ISSN 2414-987X

VISNYK

OF THE NATIONAL BANK OF UKRAINE

QUARTERLY RESEARCH
JOURNAL OF THE NATIONAL BANK OF UKRAINE

№ 234 December 2015

ISSN 2414-987X

VISNYK
OF THE NATIONAL BANK OF UKRAINE

№ 234

Quarterly research Journal
of the National Bank of Ukraine
Published since March 1995

Founder and publisher:
National Bank of Ukraine

https://doi.org/10.26531/vnbu2015.234

Address: 9 Instytutska Street, Kyiv, 01601, Ukraine
E-mail: journal@bank.gov.ua

Design and layout:
PJSC "INFOCON" Agency.
Address: 46 Khreschatyk st., Kyiv, 01001, Ukraine.
Tel.: +380 (44) 288-33-57.
www.infocon.ua

PREFACE OF THE CHAIRMAN OF THE EDITORIAL BOARD

Dear readers!

The second issue of the updated *Visnyk of the National Bank of Ukraine* contains articles that focus on financial stability issues and highlight the ongoing work of the National Bank of Ukraine to ensure the stability of the banking sector. The passing year has significantly changed our country's banking market - nearly 30 banks have been declared insolvent, while operating financial institutions are required to restore an adequate level of capitalization within the next three years. Thus, the regulatory efforts of the National Bank of Ukraine are aimed at leaving only solvent banks in the market, which will define the architecture of the financial sector in the future. The materials in this issue of *Visnyk of the National Bank of Ukraine* reveal some aspects of the work being done by the National Bank of Ukraine to restore the confidence of households and businesses in the Ukrainian banking system.

The December issue of *Visnyk of the National Bank of Ukraine* starts with an article by Vladyslav Rashkovan and Roman Kornyliuk entitled *Concentration of Ukraine's Banking System: Myths and Facts*. Analyzing the level of concentration of the banking system compared to other countries, the authors evaluate possible potential risks of mergers and acquisitions at the macroeconomic level. In particular, the results of their empirical analysis reveal that the level of concentration of banking assets in Ukraine is not significant under the Herfindahl-Hirschman Index (HHI), CRn concentration index, and other ratios. However, given the upward trend of concentration of the banking system within moderate average European levels, regulatory agencies (the National Bank of Ukraine and the Antimonopoly Committee of Ukraine) are recommended to focus on monitoring and forecasting possible consequences of mergers and acquisitions. In addition, the article recommends a set of preventive macroprudential measures aimed at minimizing the negative effects of concentration and reaching optimal market consolidation.

The article by Yuliia Diuba and Hanna Murina, *The NBU Approach to Stress Testing the Ukrainian Banking System*, outlines the methodological basis of stress tests for twenty largest banks held during 2015 in accordance with the requirements of the Memorandum between Ukraine and the IMF. The methodological principles that have been developed by NBU staff incorporate the practices of other European central banks, while taking into account the specific nature of Ukrainian banks.

The article explains, among other things, why the NBU has decided to check the solvency and to assess the credit risks of the largest borrowers on an individual basis. The findings of the stress tests that have been carried out in accordance with the above principles support programs for increasing the capital of Ukrainian banks for the period until 2018, which financial institutions submit to the central bank for approval.

Dmytro Pokidin's article *National Bank of Ukraine Econometric Model for the Assessment of Banks' Credit Risk and Support Vector Machine Alternative* deals with Ukrainian commercials banks' statistical assessments of credit risk. NBU regulations require that banks use one model of borrower credit risks, and assess these risks on an individual basis. The NBU developed the model on the basis of statistics for the entire banking sector. The article considers various statistical approaches to credit risk assessment. The main focus is on the support vector method, which provides for a high accuracy of assessments, but is difficult to put into practice, and on the logistical regression model, which the NBU plans to phase in during 2016.

The articles published in the current issue address the first steps that the NBU has taken towards new approaches to banking regulation, and certainly have to be discussed in a constructive manner by experts. The editorial staff invite readers and experts in banking, financial analysis, macro-forecasting, and modeling to join the ongoing discussion. New authors are also invited to submit their studies to *Visnyk of the National Bank of Ukraine*.

Best regards ***Dmytro Sologub***

CONTENTS

CONCENTRATION OF UKRAINE'S BANKING SYSTEM: MYTHS AND FACTS

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ABSTRACT

This article attempts to find answers to questions of current significance: How concentrated is Ukraine's banking system from the viewpoint of the world's best regulatory practices and in comparison with other countries? What has been the driving force behind the growing concentration in recent years and does this process pose a threat to competition in the banking system? What effect would mergers and acquisitions in the banking sector have on the concentration of the banking system? And finally, do public authorities have to stimulate consolidation in the banking system or, on the contrary, restrain potential bank mergers and acquisitions?

The results of empirical analysis dispel the persisting myths about the risks of fast and excessive concentration resulting from continuing market consolidation and about the substantial impact of inequality on the growing concentration, and refute the perceived danger of mergers and acquisitions in the banking sector. Instead, it was discovered that concentration of banking assets in Ukraine is not substantial according to the Herfindahl–Hirschman Index (HHI), CRn concentration index and other ratios. At the same time, in the conditions of continuing consolidation of the banking system via mergers and acquisitions and a decreasing number of banks, upward trends are observed within moderate, average European levels. Therefore, these new conditions require closer attention on the part of banking regulators to assess possible consequences of concentration.

This article provides recommendations to the National Bank of Ukraine (NBU) and the Antimonopoly Committee of Ukraine (AMCU) on how to improve monitoring of banking concentration processes and better regulate consolidation processes in bank mergers and acquisitions. A complex of preventive macroprudential measures was offered to offset the negative consequences of concentration and achieve an optimal degree of market consolidation.

JEL Codes: G18, G21, G28, L1, L4
Keywords: banking system, concentration, consolidation, macroprudential regulation, systemic risk.

I. Introduction

During the past two years, Ukraine's banking system has been undergoing active structural transformation: the number of banks has been declining and requirements for transparency of banking transactions and bank equity were becoming more stringent. The decline in the number of market participants and the growing inequality among them lead to an increasing concentration which, on one hand, is boosting the banking market's capacity and effectiveness, but, on the other hand, may facilitate formation of an oligopoly or monopoly on a regional or product market with numerous adverse external effects or the appearance of problematic "too big to fail" banks. In other words, concentration simultaneously generates positive consequences for the banking system and bank customers while posing a threat to competition.

  https://doi.org/10.26531/vnbu2015.234.006

Therefore, concentration is gradually turning from a subject for scholarly discussions to a case study for the Ukrainian financial regulator. The increasing attention on part of the NBU to the assessment of concentration is manifested by the inclusion in the *HHI* of at least 800 points in terms of assets to the list of key fulfillment indicators for the Comprehensive Program of Ukraine Financial Sector Development until 2020 (NBU, 2015). Since the target minimum concentration level was achieved in 3Q 2015, it might be necessary to set additional parameters for a maximum concentration level in order to prevent its long-term negative consequences.

Simultaneously with increasing concentration, Ukraine's banking market experiences the following process: consolidation of the banking system that manifests itself in a decreasing number and growing size of banks, partially boosted by the increasing regulatory and market requirements for the minimum amount and adequacy of capital. Depending on the individual stress resistance of banks and decisions by the top management of financial institutions and the banking regulator, consolidation processes may take the form of removal of insolvent financial institutions from the market, intensifying mergers and acquisitions, and uneven natural growth of assets among banks. Some of the aforementioned processes, e.g., the declining number of banks due to failure to comply with the NBU's norms, have been actively taking place in Ukraine since the beginning of 2014, while mergers and the growing positions of the largest banks have a certain potential for intensification in the future.

However, even active consolidation is not always able to cause substantial increases of concentration. Consequently, consolidation may, under certain conditions, limit its own positive impact at an individual bank level or, under different circumstances, be the reason for realization of positive (or negative) consequences of concentration. In order to understand what consequences may cause consolidation which the NBU mentions in paragraph A.6 (xi) of the NBU, 2015 regarding *Improvement* of *Legislation Regulating Mergers of Financial Sector Participants*, it is advisable to determine first: a) what is consolidation?; b) how to measure concentration; and c) what are the relationships between them?

To answer these questions, the authors made a retrospective study of dynamics of certain bank concentration indicators from 1998-2015 and a comparative analysis of banking concentration levels in Ukraine and other countries of the world. The differences in concentration levels and competition among banks on various banking products markets and underlying reasons for growing concentration indexes in the course of cleansing and transformation of Ukraine's banking system were discussed. The problems of different sensitivity of concentration indexes to the number of banks, consolidation processes and structural changes in the banking system driven by different speeds of organic growth and capitalization of financial institutions were reviewed.

The goal of this article is to provide a comprehensive assessment of trends, reasons, and possible magnitude of increasing concentration of Ukraine's banking system and provide, based on assessment results, recommendations for the financial regulator on how to improve monitoring of concentration in the banking sector and better regulate consolidation processes in bank mergers and acquisitions.

Article's structure. Section 2 offers an overview of literature. **Section 3** describes theoretical approaches to the study of consolidation and concentration processes, and it contains a number of assumptions lying at the core of this study. **Section 4** explains the methodology for measuring concentration level. **Section 5** provides key empirical results that provide answers to the following questions:

a) Is Ukraine's banking system concentrated?

b) What has been driving the growing concentration in 2014-15?

c) How concentrated is Ukraine's banking market in comparison with other countries?

d) What is the level of concentration of particular banking products markets?

e) How may the exit of banks affect concentration?

f) Do regulators need to limit further mergers?

Section 6 features recommendations for the NBU and the AMCU based on the comparison of theoretical conclusions, international experience, and empirical results obtained by the authors. **Section 7** contains general concluding remarks.

II. Overview of literature

For the past few decades, the problem of consolidation and concentration of banking systems has been actively studied by foreign scholars. The interest of researchers and regulators in this problem stems from deregulation, globalization, and integration of financial services markets, and later from the substantial effect that transnational banks established as a result of consolidation had on the unfolding of the global financial crisis of 2007-2009.

An in-depth analysis of methodological approaches to calculation of concentration and inequality indexes can be found in the works by Tirole (1988), Hay (1991), Florian (2014), Hall & Tideman (1967), Atkinson & Micklewright (1992), Jacquemin (1975), and Hirschman (1964). The range of the HHI is set in international legislative acts regulating horizontal mergers: EC (2004), U.S. (1992, 2010). A historical overview of consolidation and concentration processes occurring in foreign banking systems is offered in the works by Pohl et al. (2001), Kalashnikov (2007), and Kozak (2013).

Positive consequences of banking market's consolidation in the form of increasing effectiveness of industries were studied by Tirole (1988), Hay (1991), and Berger (2000) who emphasized that concentration can increase banks' revenues due to the scale effect, higher degree of price control, and better diversification opportunities opened to larger-size banks. As empirical studies prove, high concentration facilitates access to debt capital markets for profitable firms. Most scholars agree that concentration of bank capital is a global trend that has a number of significant positive effects, such as growing effectiveness, risk diversification, cost reduction and increased quality of products.

Negative consequences of concentration were tested in a broad range of empirical studies concerning the relation between concentration and financial strength. De Nicolo et al. (2003) discovered that consolidation increases risks for large financial conglomerates, while excessively concentrated banking markets are exposed to a higher degree of systemic risk. The "concentration-fragility" relation at the global level was studied by Beck et al. (2007), Allen & Gale (2004), and Claessens & Laeven (2003); based on EU data - Pawlowska (2015), Fiordelisi (2009), and Ijtsma (2015); and in Asia - Abbasoglu (2007), Yaldiz (2010), and Rath et al. (2014). Consolidation processes, concentration, and market organization within Ukraine's banking system were studied by Stephan et al. (2012), Prozorov (2003), Koretska (2014), and others.

Works devoted to large banks are closely related to the problem of banking concentration: De Nicoló et al. (2003), Haldane (2012), Laeven et al. (2014), Vickers (2012), and Liikanen (2012). Growing concentration, especially if driven by increasing inequality, may turn the largest banks into institutions "too big to fail" that do not foster competition, are prone to heightened moral hazard and excessive risky activity, may be inclined to breach generally-accepted market discipline, and are capable of putting pressure on public authorities.

Substantial interest in the matters of capitalization, concentration, and consolidation is present in the works discussing the optimal size and organization of the banking market. Thus, answering the question "is there an optimal size of financial sector?", Santomero et al. (2000) arrives at the conclusion that highly-capitalized banks can better perform their key role on orders from their creditors (depositors): monitoring borrower solvency. Hence, the significance of bank capital and regulation of its adequacy is required to ensure efficient intermediation of the cross-flow of credit resources from household sector to real sector of economy.

Discussing the search for the banking market's optimal organization, Amable et al. (2002) point out the role of mergers and acquisitions as bankruptcy substitutes in the course of the banking system's transformation process, and compare the effect of high concentration of oligopolistic and low concentration of competitive banking markets on their financial strength. Among important consolidation studies, the works by Group of Ten (2001) offering comprehensive analysis of reasons for and consequences of consolidation of financial services markets, English (2002) studying its effect on monetary policy, and Uhde (2009) studying the effect of consolidation on financial stability in Europe are worth noting. Key theories of motives behind mergers and acquisitions (synergy theory, agency theory of free cash flow, and hubris theory) and a number of empirical studies devoted to their testing are reviewed in detail in the book by Rudyk, Semenkova (2000).

III. Theoretical assumptions

Concentration and consolidation play a key role in many empirical studies, but still require clear formulation in view of discrepancies in the interpretation of terms. In this article, we go by the definition set out by *Group of Ten (2001)*, according to which *consolidation of the financial services sector involves the resources of the industry becoming more tightly controlled,* *either because the number of key firms is smaller or the rivalry between firms is reduced*. Therefore, consolidation becomes a consequence of the processes, which are also referred to as the following: a) unifying reorganization (mergers and acquisitions) of existing banks, b) growing volumes of market leaders, or c) market exit of weaker institutions. We have to make this clarification, because the term "consolidation" is often used in a narrow sense at an individual level and applied solely to bank mergers and acquisitions.

The term "consolidation" means *market (industry-wide) concentration, i.e., the division of market shares*. In our case, we study the banking services market with bank assets as the key characteristic of volumes (in a general case), whereas we used other relevant indicators to calculate concentration of the banking market's product segments (e.g., credit or deposit).

