.491	-0.975**
	(-1.57)	(-2.70)
Net interest income /Total assets (-3)	-8.429*	-0.583
	(-2.44)	(-1.62)
Net interest income /Total assets l(-4)	4.116	0.342
	(1.27)	(0.92)
Corporate deposit growth	-0.194	-0.00754
	(-1.65)	(-0.51)
Corporate deposit growth(-1)	-0.0404	0.00903
	(-0.35)	(0.62)
Corporate deposit growth(-2)	-0.0477	0.00369
	(-0.43)	(0.26)
Corporate deposit growth(-3)	0.0176	0.00570
	(0.18)	(0.41)
Corporate deposit growth(-4)	-0.0587	-0.000325
	(-0.60)	(-0.03)
Households deposit growth	0.334	0.0329
	(1.35)	(1.13)
Households deposit growth(-1)	0.566*	0.0531
	(2.29)	(1.75)
Households deposit growth(-2)	0.452	0.0369
	(1.94)	(1.28)
Households deposit growth(-3)	0.253	0.0158
	(1.14)	(0.56)
Households deposit growth(-4)	0.213	0.0259
	(1.01)	(0.94)
Interest expenses/Total liabilities	-10.02***	-1.249**
	(-3.67)	(-3.29)
Interest expenses/Total liabilities(-1)	-6.988*	-1.075**

TABLE 9 — Continued

Variable	Probit	LPM
	(-2.49)	(-2.75)
Interest expenses/Total liabilities(-2)	-4.886	-0.541
	(-1.88)	(-1.52)
Interest expenses/Total liabilities(-3)	-5.582*	-0.490
	(-2.21)	(-1.47)
Interest expenses/Total liabilities(-4)	-3.588	-0.373
	(-1.39)	(-1.16)
Provisions/Total assets	-2.237*	-0.122
	(-2.14)	(-1.03)
Provisions/Total assets(-1)	0.186	-0.0544
	(0.15)	(-0.39)
Provisions/Total assets(-2)	1.948	0.0339
	(1.32)	(0.22)
Provisions/Total assets(-3)	-1.542	-0.0492
	(-1.07)	(-0.31)
Provisions/Total assets(-4)	-1.154	-0.00459
	(-0.98)	(-0.04)
Total equity/Total assets	-1.437	-0.177
	(-1.13)	(-1.11)
Total equity/Total assets(-1)	1.869	0.170
	(1.10)	(0.86)
Total equity/Total assets(-2)	2.149	0.155
	(1.14)	(0.74)
Total equity/Total assets(-3)	-1.787	-0.0791
	(-0.89)	(-0.38)
Total equity/Total assets(4)	-1.889	-0.123
	(-1.14)	(-0.74)
Common equity/Total assets	-1.828	0.00258
	(-1.48)	(0.02)
Common equity/Total assets (-1)	-0.722	-0.0664
	(-0.45)	(-0.34)
Common equity/Total assets(-2)	-0.473	-0.0216
	(-0.27)	(-0.11)
Common equity/Total assets(-3)	0.276	-0.0702
	(0.14)	(-0.34)
Common equity/Total assets(-4)	0.510	-0.0426
	(0.32)	(-0.26)
ROE	0.0421	0.00263
	(0.32)	(0.42)
ROE(-1)	0.00859	0.00208
	(0.14)	(0.32)
ROE(-2)	0.226	0.00455
	(0.68)	(0.69)
ROE(-3)	0.827*	0.00442
	(1.99)	(0.90)
ROE(-4)	-0.0337	-0.00804
	(-1.18)	(-1.63)
ROA	-0.708	0.0318
	(-0.39)	(0.17)
ROA(-1)	1.054	0.285
	(0.56)	(1.16)
ROA(-2)	-2.201	0.209
	(-0.69)	(0.84)
ROA(-3)	-2.725	0.00985