Consolidation and concentration are closely related. Moreover, concentration is regarded as a result, a certain marker of consolidation processes, and one of the factors determining the banking system's competition level and financial strength. The possibility of growing concentration makes the assertion regarding a positive effect from consolidation not quite obvious and requiring substantiated proof, assessment of side effects, and communication of results to the public. First, one has to calculate, in quantitative terms, the range of concentration increase after the reduction of banks, which has been done in this article. Second, not denying the existence of positive effects from a reduction in the number of banks, it is worth comparing them to possible threats to the system: Would consolidation not result in the excessive growth of concentration threatening to monopolize the sector? What effect would consolidation have on increasing inequality? What consequences may result from raising barriers to entry for new participants? To answer these questions, we will attempt to calculate the effect from the sector's consolidation on its concentration since the beginning of 2014 and compare it with the effect of increasing inequality – the growing heterogeneity of market participants' market shares.

Hay (1991) considers concentration as one of the three primary characteristics of market organization, on par with savings from scale and product differentiation, which determine market type depending on their combination. Thus, low values of all three components point to structural market conditions similar to sophisticated competition. When the scale and concentration of an industry are low while the product differentiation is high, it produces a type of monopolistic competition with a certain level of pricing freedom. High scale effect and market concentration without product differentiation prove the existence of a homogeneous oligopoly, whereas a combination of maximum values of all three parameters leads to the establishment of a monopoly or differentiated oligopoly that minimizes pricing and intensifies non-pricing competition by forming loyalty to brands via marketing and advertising campaigns and by offering unique product lines.

In addition to pricing advantages gained by an oligopoly from savings on the scale, a high concentration of the banking market may create an additional entrance barrier preventing market penetration by new banks which will have to make substantial outlays to win customer loyalty. Moreover, high concentration combined with product differentiation increases the probability of cooperation and collusion among an oligopoly's major participants; combined with high entrance barriers, that can increase the profit norm and margin for banks but may adversely affect the rest of the banking system's stakeholders.

Contemporary theories of market concentration are based on the literature of the *New Empirical Industrial Organization (NEIO)* featuring empirical testing of hypotheses by using aggregated industrial data or individual data at the firm level. As we said earlier, according to the NEIO methodology, the level of market competition does not always depend solely on concentration measures but envisages accommodation of such market characteristics as dynamics of entrance barriers and intensity of firms' exit (Pawłowska, 2015). Therefore, the level of competition in the banking market changes mainly via two channels: consolidation and regulatory requirements (in particular, concerning capital) setting barriers to the entrance of new participants.

It is worth noting that when measuring concentration of the banking market's assets, the following assumptions were made in this article:

1) *Non-differentiation of products*, because product differentiation may lead, even in the conditions of low concentration, to the formation of a segmented monopoly or oligopoly;

2) *Evenly-spread geographical location of branches*: this way, we abstract away from the possible existence of regional or local monopolies, the risk of whose appearance is objectively minimized with the development and wider penetration of online banking;

3) *Absence of collusion and strategic alliances among banks*, which de-facto increases the level of concentration as banking unions have higher market shares. For the purposes of further studies and monitoring, it is advisable to take into account that a more precise measurement of concentration should not be confined within the legal framework of banks operating for common strategic goals and have common or related owners.

Because of the difficulties with the use of Ukrainian empirical data series on the way towards adequate assessment of the effect of concentration on competition, profitability, or financial risks, for the purposes of this study we will confine ourselves to the analysis of reasons for and forecasts of future levels of banking concentration in Ukraine. Calculation of dependence between concentration and financial strength is not a subject of this study because a relatively short series of empirical data, a strong cyclical nature, and the much greater effect of other factors prevent us from precisely assessing the effect of concentration on risks and effectiveness of the banking system. When determining potential positive and negative consequences of concentration, we will use basic theoretical conclusions of mainstream economic science and the best regulatory practices of understanding the levels of low or threatening concentration. Our assumptions are based on generally-accepted theoretical and empirical results incorporated in EU and U.S. antimonopoly legislation. According to conclusions of most studies and the logic of regulatory acts, low concentration is incompatible with monopoly, yet it lowers effectiveness of the banking system. On the other hand, excessive concentration threatens with adverse effects from monopolization while at the same time stimulating the growth of effectiveness.

IV. Methodology and data

How can the level of the banking market's concentration be measured? To do that, there is a wide choice of methods and indicators that all have their upsides and drawbacks. However, before selecting the most efficient concentration indexes, we should make a number of additional assumptions by answering the general questions regarding quality of base data Hay (1991):

1) What business unit classification method is best for use on the banking services market?

2) How was the size of every bank measured?

3) How is the total volume of banking (general/deposit/credit) market calculated?

First, the studied market will include banks whose indicators were published quarterly in statistical bulletins disclosing financial statements of Ukrainian banks. Theoretically, credit unions, pawnshops, financial companies, and life insurance companies may compete with banks and affect concentration indexes of particular markets for deposit and credit products. However, considering the lack of a long time series (and also a negligible market share), the segment of non-bank financial intermediaries was not included to credit and deposit markets.

Second, to evaluate the size of every bank (*i*) as of the beginning of a quarter (*t*), we used the asset volume data ($assets_{it}$), and to calculate the bank's share of particular product markets: amount of loans issued to and deposits received from retail and corporate banking businesses (*ret_loans, corp_loans, ret_dep, corp_dep, respectively*). Balance or authorized capital may serve as ancillary base indicators for concentration calculation purposes; however, their use often distorts the actual market organization as equity may have negative value or share of authorized capital on the balance sheet may vary depending on banks' internal policy on capital formation.

Third, we calculated market volume as the sum of corresponding indicators of every bank's financial statements as of the beginning of the quarter. Thus, the total volume of banking market in terms of assets was:

$$\mathrm{A_t} = \sum_{i=1}^{n} assets_{it}. \tag{1}$$

Therefore, s_{it} is the market share of *i*-th bank as of the date *t*:

$$s_{it} = \frac{assets_{it}}{A_t} \times 100\%. \tag{2}$$

Considering the high aggregate share of insolvent (de-facto removed from market) banks, calculation of market volume for three quarters of 2015 did not include banks placed under temporary administration. In the preceding periods, market volume was calculated for all banks mentioned in NBU reports. Therefore, our aggregate indicators may insignificantly diverge from certain aggregated official data. Nevertheless, it cannot affect the accuracy of our study.

To measure concentration in banking systems, we used traditional indicators which proved their effectiveness but, however, not without their strengths and weaknesses. Let's go over the most popular ones.

a) Concentration indexes:

– CR_n (n-firm Concentration Ratio): aggregate market share of n largest banks:

$$CR_n = \sum_{i=1}^{n} s_i, \tag{3}$$

where s_i is the market share of the *i*-th bank, n is the number of largest banks ranked in the descending order of their market share. The most popular concentration indexes are *CR3, CR4, CR5, CR8* and *CR10*. The sum of CR_n indexes for the entire n series as of the date t is (*1;k*), where k, the number of active banks on the market, forms a concentration curve. We can use the concentration curve to calculate the more seldom-used *CR*–inversed indicator: the number of banks holding the s market share set as a percentage.

– *HHI* ***(Herfindahl-Hirschman Index)***: the sum of the square of the market shares of every bank in the system, i.e.:

$$HHI = \sum_i s_i^2, \tag{4}$$

where s_i is the market share of the *i*-th bank. Considering the availability of individual data for every bank in the system, the authors have calculated "full-fledged" *HHIs*, whereas in the conditions of a lack of required data, these indexes may be calculated on the basis of indicators from the top 50 firms operating on the studied market. According to the requirements of U.S. antimonopoly laws amended in 2010, a market shall be considered competitive if *HHI*<1,500; moderately concentrated if 1,500<*HHI*<2,500; or highly concentrated if *HHI*>2,500 (*US(2010)*). Prior to 2010, the official *HHI* range in the United States for moderately concentrated markets was lower: between 1,000 and 1,800 (US(1994)); today, a similar range in the EU is between 1,000 and 2,000 (*EC(2004)*).

– Hannah-Kay Index: *other HHI-related concentration indexes of the type:*

$$R = \sum_i s_i^{\alpha}, \tag{5}$$

where s_i is the market share of the *i*-th bank; α is an elasticity parameter indicating weight given to the largest banks vis-à-vis the smallest. If *α=0*, then *R=max(i)*, i.e., the concentration is determined only by the number of banks on the market while the inequality factor is disregarded. If α grows, the weight of large banks' effect on the concentration index substantially increases, which can make sense if a study is focused on the banks' inequality aspect. Most scholars use the standard value of *α=2*, for which *R=HHI* (Hay, 1991). The varieties of this index are *THI (Hall-Tideman Index), ECI* (*Entropy Concentration Index*), etc. (Jacquemin, 1975).

b) Inequality indicators are traditionally used to measure concentration, because they point out the inequality in distribution of market shares: inequality that, together with a low number of banks on the market, may become a reason for substantial concentration. However, the inequality per se does not depend on the number of market participants, and therefore, it provides only an indirect indication of concentration.

– Gini Coefficient: an indicator of the unequal distribution of bank volumes derived from the Lorenz curve (Figure 4). If assets were equally distributed among all banks on the market, the Lorenz curve would appear as the diagonal of the unit square. As inequality among banks grows, it attains a convex shape below the diagonal of equal distribution and shows the dependence between p, share of the number of banks ranked by asset growth, and *L(p)*, the cumulative market share of these banks. The Gini Coefficient represents the ratio of the area of the shape between the curve and diagonal to the total area of the triangle. The maximum value of *Gini* = 1, which would show the absolute inequality when one largest bank possesses all assets in banking system; the minimum value of *Gini* = 0, which is attained upon the absolute equality of all banks.

– Atkinson Index: a group of inequality coefficients that includes the sensitivity parameter (ε) varying within the range from 0 to infinity and enables a shift in the focus of analysis on distribution of the smallest market participants (Atkinson, 1992). We have calculated the Atkinson Index as an ancillary indicator with the standard value of ε = 0.5.

– GE (Generalized Entropy Index): a group of inequality indicators that includes the preset sensitivity component (α) which, when increasing, increases the sensitivity of GE(α) to inequalities in distribution among the system's largest banks. For the purposes of this work: GE(0.5), where α=0.5.

– Theil Index: a particular case of the entropy index:

$$Theil = GE(1) = \sum_i s_i \log s_i \, . \quad (6)$$

- Var (Variation Coefficient): the ratio of the standard deviation of assets (or other bank size indicators) to the average mean distribution of their values.

- σ ² (*variance of bank size logarithms*): squared standard deviation of logarithms. The *HHI* may be expressed as a function of the number of banks (*n*) and variance of market shares (σ^2), which for a certain *HHI* form the uniform concentration curve (*Hay, 1991*):

$$HHI = n\sigma^2 + \frac{1}{n}. \quad (7)$$

Apparently, the inequality indicators like variance, variation, or Gini coefficients are rather supplementary than full-fledged measures of concentration, because they do not take into account the number of banks on the market. Thus, the Gini coefficient will be equal to zero for systems with both 2 and 200 banks of equal size, despite the greater concentration of the former scenario of market organization. On the other hand, changes in heterogeneity of market organization help better understand the reasons that cause growth or decline of concentration, because in combination with the increase in the number of banks, they determine its dynamics as formula 7 shows.

The aforementioned coefficients became key indicators for descriptive analysis of panel and cross-sectional data, aimed at complete understanding of concentration dynamics on banking products markets and relative concentration indices vis-à-vis EU states. Methodologies of the rest of the empirical studies were described in paragraphs where pre-calculated concentration and inequality coefficients served as both dependent and independent variables.

For the majority of empirical calculations, we used the NBU data containing individual indicators of banks' quarterly financial statements for the period from 1 January 1998 to 1 October 2015. In addition, we used the European Central Bank's data concerning *HHI* and CR5 for particular EU states as of 1 January 2015.

V. Empirical results

a. Is Ukraine's banking system concentrated?

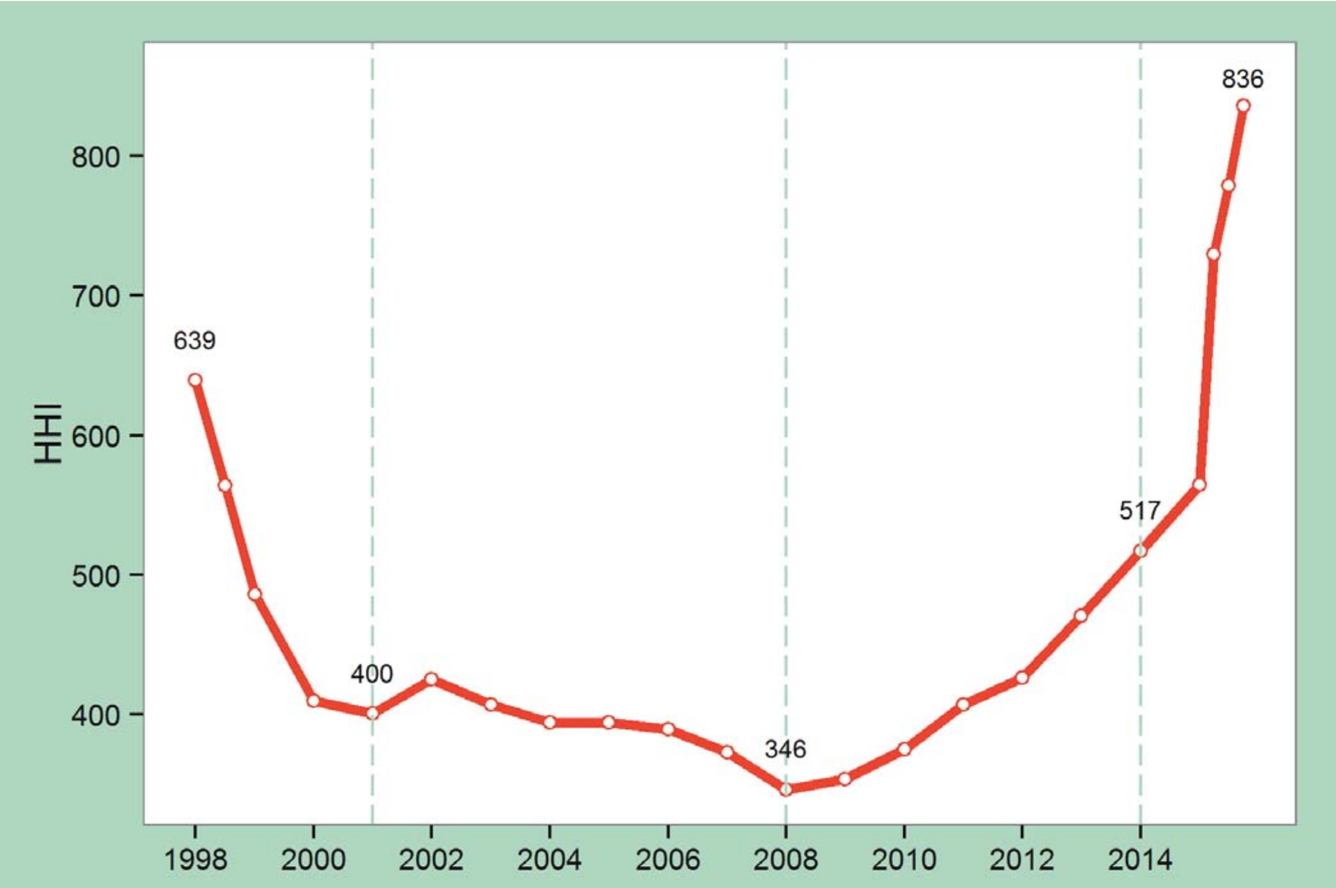
The first objective of our empirical study, which, once fulfilled, could allow us to move to the next itemization and forecasting phases, was to measure the existing concentration level of assets in Ukraine's banking market and dynamics of concentration over the past decades. Overall, large firms operating on a concentrated market are prone to uncompetitive behavior, thus creating a systemic risk according to the so-called "structure-conduct-performance" paradigm. Therefore, the growth of concentration per *HHI* by more than 100 points in the conditions of a highly-concentrated market (HHI>2,500) or by 200 points for a moderately-concentrated market (1,500<*HHI*<2,500) indicates a substantial increase of market force according to the U.S. antimonopoly law regulating horizontal mergers U.S. (2010). According to EU requirements, in the conditions of high concentration (*HHI*>2,000) the critical limit for a competition-safe increase of *HHI* is 150 points, whereas for moderate concentrations (1,000<*HHI*<2,000), an increase rate of over 250 points is considered threatening EC (2004).

Therefore, in order to refute the myth concerning threatening levels of concentration and spreading together with its growth, we have tested the *hypothesis regarding low concentration level of Ukraine's banking system* by calculating the key concentration and inequality indicators.

Our *HHI* calculations point out a low concentration of Ukraine's banking market: during the period from 1 January 1998 to 1 October 2015, the average *HHI* was 454 points and standard divergence of indicators 119. By the end of 3Q 2015, the *HHI* reached the maximum value of 836. Nevertheless, the overall banking concentration in Ukraine still remains low from the viewpoint of both stricter EU norms (1000) and softer U.S. norms (1500), fostering liberalization of mergers and acquisitions market.

Concentration level dynamics in Ukraine's banking system have four clearly-visible phases:

Figure 1. *HHI* dynamics (in asset terms) of Ukraine's banking system 1 January 1998 to 1 October 2015



1) 1998-2001: *HHI*'s sharp decline from 639 to 400 due to reformatting the market's organization and smoothening of inequality as a result of a series of liquidations, mergers and acquisitions, and growth of medium private banks with simultaneous shrinkage of market shares held by previous leaders – post-Soviet banks;

2) 2002-2007: *HHI*'s gradual decline to 346. We assume that strengthening market positions of "middle-echelon" banks, particularly due to development of retail banking and influx of foreign capital, was the key driving force behind that;

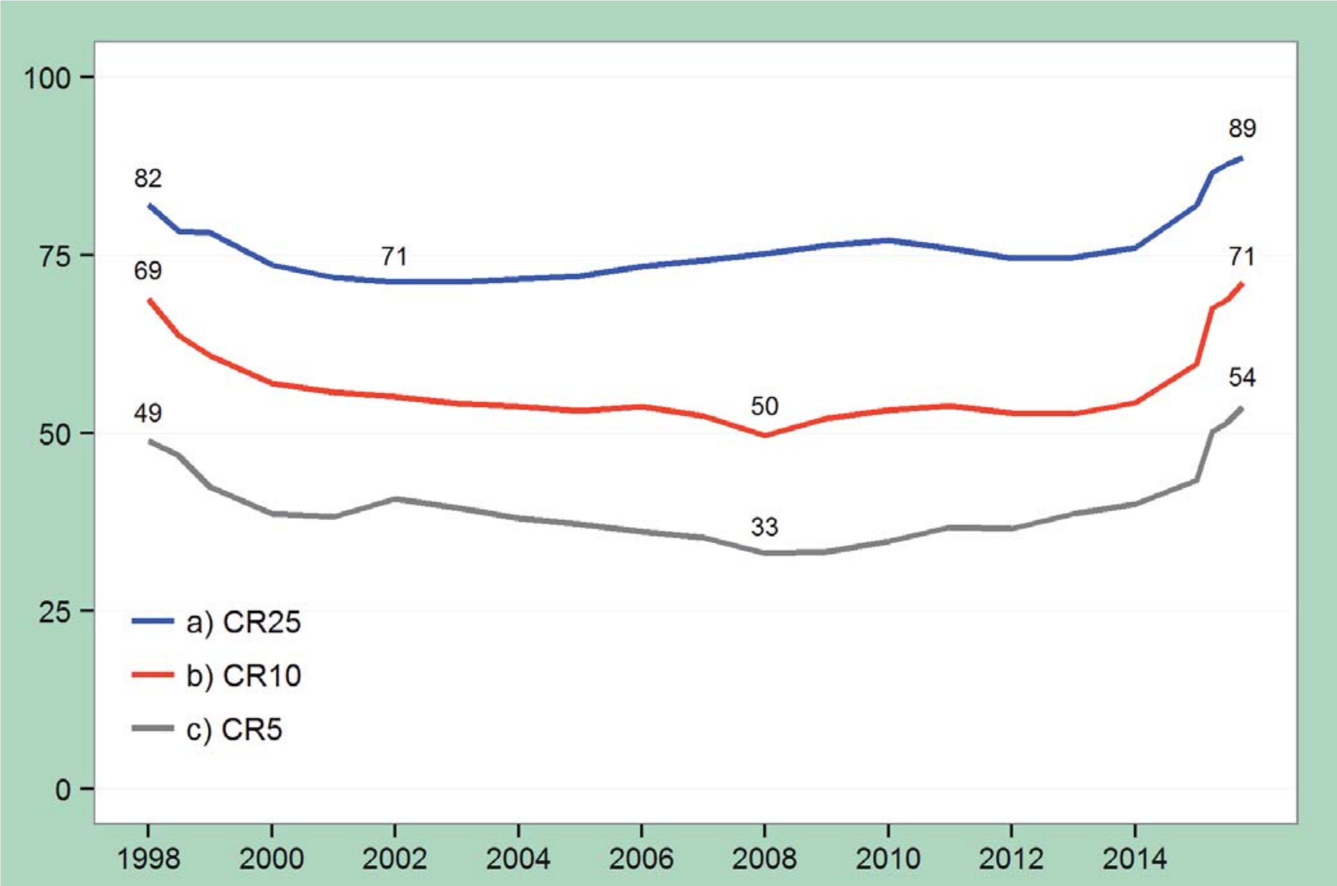
3) 2008-2013: concentration growth to *HHI*=517 after a wave of liquidations in the wake of crisis and growing market share of market's leaders;

4) 2014-2015: accelerating growth to the peak value of *HHI*=836 due to closure of over 60 banks as part of the cleansing and transformation of the banking system.

As we can see, the dynamics of concentration levels in Ukraine do not coincide with the phases of economic cycle, because the 2008-2009 financial crisis was characterized by minimal *HHIs*, while the crises of 1998 and 2014-2015 featured local maximums of this index. Even if a correlation between instability and concentration was discovered, it should not be interpreted as the proof of a cause-and-effect relationship, because there are many additional factors that had an independent effect on concentration and economic growth. Correlation does not imply causation, especially since the conclusion is made on the basis of one country, without doing a wider, cross-border sampling.

Similar trends in the decline and growth of concentration, with the turning point occurring in 2008, are corroborated by dynamics of simpler concentration indexes CRn (Figure 3). Maximum values of *CR3* = 45%, *CR5* = 53%, *CR10* = 71% were recorded as of the end of 3Q 2015 (Table 1). Therefore, market concentration has been intensifying in recent years, although still remaining, as we will see, not very high in comparison with EU states.

Figure 2. Dynamics of concentration indicators (in asset terms) of Ukraine's banking system



The widening spread between *CR10* and *CR25* from the beginning of 1998 to 2008 is worth noting: it confirms our assumption regarding the effect of increasing market potential of "middle-echelon" banks on declining concentration, for the strengthening of this layer of market participants smoothened the existing inequality between the largest and small banks. After the global financial crisis, this difference began to shrink, causing the reverse effect of increasing concentration. Having compared the empirical results, we came to the conclusion that the *HHI* dynamics correlate with CRn (if n<10).

The growing curvature of the concentration curve with a simultaneous upward movement also proves the increasing banking concentration during 2000-2015 (Figure 3). The key factors that drove the increase were, first of all, the growing role of five market leaders with Ukrainian (including public) capital, thus causing the curve to rise along the n=5 line.

Second, the cumulative market share of banks of groups II and III per NBU classification has grown on a much larger scale, resulting in the maximum increase of concentration of the top 25 banks. Besides the spreading layer of large banks, the "tail' of the smallest banks that hardly had any effect on the level of concentration has disappeared in the course of formation of the banking system, as the proximity of curves along the n=123 line shows. Therefore, consolidation due to the exit of the smallest banks had an insignificant effect on concentration.

The change of the shape of the Lorenz curve over time points to a certain intensification of inequality among Ukrainian banks (Figure 4). The higher a degree of its curvature is, the greater the inequality in distribution of assets among banks, expressed by the Gini coefficient, becomes. In our case, *Gini* grew from 0.74 as of the beginning of 2000 to 0.83 as of 1 October 2015 (Table 1). The maximum growth has occurred in the total share of the first 10% of banks.

Despite the overall similarity, the trajectory of inequality indicators was somewhat different from the dynamics of concentration indicators. With the exception of variation, increasing inequality in market organization already began in the second phase, simultaneously with decreasing concentration, continuing from 2001 to 2010 (Figure 5, 6).

Figure 3. Asset concentration curves for Ukraine's banking system as of 1.01.2000 and 1.10.2015

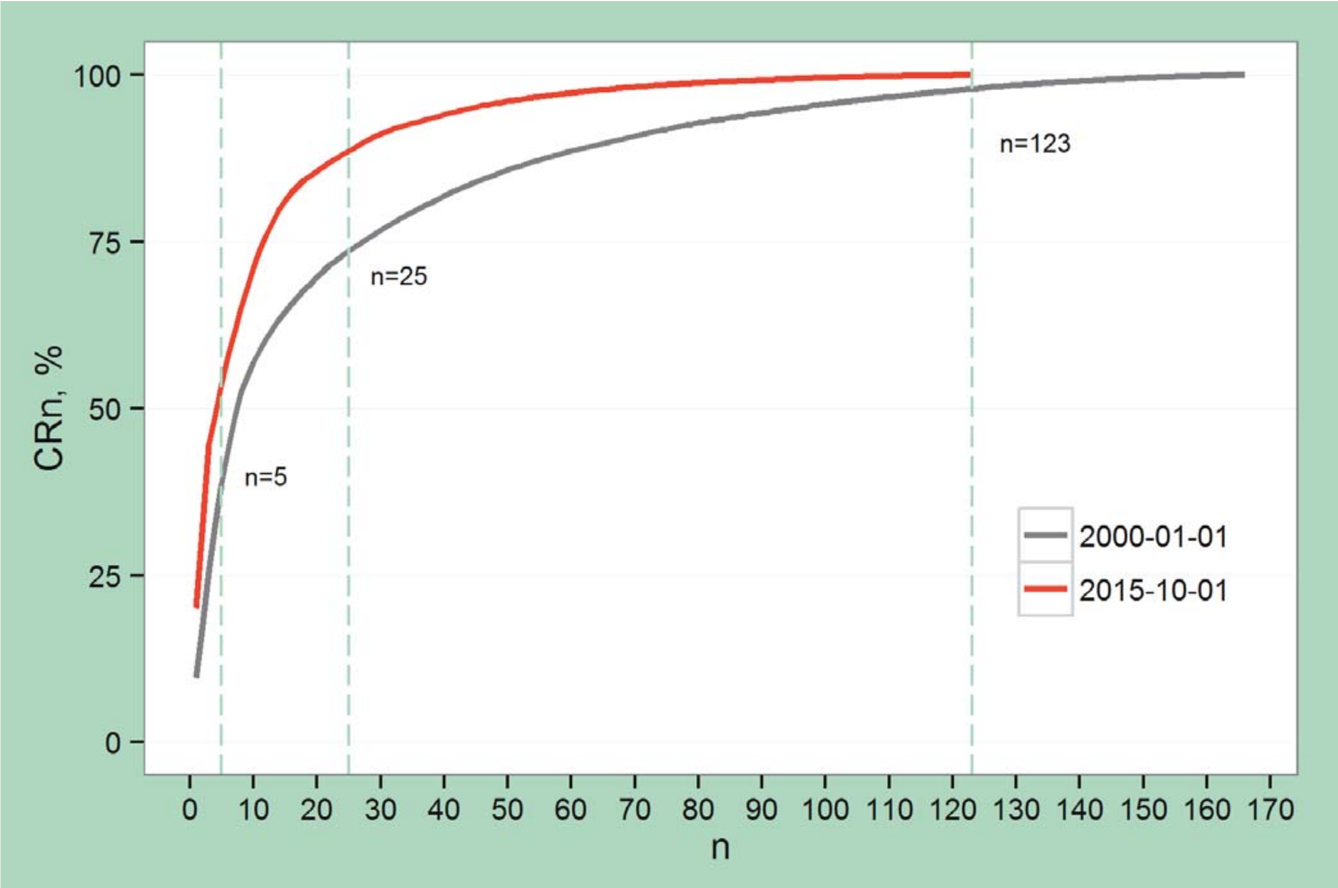


Figure 4. Lorenz curves for assets of Ukraine's banking system from 1 January 2000 (black curve) to 1 October 2015 (red curve)