TABLE 9 — Continued

Variable	Probit	LPM
	(-0.84)	(0.04)
ROA(-4)	0.347	0.0657
	(0.18)	(0.32)
Real GDP YoY	-0.0836	-0.00765
	(-1.61)	(-1.54)
Real GDP YoY (-1)	-0.0488	-0.00117
	(-0.71)	(-0.18)
Real GDP YoY(-2)	0.158**	0.00859
	(2.62)	(1.55)
Real GDP YoY(-3)	-0.0609	-0.00184
	(-1.23)	(-0.36)
Real GDP YoY(-4)	-0.0391	-0.00453
	(-0.94)	(-1.10)
Inflation	-0.0593**	-0.00309
	(-2.64)	(-1.36)
Inflation(-1)	-0.0101	-0.000885
	(-0.26)	(-0.29)
Inflation(-2)	0.00748	0.000341
	(0.21)	(0.12)
Inflation(-3)	-0.0461	-0.00407
	(-1.32)	(-1.44)
Inflation(-4)	0.0226	-0.00327
	(0.85)	(-1.57)
Money Supply M3 growth	5.585	0.290
	(1.31)	(0.68)
Money Supply M3 growth(-1)	7.186	0.607
	(1.23)	(1.25)
Money Supply M3 growth(-2)	6.044	0.837
	(0.84)	(1.57)
Money Supply M3 growth(-3)	16.87*	0.757
	(2.30)	(1.47)
Money Supply M3 growth(-4)	8.770	0.394
	(1.47)	(0.85)
REER	6.466	0.564
	(1.76)	(1.55)
REER(-1)	-8.113	-0.643
	(-1.72)	(-1.39)
REER(-2)	-1.775	0.268
	(-0.31)	(0.55)
REER(-3)	3.631	0.581
	(0.69)	(1.21)
REER(-4)	2.794	0.277
	(0.71)	(0.72)
Consumer lending growth	-0.0630	-0.00924
	(-0.78)	(-0.78)
Consumer lending growth(-1)	-0.0176	-0.00843
	(-0.22)	(-0.72)
Consumer lending growth(-2)	-0.0735	-0.0108
	(-0.80)	(-0.91)
Consumer lending growth(-3)	-0.0776	-0.00965
	(-0.86)	(-0.80)
Consumer lending growth(-4)	-0.106	-0.0148
	(-1.11)	(-1.16)
Corporate lending growth	0.509*	0.0476

TABLE 9 — Continued

Variable	Probit	LPM
	(1.98)	(1.39)
Corporate lending growth(-1)	0.527*	0.0574
	(2.03)	(1.67)
Corporate lending growth(-2)	0.362	0.0450
	(1.45)	(1.32)
Corporate lending growth(-3)	0.336	0.0489
	(1.33)	(1.46)
Corporate lending growth(-4)	0.581*	0.0820*
	(2.40)	(2.46)
Nominal public debt/GDP	1.418*	0.144*
	(2.29)	(2.24)
Nominal public debt/GDP(-1)	-0.338	-0.00871
	(-0.43)	(-0.13)
Nominal public debt/GDP(-2)	-0.341	0.0136
	(-0.33)	(0.19)
Nominal public debt/GDP(-3)	-0.724	0.0486
	(-0.70)	(0.61)
Nominal public debt/GDP(-4)	0.131	-0.0843
	(0.16)	(-1.24)
Capital adequacy ratio	-0.197	-0.00971
	(-1.90)	(-0.96)
Capital adequacy ratio(-1)	-0.243*	-0.0263*
	(-2.17)	(-2.46)
Capital adequacy ratio(-2)	-0.295**	-0.0187
	(-2.75)	(-1.95)
Capital adequacy ratio(-3)	-0.174	-0.0180
	(-1.36)	(-1.76)
Capital adequacy ratio(-4)	0.0862	-0.0131
	(0.87)	(-1.36)
Unemployment	-0.470	-0.0616
	(-1.10)	(-1.39)
Unemployment rate(-1)	-0.918	-0.0515
	(-1.50)	(-0.99)
Unemployment rate(-2)	-0.157	-0.0169
	(-0.29)	(-0.35)
Unemployment rate(-3)	0.449	0.0671
	(0.73)	(1.27)
Unemployment rate(-4)	1.242*	0.00970
	(2.02)	(0.20)
Loans to GDP ratio	0.161	0.0372
	(0.20)	(0.51)
Loans to GDP ratio(-1)	2.008	0.0769
	(1.93)	(0.93)
Loans to GDP ratio(-2)	0.663	0.00781
	(0.67)	(0.10)
Loans to GDP ratio(-3)	0.124	-0.109
	(0.12)	(-1.43)
Loans to GDP ratio(-4)	-0.590	0.0921
	(-0.65)	(1.57)
Cons	2.491	0.738
	(0.22)	(0.59)
N	3559	3559
	* p<0.05	
t-statistics in the parentheses	** p<0.01	*** p<0.001"