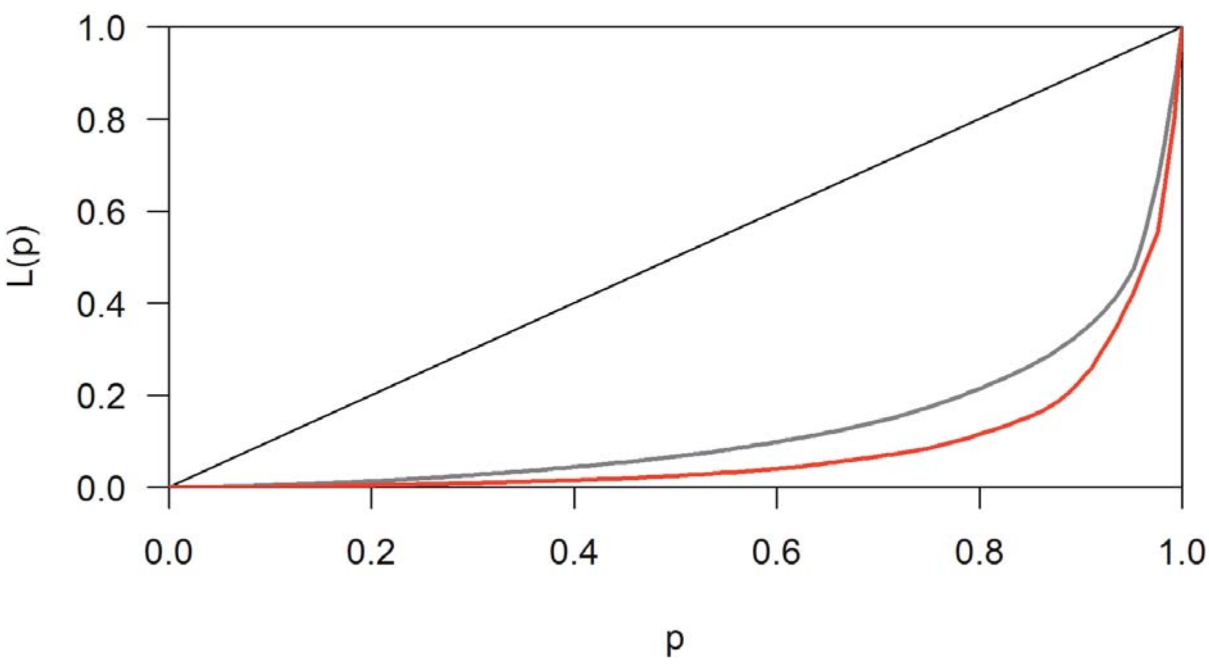


Figure 5. Dynamics of the Gini and Atkinson coefficients in asset terms

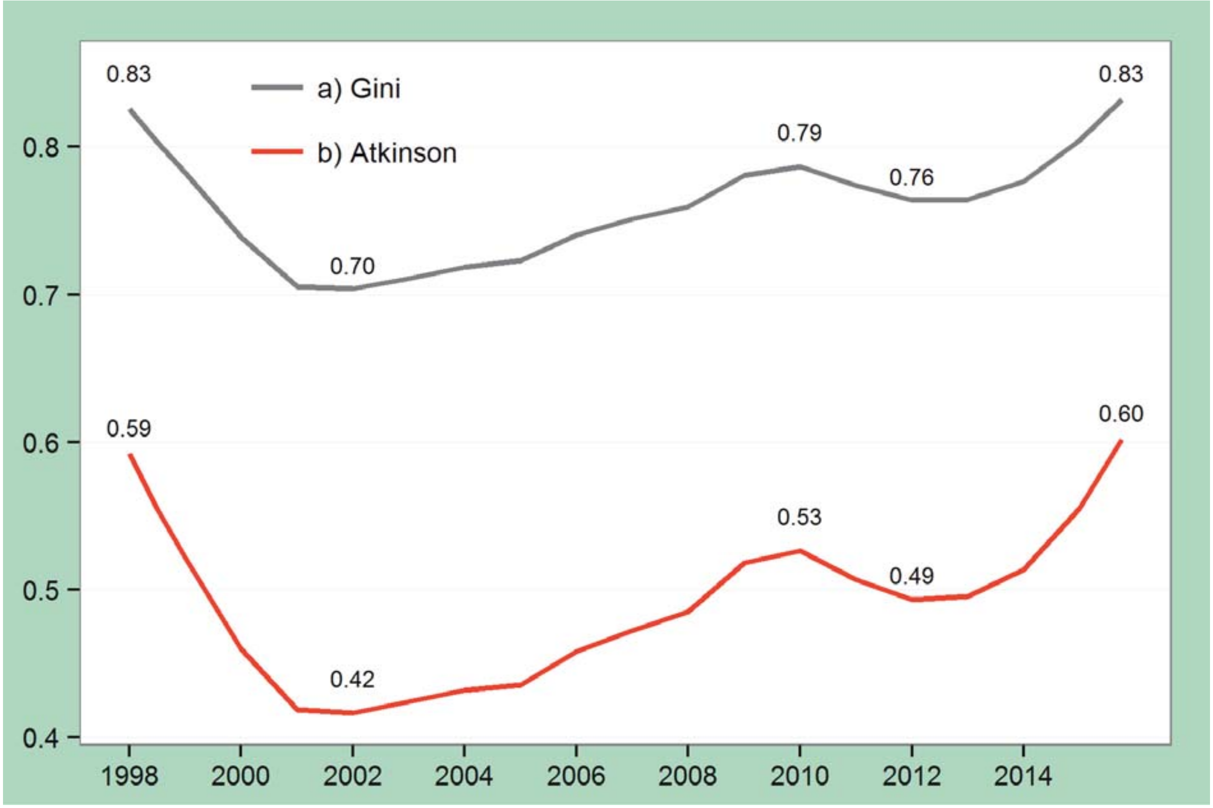
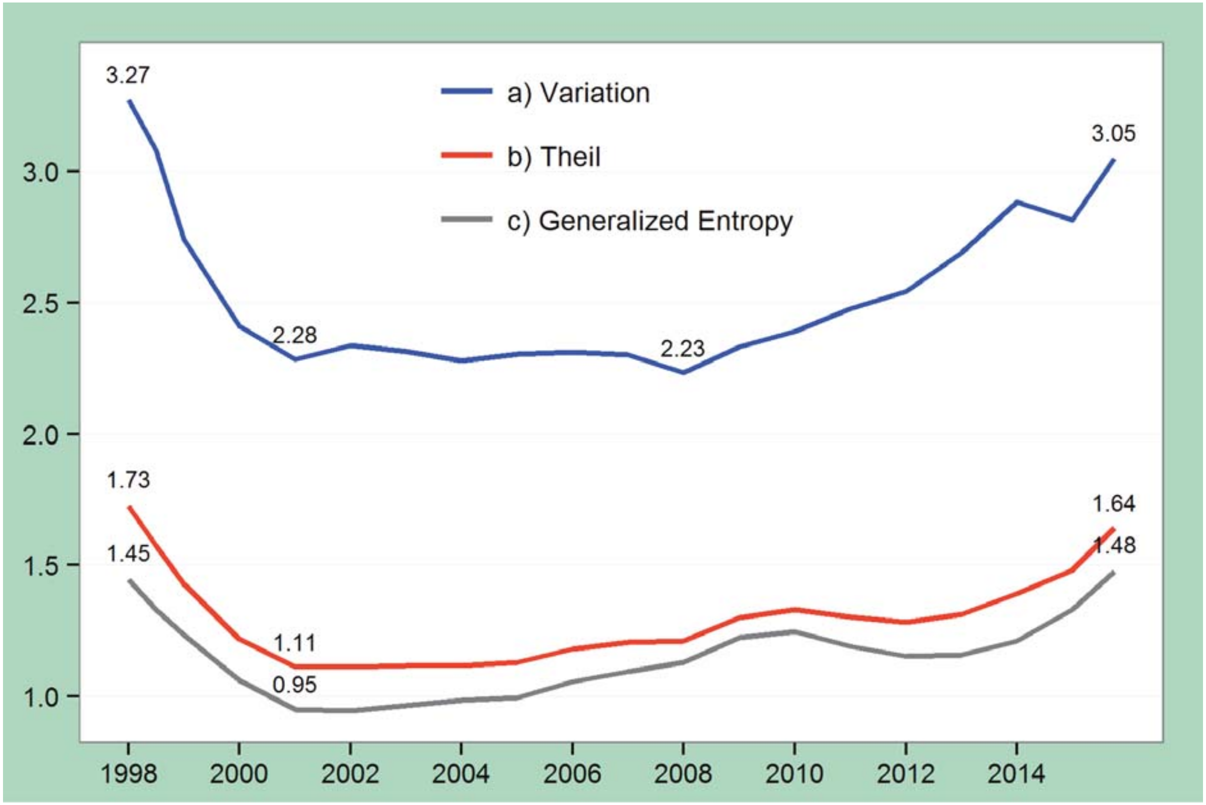


Figure 6. Dynamics of the Generalized Entropy, Theil, and Variation indexes in asset terms



After an insignificant three-year decline, inequality within the system, expressed via the Gini, Atkinson, Theil, and Generalized Entropy indexes, began to grow starting from 1 January 2013, nearing the historical maximums of 1998 (Table 1).

Summing up the results of our retrospective analysis, we can see that the hypothesis concerning low concentration level was proved, pointing to the absence of barriers to consolidation. However, Ukraine's banking system is moving toward the minimum threshold of moderate concentration area envisaging a somewhat closer monitoring of horizontal mergers and acquisitions. For a more accurate interpretation of Ukraine's banking concentration indicators, we suggest an additional comparative analysis with similar indicators of EU states.

b. What has been driving the growing concentration in 2014-15?

Expert discussions sometimes mention a myth regarding concentration resulting from the growth of market leaders, especially the largest and two state banks, and the overall increase of market inequality as the banking system undergoes cleansing. To better understand the true reasons behind concentration dynamics during the 2014-2015 crisis, we made an additional factor analysis. The purpose of this analysis was to evaluate the relative weight of the following two key factors for *HHI* growth:

1) A bank's exit from the market due to classification as insolvent; and

2) The increasing inequality among remaining banks on the market.

Let's test the hypothesis stating that concentration of Ukraine's banking system after 1 January 2014 was growing due to a decrease in the number of market participants, not increasing inequality among banks.

To calculate the net effect on the *HHI* of the decrease in the number of banks during 2014 and the first 9 months of 2015, let's take a fixed number of banks, n, by selecting from all the banks that were active as of the beginning of 2014 only those that remained solvent as of 1 October 2015. For this number of future solvent banks, let's calculate hypothetic values of market shares as of the beginning of banking crisis:

$$s_i^* = \frac{assets_{it}^*}{A_t^*}, \tag{8}$$

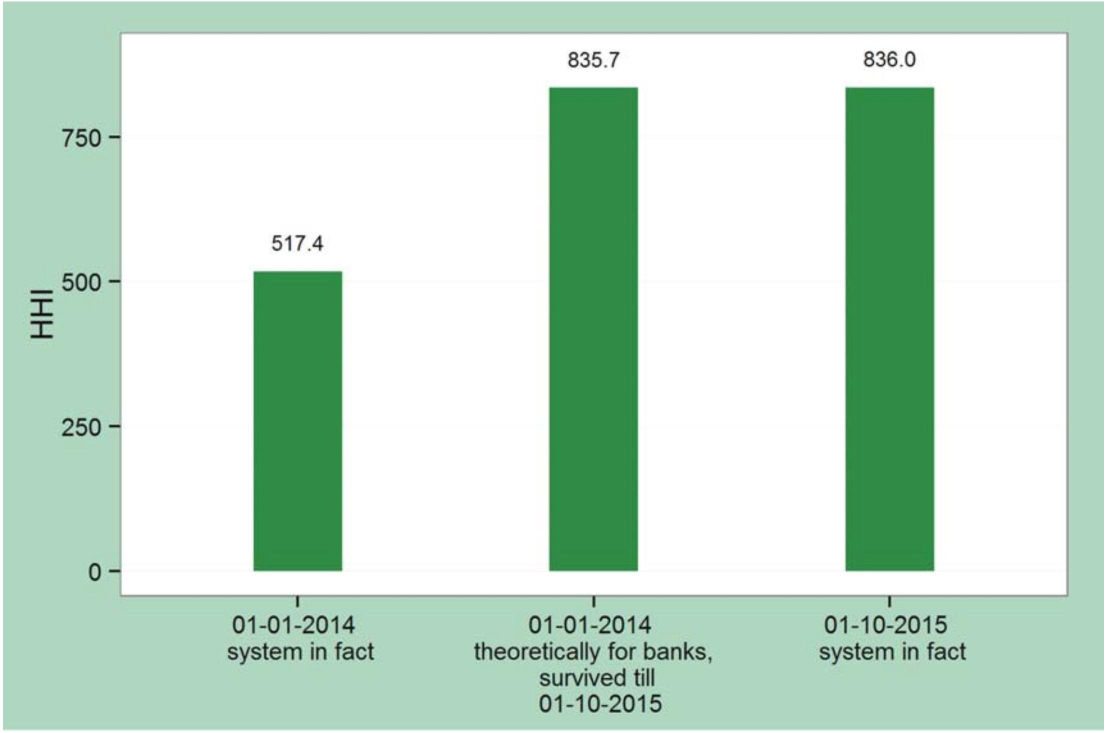
where t = 1 January 2014, $assets_{it}^*$ - assets of the *i*-th bank that remained solvent after the crisis as of 1 October 2015, A_t^* - aggregate value of assets as of 1 January 2014 for all the banks solvent as of 1 October 2015.

Apparently, if there were no banks that were later placed under temporary administration, hypothetic market shares of solvent banks would have been higher than the actual figures as of 1 January 2014. To ascertain the role played by the inequality factor, we'd like to know what the concentration indicators of our hypothetic banking system were as of the beginning of 2014 vs the most recent actual figures as of the end of 3Q 2015 (Table 2).

As our calculations show, the key concentration factor was the exit of problematic banks from the market (reduction of n), whereas the inequality in distribution of assets (σ^2) among active banks almost did not change. Concentration before and after crisis among banks that later turned out to be healthy was almost identical. For this hypothetic sample purged of the n reduction effect, the *HHI* was 835.7, which is only 0.3 points lower than the actual figure of 836.0 as of 1 October 2015. A factor analysis proves that the growth of the actual concentration per *HHI* during the period from 1 January 2014 to 1 October 2015 by 318.32 points (+99.9%) was driven by the decline in the number of banks, whereas the effect of changes in inequality was 0.1%.

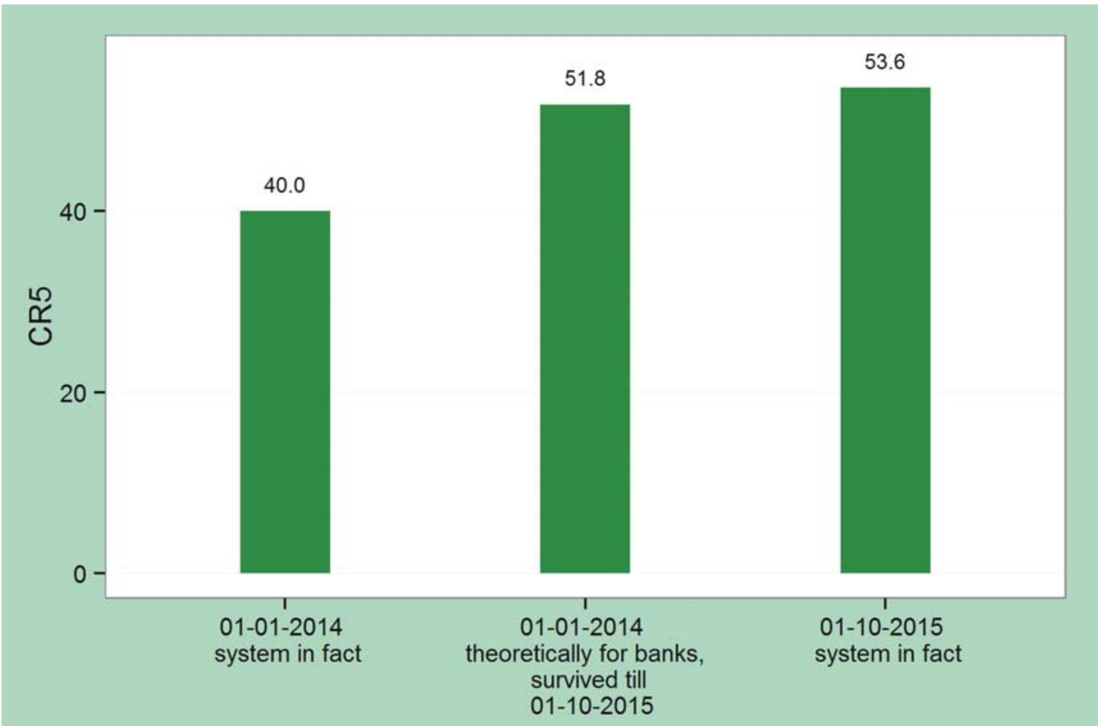
As we can see, the key concentration factor was the exit of banks from the market (reduction of *n*), whereas the growth of the share of top 5 banks in assets of survived banks was insignificant. The effect of the decline in the number of banks on the growth of concentration coefficients CR4, *CR5*, CR10 and CR25 varied within the 80-85% range, while the effect from the strengthening of market positions of the largest banks that survived the crisis was only 15-20% (Table 2). Different effects from structural changes unrelated to market exit on the increase of the *HHI* and concentration indicators can be explained by the features of CR_n concentration indexes, namely their insensitivity to dynamics of market shares of medium and small banks. The *HHI* does not have this flaw, comprehensively showing the overall level of fragmentation and inequality within the system.

Figure 7. *HHI* growth from 1 January 2014 to 1 October 2015



System's actual as of 1 January 2014; Theoretical for banks that avoided default between 1 January 2014 and 1 October 2015; System's actual as of 1 October 2015

Figure 8. *CR5* growth from 1 January 2014 to 1 October 2015



System's actual as of 1 January 2014; Theoretical for banks that avoided default between 1 January 2014 and 1 October 2015; System's actual as of 1 October 2015

The growth of the inequality indicators (Gini, Atkinson, Entropy, and Theil) has occurred, in particular, in the subgroup of healthy banks. The effect from internal structural changes was 40-45%, whereas the exit of banks from the market had a 55-60% effect on the increase of inequality indicators. Nevertheless, the overall increase of inequality in the system after structural changes was not significant: the Gini index has grown by 7% to 0.83, and the Atkinson index by 17% to 0.6.

What makes interpretation of transformational processes in Ukraine's banking sector difficult is the different dynamics rates of both concentration indexes and inequality coefficients in the subgroup of *healthy* banks. Nevertheless, these differences are insignificant in comparison with the consolidation effect on concentration growth by the decrease in the number of market participants, the factor that contributed 99.9% to the *HHI* increase. Therefore, **the hypothesis regarding the decisive effect of banks' exit was confirmed and refuted the myth concerning the substantial contribution of increasing inequality to concentration growth**.

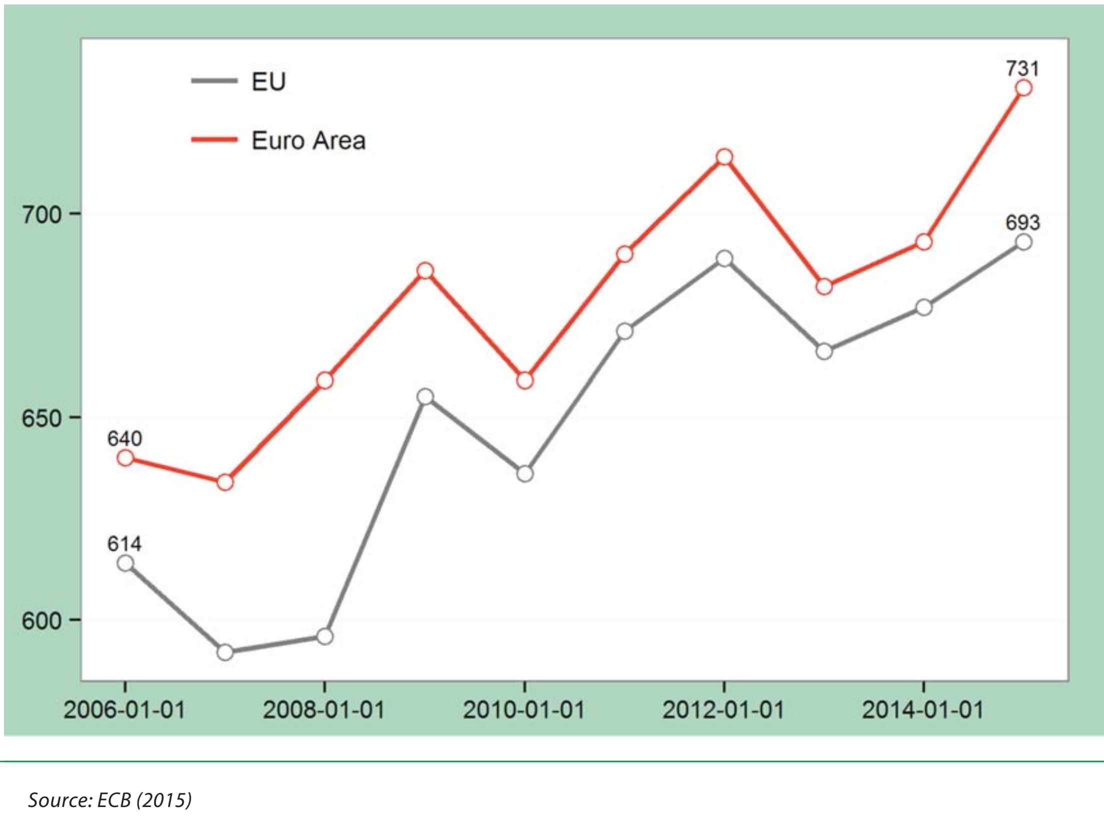
c. How concentrated is Ukraine's banking market in comparison with EU states?

A more accurate interpretation of concentration and inequality dynamics in Ukraine's banking system requires comparison of domestic indicators with similar coefficients of other countries of the world. The myth regarding concentration threat may be finally dispelled only by comparing concentration with not only general normative indicators, but also with actual industry indicators of foreign countries. Thus, according to our hypothesis, Ukraine's banking market is insufficiently concentrated when compared to European countries.

To compare our calculated concentration indexes with European, we used the *HHI* and CR5 indicators of EU states as of 1 January 2015 (ECB, 2015). According to data by the ECB, market concentration in EU continues its upward trend that began in the pre-crisis period (Figure 9). The growth of concentration indexes in the EU, as in Ukraine, is driven mainly by a decline in the number of credit institutions.

Banking sectors with the maximum concentration are found in Estonia, Greece, and the Netherlands, whereas the banking systems of Germany, Luxembourg, Finland, Austria, and Italy are the least concentrated.

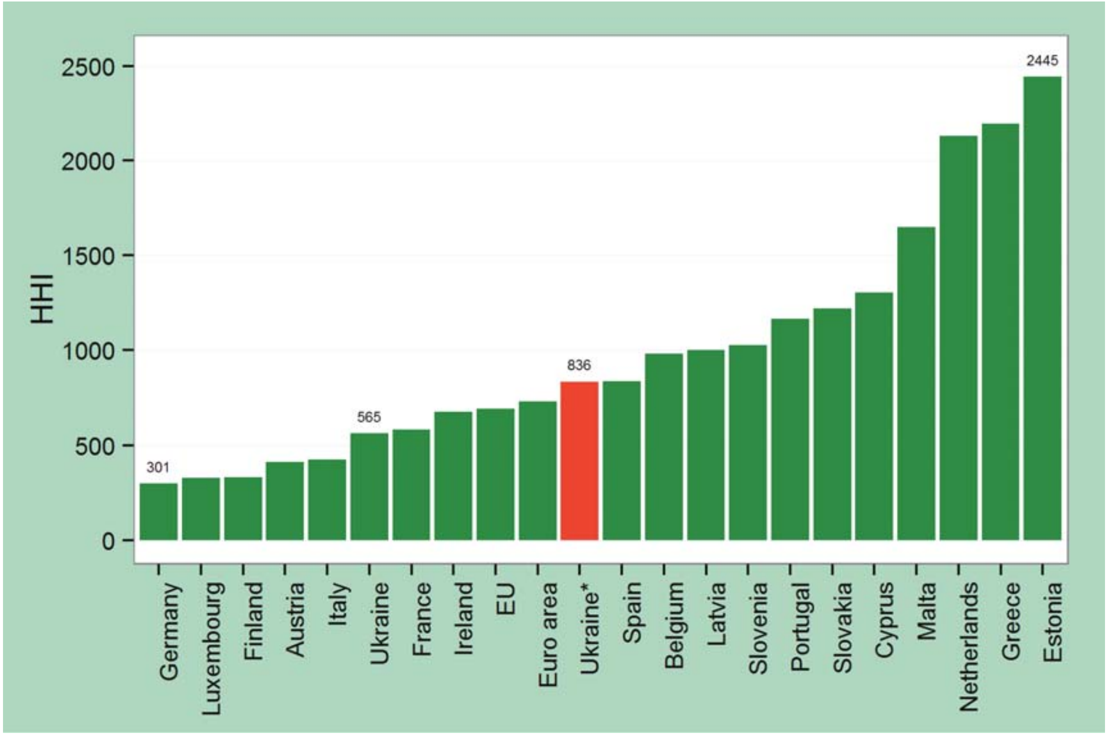
Figure 9. Dynamics of banking concentration (HHI) in the Euro Area and EU



Source: ECB (2015)

At the same time, the present increase of concentration in Europe is driven by consolidation processes in France, Germany, and Spain, the countries that traditionally have more fragmented banking systems with strong sectors of savings and cooperative banks. Smaller EU states (except Austria, Ireland, and Luxembourg) have much higher concentration indicators than Ukraine (Figure 10).

Figure 10. Concentration level in banking systems of European countries (*HHI*), 01.01.2015



**- data for Ukraine as of 1 October 2015*

Our descriptive analysis of cross-sectional data shows that as of the beginning of 2015, concentration in Ukraine was lower than Europe's average. Even today's historical maximums of the *HHI* in Ukraine are quite acceptable compared to many EU states. At the same time, Ukraine's *HHI* has exceeded contemporary average European figures, which suggests closer regulatory attention to consolidation processes and development of preventive instruments that would foster positive consequences, such as growing effectiveness and affordability of financing, while at the same time minimizing systemic risk and protecting rights of financial services consumers.

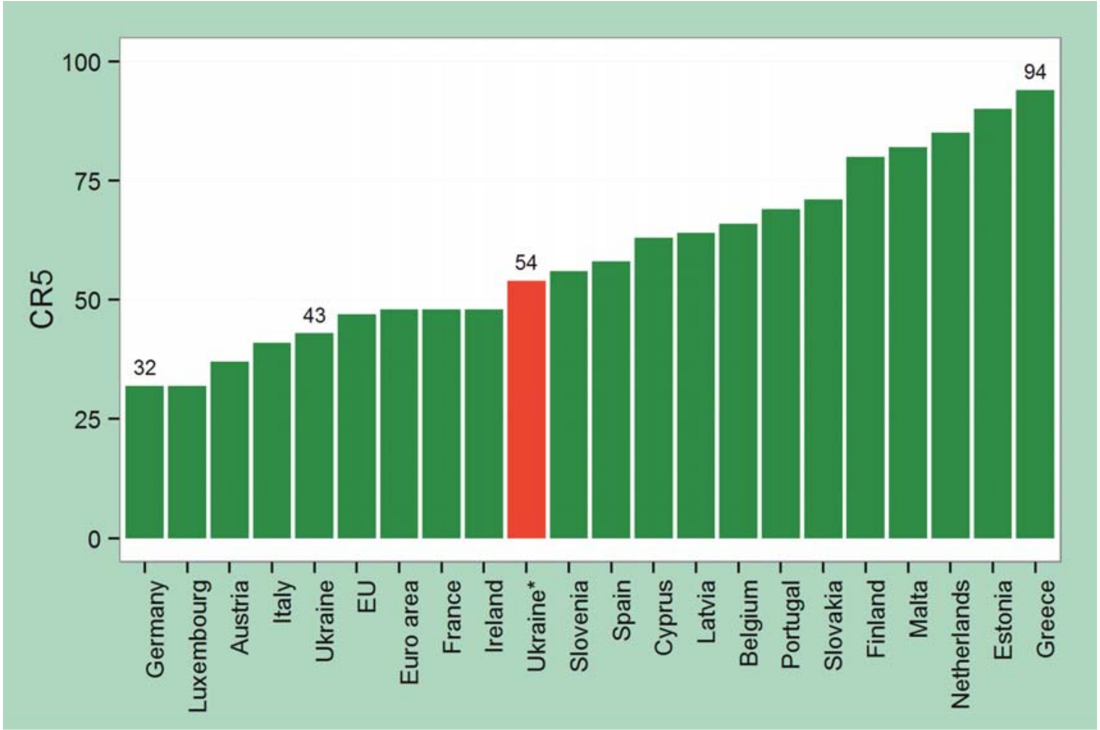
Overall, as of the beginning of 2015, market concentration (measured by the share of assets of five largest banks, *CR5*) varied from 95% in Greece to 32% in Germany and Luxembourg. From the viewpoint of *CR5* change during 2008-2014, the banking sector has trended toward growing concentration in many EU states, especially those undergoing profound banking restructuring processes: Greece, Spain, Malta, Lithuania, etc. Concentration in other large economies, such as Germany and Italy, has increased during that time, whereas concentration declined in Estonia, Belgium, and Slovenia (ECB, 2015).

Multidirectional dynamics of concentration in EU states shows that the European trend toward increasing concentration is not completely unambiguous, while the growth of averaged indicators was driven, to a large degree, by the greater weight of national economies with a positive increase and by a substantial potential for concentration considering historical fragmentation of their banking systems.

The reasons for the surge in banking concentration in Ukraine, like in Germany and Italy, are also related to low starting levels and substantial growth opportunities; however, the growth rate may significantly decline after entering the moderate concentration area. Therefore, it would be erroneous to directly extrapolate today's concentration rate of Ukraine's banking market onto future periods.

In terms of the aggregate share of assets of the 5 largest banks, Ukraine again ended up below EU's average, still substantially climbing in ranking during the year. By the end of 3Q 2015, Ukraine's *CR5* indicator was higher than the corresponding banking market concentration index in Euro Area countries as of the beginning of 2015 (Figure 11).

Figure 11. Asset concentration indexes of top 5 banks (CR5) in European countries, 1 January 2015



**- data for Ukraine as of 1 October 2015*

As we can see, Ukraine's banking market is not as concentrated in asset terms as markets in many EU states, while already reaching the EU's average concentration level.

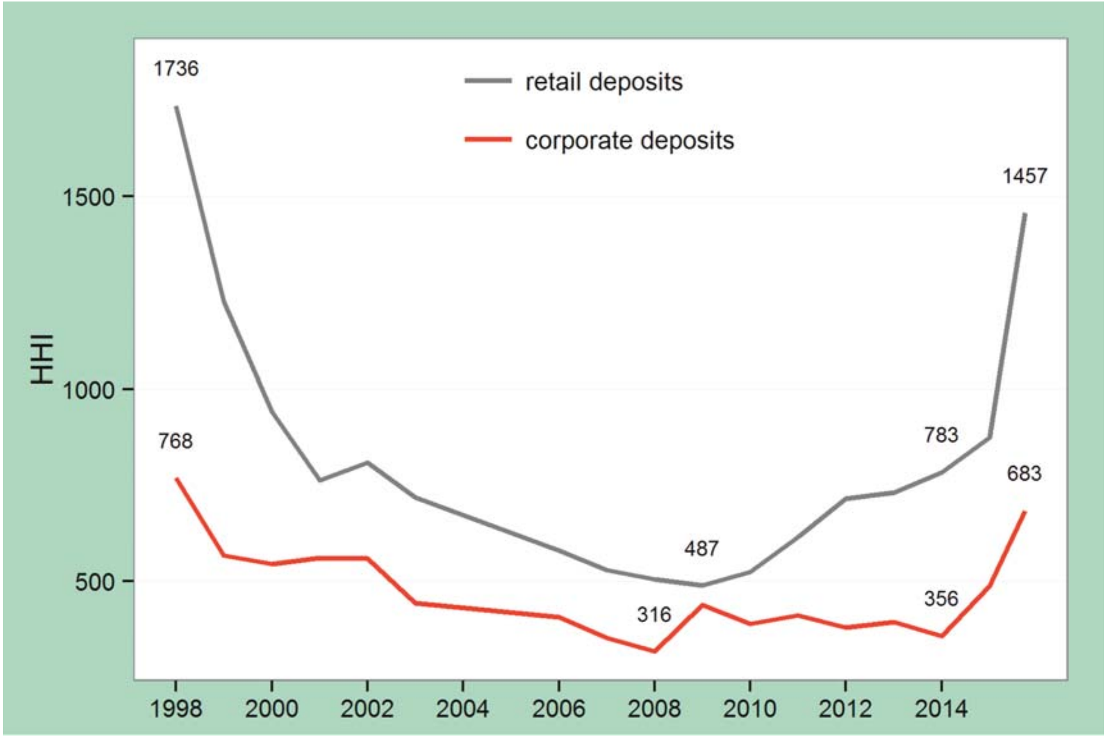
d. What is the level of concentration of particular banking products markets?

The first conclusion, which suggests an insignificant level of overall banking concentration in Ukraine is this: "so, there is no need whatsoever in any actions by the regulator for the time being?" A positive answer to this question would be somewhat premature in view of the differences in concentration levels of particular banking products markets. It is better to call this myth a generalization error, because experts often tend to assess the overall concentration of the banking market without breaking it down by products. Therefore, let's check the *hypothesis claiming that concentration of markets for particular banking products in Ukraine still differs from the overall picture*.

As we stated earlier in the methodological part of this study, objective analysis envisages additional study of concentration on particular product markets, because specialization and focusing make formation of even the so-called "segmented monopoly' in banking systems with low concentration theoretically possible.

According to our calculations, the market share of the largest Ukrainian bank differs substantially between its corporate and retail segments of the deposit and credit markets. This fact, and also differences in the total number of competitor banks in various segments, lead to substantial divergences in "product' concentration indicators. Let's illustrate the existing differences using *HHI* dynamics as an example for the individual bank deposit market. As Figure 12 shows, the overall concentration level of the retail deposit market is higher in comparison with indicators of the corporate deposit market. It can be explained by a substantial number of banks with corporate specialization.

Figure 12. HHI dynamics on retail and corporate deposits market



retail deposits; corporate deposits

The emergence of banks with retail business models during the formation of Ukraine's banking system and the loss of market-dominating positions by large post-Soviet financial institutions led to a sharp decline in the concentration of the individual deposit market in the late 1990s from 1,736 to 940 at the turn of the century. The concentration level continued to decline thereafter as well, but each year at a slower rate, reaching the minimum of 487 in the midst of the global financial crisis in 2009.

The introduction of over 90 temporary administrations in the wake of the 2008-2009 and 2014-2015 crises led to a sharp reduction of deposit product options on the market, while "cherry-picking" by certain banks, in view of the falling trust in most financial institutions, increased the inequality in the amount of deposits received by other existing banks. As a result, we observe the growth of the *HHI* for retail deposits market to 1,457 as of 1 October 2015. The corresponding concentration indicator for corporate deposits market is half that amount: 683 (Table 3).

These trends in concentration dynamics in various segments of the deposit market are corroborated by CR_n indexes, in particular, CR5 shown on Figure 13. The differences in concentration levels in various segments of the loan market are less significant than on the bank deposits market (Figure 14). A substantial decline in concentration of the retail loans market took place during 2006-2012 – hypothetically, as a result of the pre-crisis boom in auto and mortgage loans caused by the activity of European banks and the subsequent post-crisis increase of the shares of certain Ukrainian and Russian banks in the consumer micro-financing market.

The overall distribution of historical *HHI* values for various products, shown on Figure 15, proves the higher concentration of the retail banking. During 2015, the *HHI* for individual deposits and loans entered the moderate concentration area according to EU standards, the corporate loans market is nearing the 1,000 mark, while the corporate deposits market remains at a low concentration (Table 3). Therefore, financial regulators conducting monitoring should pay greater attention to the banking retail market inclined to higher concentration than the market in general, while consolidation processes on the retail market will produce bigger changes in concentration.

We assume that further segmentation of the banking market by various product subcategories might show even more substantial differences in concentration, but such a detailed study cannot be done on the basis of publicly-available data.

Figure 13. Dynamics of *CR5* concentration indexes per assets and deposit market segments

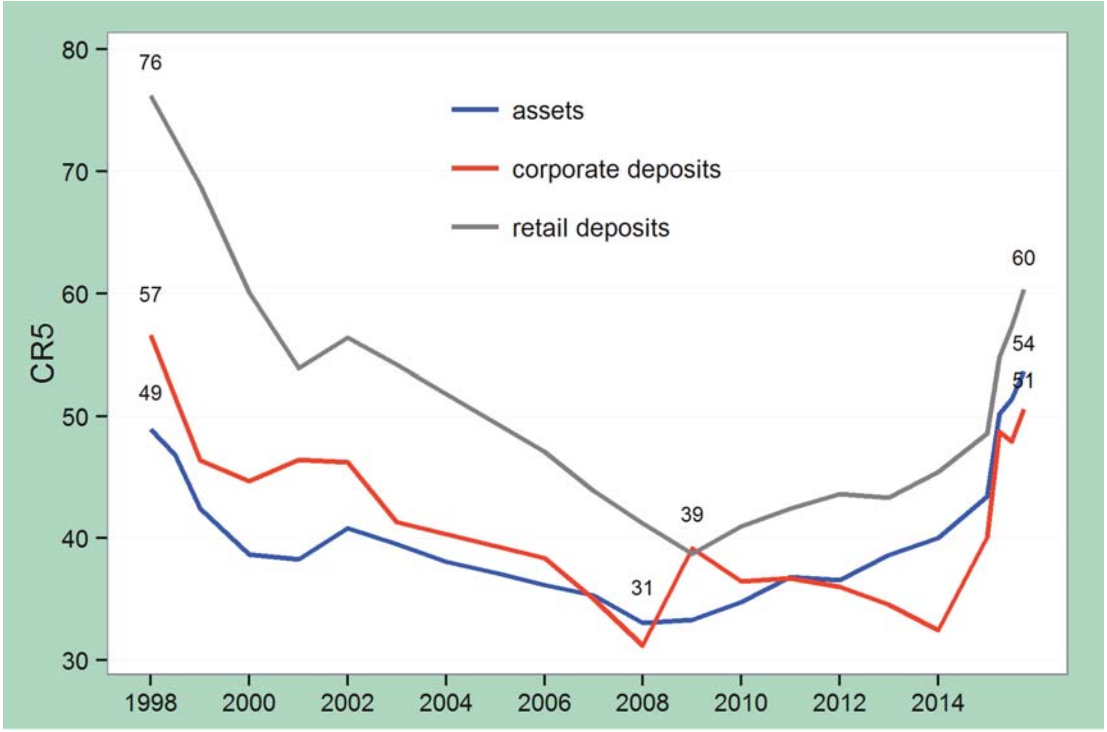
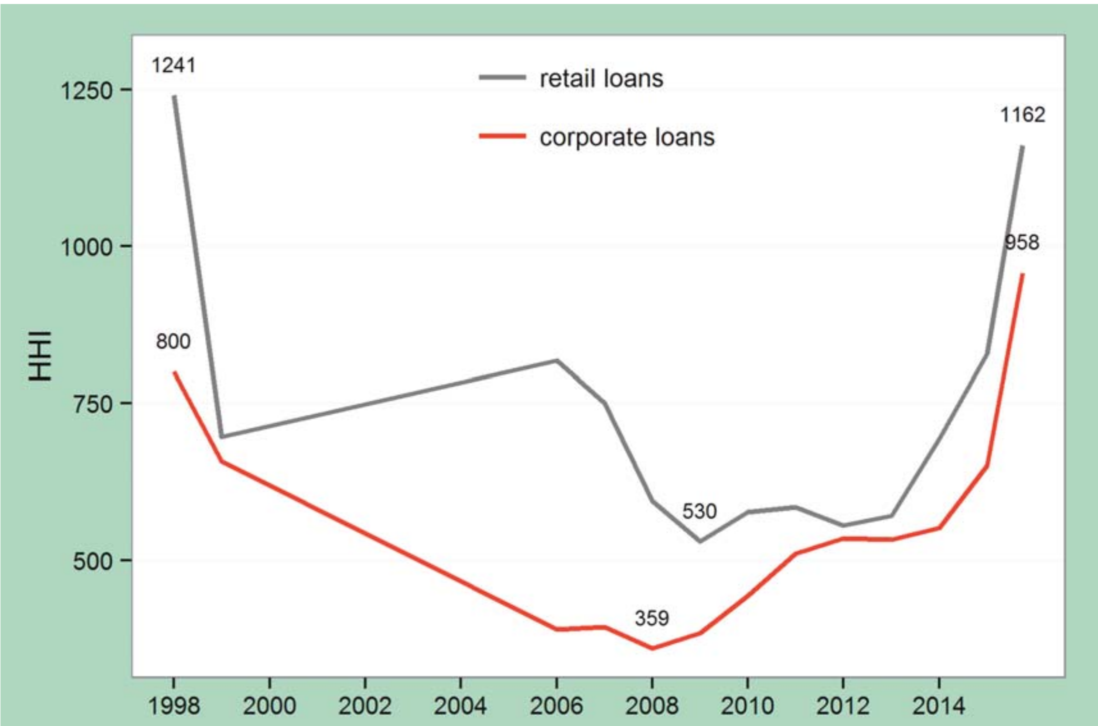
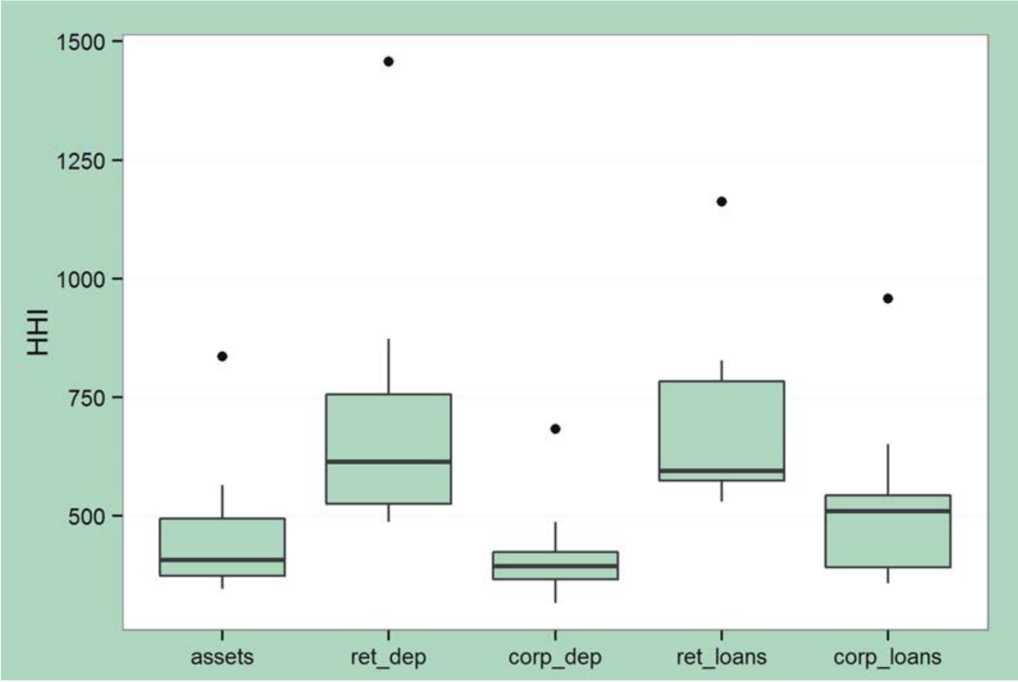


Figure 14. *HHI* dynamics on the retail and corporate loan market



retail loans; corporate loans

Figure 15. Distribution of historical *HHI* values on banking product markets, 2005-2015



The same is true for the rest of markets for non-interest banking products. Considering the open data, we assume that there are signs of excessive concentration in certain segments of the bank payments market. For example, assuming that banks' market shares are distributed proportionally to the number of such nonfinancial indicators as active payment cards issued by these banks, operational ATMs, and other, we can obtain the following *HHI* values: 3,062 (number of active payment cards), 3,372 (ATM network), and 4,163 (POS terminal network).

Therefore, before jumping to conclusions based on the general aggregated data for asset or capital concentration, or the total amount of loans or deposits without breaking them down by product types, it is worth paying attention to problems related to the limits of the banking services markets and structural particularities of inequality.

e. How may the exit of banks affect concentration?

Our retrospective analysis shows that the exit of banks from the market as a form of systemic consolidation was the key factor behind the growing concentration in recent years. Therefore, there are grounds for the myth that continuing cleansing of the banking system will produce a significant concentration increase in the future, even though its levels today are low or moderate. *However, our hypothesis will state that the exit of small and medium banks would have an insignificant effect on the future level of concentration*.

Within this context, let's tackle the practical problem of assessing the effect of a decline in the number of banks on the concentration level. Using the Monte Carlo method, we'll calculate the maximum and minimum increase of bank concentration indexes in Ukraine due to the continuing trend toward a reduction in the number of active banks after introduction of temporary administration.

Let's take the target number of banks after reduction as: k = 100. First, we'll make a number of assumptions for a simulated model of banks exiting the market:

- There are two periods: before (t) and after ($t+1$) the exit of banks.

- Let t= *1* October 2015, then the total number of solvent banks on the market is $n=123$.

- The number of banks removed from the market in the future period: $n_{def}=n-k$ = 123-100 = 23.

- During the (*t+1*) period, the market will lose assets of liquidated banks which will not be taken over by active financial institutions.

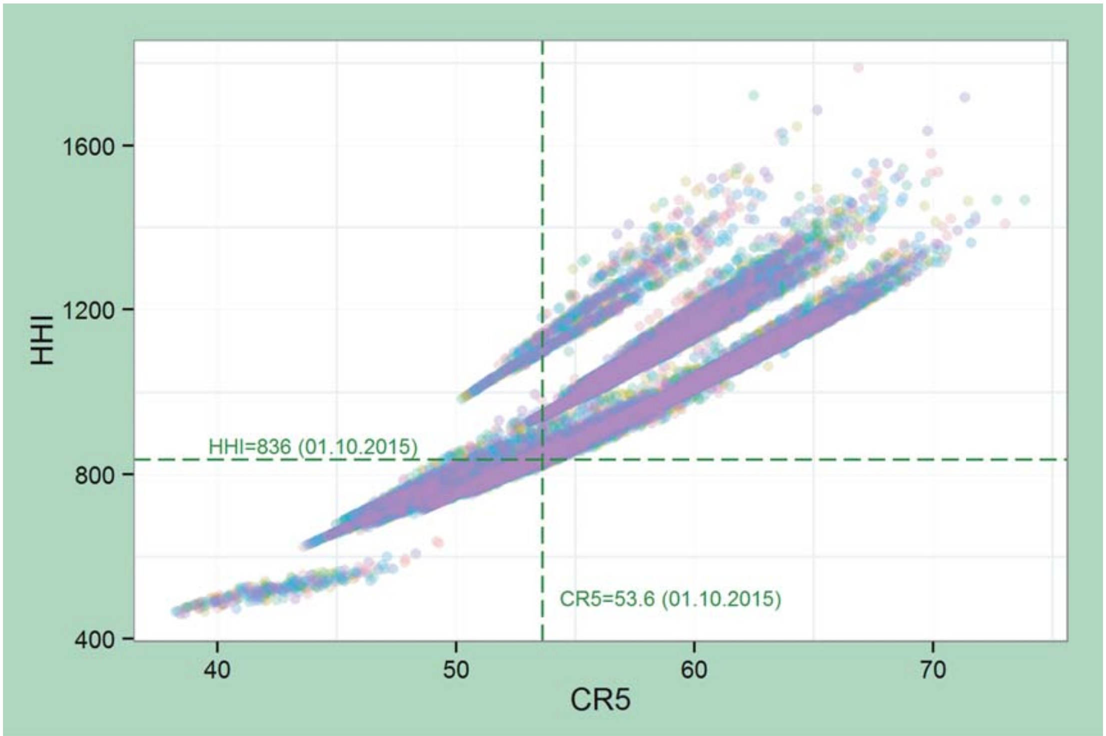
- The volume of assets of every active bank remains the same as of t and as of (t+1).

1) Let’s assume that the probability of liquidation is the same for all banks in the system regardless of their size

By taking 10,000 random samples of banks containing k out of n banks operating during the t period each, we’ll calculate 10,000 scenarios for future distribution of market shares in Ukraine’s banking system. For every set of market shares showing possible future scenarios of market organization, we’ll calculate potential concentration indicators. To determine the standard deviation of the study, we’ll conduct several series of similar simulations.

The statistical characteristics of our calculation results regarding the range of possible *HHI* and *CR5* values are shown in Table 4 and illustrated in Figure 16.

Figure 16. Distribution of asset concentration indicators due to a decrease of the number of banks to 100 (simulation of 50,000 possible bank exit scenarios for the overall system)



The results show that the maximum possible and very improbable *HHI* values after reduction of the number of banks to 100 will be less than 1,800, not reaching the lower boundary of the high concentration area (given the invariable volume of assets and absence of mergers and acquisitions). On average, the *HHI* will grow to 1,007 and *CR5* to 58%. At the same time, there are possible yet hardly probable scenarios of declining concentration indexes to 458 and 38%, respectively (Table 4).

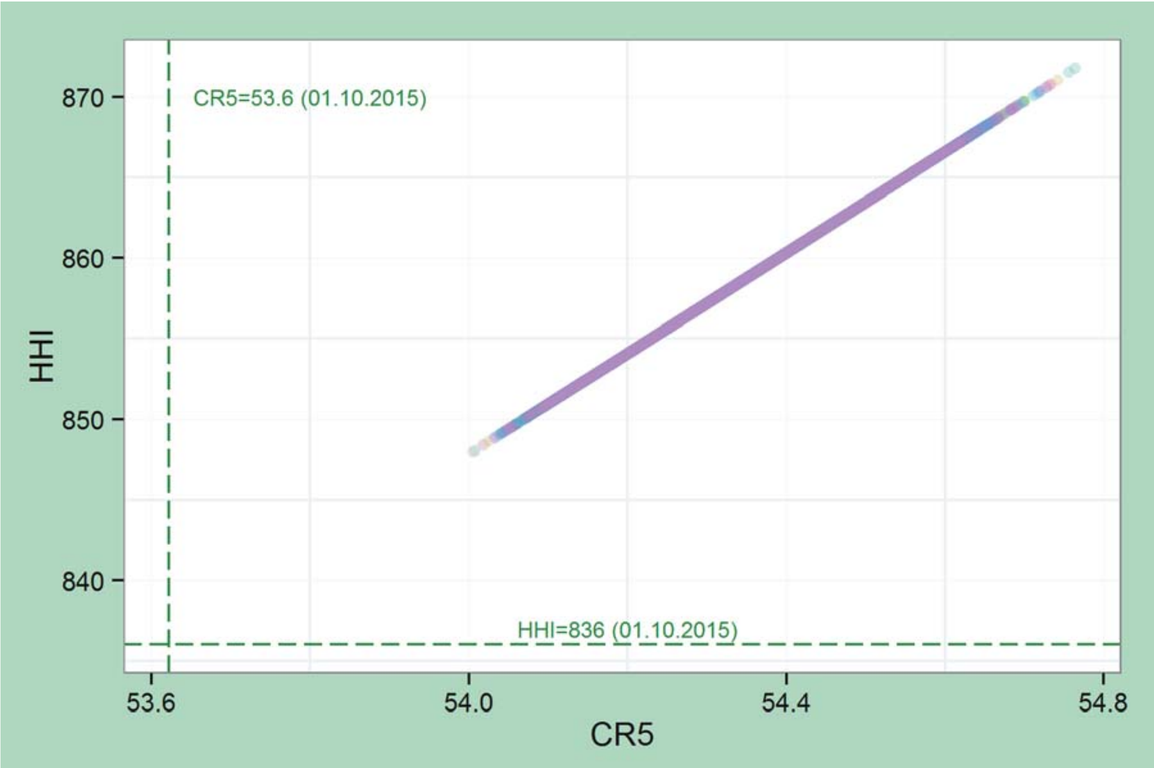
It is worth noting that of the many hypothetical combinations we received, especially those involving simultaneous liquidation of many systemically-important banks with preservation of small ones, make no economic sense, and therefore, one has to take into account that the probability of a bank default is historically higher for small financial institutions.

2) Let's assume that only the small banks of group 4 per NBU classification will exit the market

In that case, 10,000 random samples will be taken first among small banks (sub-sampling), so that, after adding them to the preserved banks of groups I to III, the total number of banks in the sampling is 100. After that, we'll calculate market shares and concentration indicators using the same algorithm.

After a decrease in the number of banks to 100 due to the exit of small banks only, the *HHI* will grow to 859 on average (which is not much higher than the initial indicator), with the maximum value not exceeding 873 and the minimum value approximately 847. The *CR5* index will vary within the 54-55% range, and therefore, will remain virtually unchanged because the aggregate share of the five largest banks will increase by 1 percentage point at the most due to proportional growth of market shares. It would be fair to disregard the factor of exit of the smallest banks, for the unevenness in natural growth of market leaders has a much stronger influence over the future *CR5* indicator.

Figure 17. Statistical distribution of asset concentration indicators due to a decrease in the number of banks to 100 (simulation of 50,000 possible market exit scenarios for the group of the smallest banks)

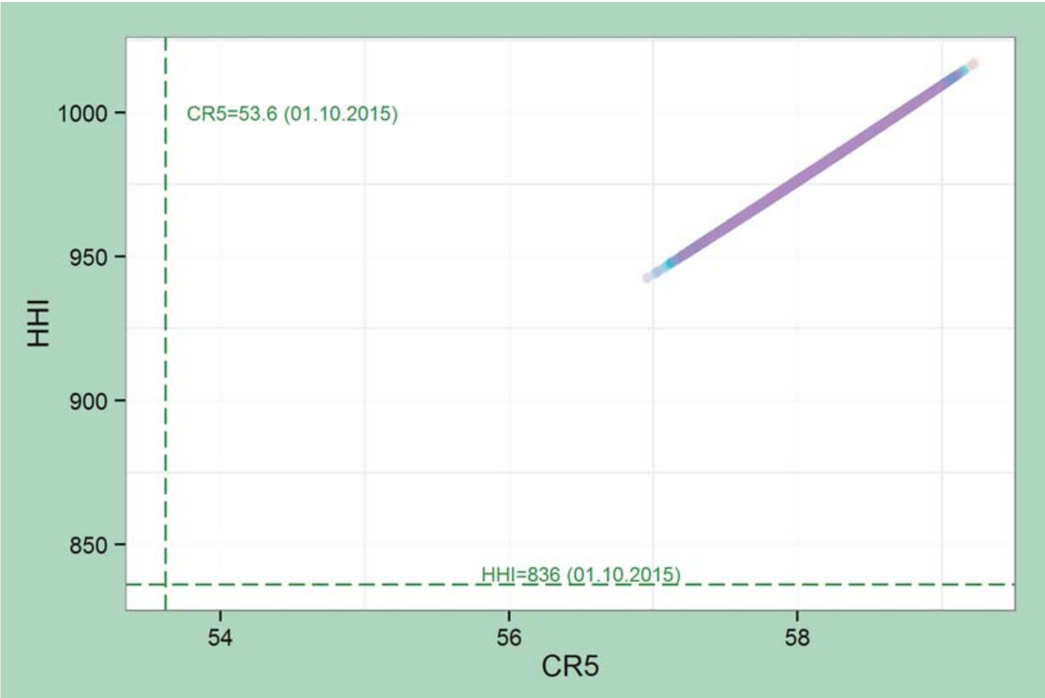


3) Let's assume that only the banks of groups 3 and 4 per NBU classification will exit the market, k=50.

Due to reduction of the number of banks to k=50 due to the exit of banks from groups III and IV only, the average *HHI* will increase to 983, which is only 18% higher than it was as of 1 October 2015. In that case, the maximum *HHI* will reach 1,016 and the minimum approximately 944. *CR5* concentration indexes will stay within the 57-60% range.

The results we obtained refute the myth regarding future monopolization and excessive concentration of assets on Ukraine's banking market solely due to a decline in the number of banks. Even if we assume the same probability of default for every bank in the system, the overall *HHI* cannot reach beyond 1,324 with a 99% probability (Table 4). On the other hand, one should not forget about the higher concentration of the retail market, uneven natural growth of certain banks and the potential effect on concentration of another consolidation channel, bank mergers, and acquisitions.

Figure 18. Statistical distribution of asset concentration indicators due to a decrease in the number of banks to 50 (simulation of 50,000 possible market exit scenarios for banks from the groups III and IV)



f. Do regulators need to limit further mergers?

The myth regarding the threat of increasing mergers and acquisitions that may intensify monopolization of the market has found a legislative reflection in the provisions envisaging a complex process of procuring mandatory permits from the AMCU and NBU for every merger. In order to dispel this myth, we'll check the *hypothesis that mergers of small and medium banks will have an insignificant effect on market concentration, and therefore, there is no sense in limiting their reorganization under conditions of moderate concentration*.

In Ukraine, consolidation of the banking market in the form of bank mergers may become an alternative to bankruptcy that will bring a positive effect on both the micro and macro levels. As a result of a merger, participating banks may achieve a number of individual goals on the way toward increased effectiveness and financial strength. According to the synergy theory, based on the assumption that managers acts in the interests of shareholders, a key motivation for a merger could be to obtain synergetic effects in the form of:

– *operating synergy* manifested in the savings on operating expenses, reduced operational ineffectiveness, savings on innovative development costs, effects from combining complementary products, and an increased size of bank's market niche;

– *financial synergy*, i.e., optimization of taxation, the possibility of buying a bank below its book value, diversification of income sources and risks, and decreases in capital costs.

A large number of empirical studies have supported the synergy theory, including Davidson et al. (2009), Mukherjee et al. (2004), and Ramaswamy (1997).

According to the agency theory of free cash flow, mergers and acquisitions using debt financing may not only create added value for shareholders, but also help solve the principal-agent conflict (Jensen, 1986). Unlike the two former theories, the hubris theory envisaging irrationality of managers' decisions regarding mergers or acquisitions (Roll, 1986) turned out to be the least empirically substantiated (Rudik and Semenkova, 2000).

According to theoretical and empirical conclusions drawn in most of the aforementioned studies, the increase of the overall capitalization and adequacy of regulatory capital, better adherence to minimum regulatory capital norms, a decline in the number of defaults and certain savings on liquidation costs, and an increase in the banking system's overall effectiveness via quality replacement of management and transformation of banks' business models may become positive macro-effects from intensification of mergers and acquisitions among Ukrainian banks.

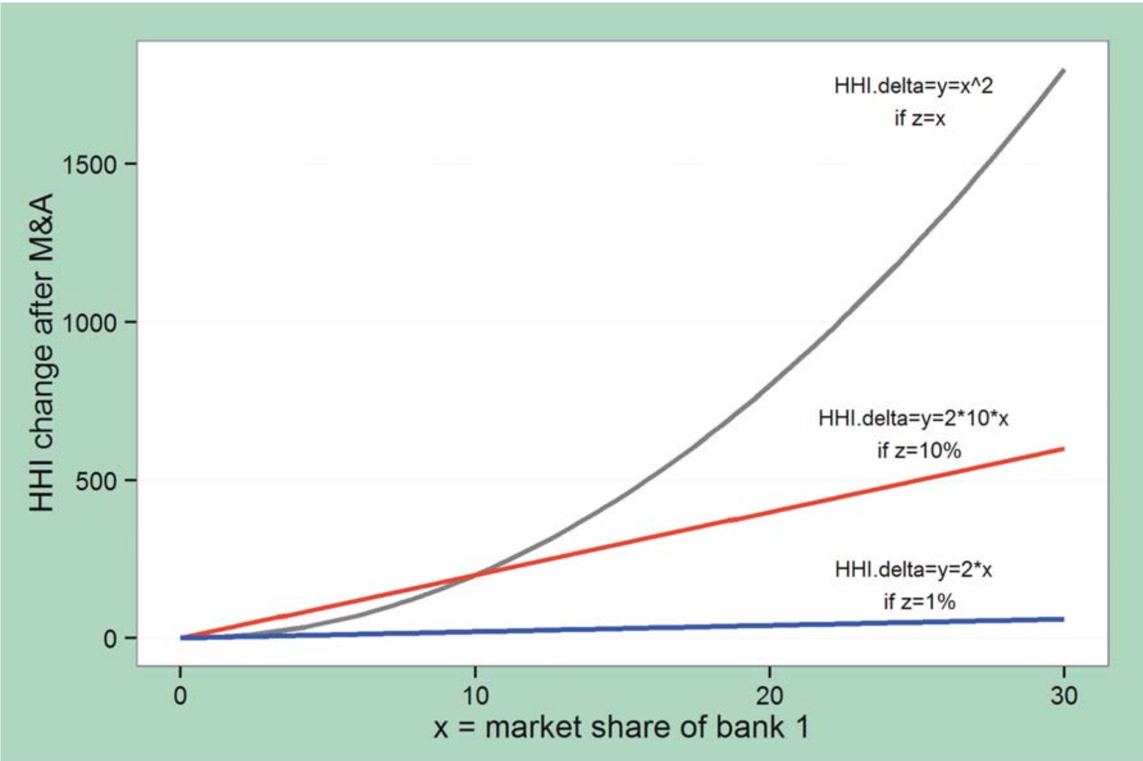
On the other hand, skeptics may retort that bank mergers and acquisitions will drive the growth of concentration given an increasing market share of financial institutions after reorganization. In that case, it is important to find out whether the increase in concentration will be so critical that it would outweigh the positive effects of a merger. Since the additional consolidation effect from a decline in the number of banks was discussed above, let's focus on calculation of the effect from the growth of market shares.

The increase in concentration expressed via *HHI* (*HHI.delta*) can be calculated regardless of the overall market concentration by doubling the sum of market shares of merged banks (EC, 2004). If *x* is the market share of bank 1 and *z* is the market share of bank 2, the contribution of these banks to the *HHI* before a merger is $(x^2 + z^2)$ and after a merger $(x + z)^2$. Therefore:

$$HHI.delta = (x + z)^2 - (x^2 + z^2) = x^2 + 2xz + z^2 - x^2 - z^2 = 2xz. \tag{9}$$

As follows from the above formula, mergers involving large banks would have the biggest effect on *HHI* growth. Consolidation of the smallest banks on the market has no significance for concentration increase.

Figure 19. Dependence of *HHI* increase on the size of consolidation participants' market shares



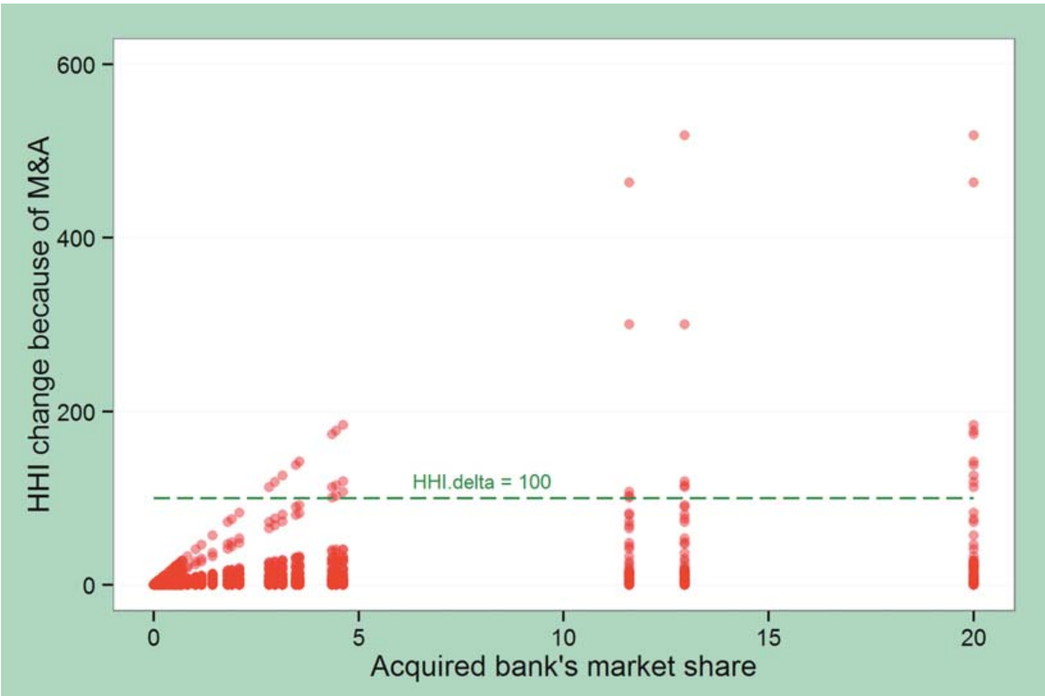
HHI increase after merger; x = market share of bank 1

If merging banks are identical in size, the *HHI* increase rate is nonlinearly intensifying as the market share of merging banks increases.

Let's calculate the HHI increase for Ukraine's banking system as a result of every possible merger or acquisition combination. For that purpose, we'll multiply the vector of solvent banks' market shares (in asset terms) as of 1 October 2015 (X) by the transposed identical vector (X^t), and then multiply the resulting matrix by 2. Then, we'll remove from the *HHI.delta* entirety the matrix of all elements of its main diagonal that indicate the results of a merger between bank *x* with bank *x* that make no economic sense.

As follows from Figure 20 above, the number of M&A agreement versions that could cause an *HHI* increase over 100 is insignificant due to a substantial gap between the sizes of market shares of three market leaders. Most of the agreements will produce an increase below 50 points.

Figure 20. The effect of hypothetical consolidation agreements on HHI increase (in asset terms) depending on the market share of an M&A participant. Market shares as of 1 October 2015



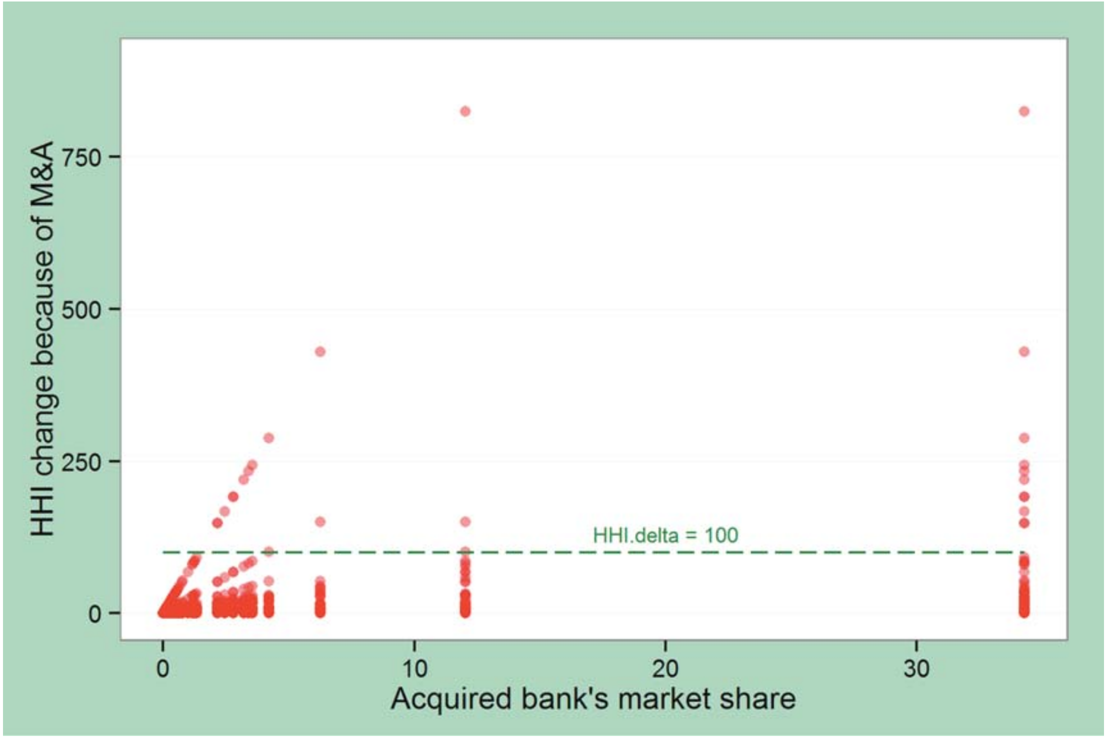
HHI increase due to an M&A agreement; Market share of an M&A participant bank, %

Similar calculations for retail deposit markets produced similar results (Figure 21). The only difference was a bigger effect on the concentration of potential acquisitions involving the market's leader because of its market share of 34%. Most Ukrainian banks (except the top 3) have a share of retail deposits market less than 5%, which produce insignificant increases in concentration if these banks will be involved in mergers.

Even if we assumed that all banks from groups III and IV merged into a single bank with a market share of almost 10% and ranked 4th in asset terms, concentration of the banking market will increase by only 105 *HHI* points to the acceptable value of 941, whereas the *CR5* would be less than 60%.

Although we can draw a conclusion regarding the insignificant effect of small banks on concentration intuitively, based on the properties of concentration coefficients, our analysis allowed us to not only theoretically understand, but also quantitatively calculate, the level of this effect, which is especially important for calculation of the effect from not-so-unambiguous scenarios of banks' mergers with market leaders.

Figure 21. The effect of hypothetical consolidation agreements on the *HHI* increase (in retail deposit terms) depending on the market share of an M&A participant. Market shares as of 1 October 2015



HHI increase due to an M&A agreement; Market share of an M&A participant bank, %

Summing up the results of our empirical study, we were able to prove that mergers and acquisitions among banks of groups III and IV per NBU classification will not have a substantial effect on concentration growth. The effect will be limited even in the event of mass consolidation agreements combined with a decline in the number of banks. The history of mergers and acquisitions of Ukrainian banks additionally corroborates our conclusions regarding the absence of a direct effect from the mergers of small and medium banks on concentration growth (Table 5). Thus, despite the largest number of M&A agreements during 1998-2003 (15 out of 25), this period witnessed a substantial decrease in concentration of Ukraine's banking system in view of decreasing inequality and growth of middle-echelon banks (including as a result of reorganization).

Strengthening of market positions of group I banks vis-à-vis the leader may become a bigger driver for concentration, increasing the number of merger and acquisition scenarios potentially important for the *HHI* (which is possible only if the largest banks are involved).

At this stage of the banking market's development, tightening requirements on capitalization and consolidation processes among small and medium banks do not pose an excessive concentration threat to the banking system from the viewpoint of best international practices and requirements of antimonopoly law. At the same time, considering the approach and transition of the banking system in terms of certain *HHI* indicators towards the moderate concentration area, it is prudent to develop a complex set of adequate preventive measures that accommodate the world's experience in regulation and oversight of systemically important banks whose involvement in consolidation processes has much higher consequences for financial strength and market organization.

VI. Recommendations for regulation policy

In the course of development of preventive macroprudential instruments concerning concentration of the banking market, we recommend the following suggestions be taken into account:

- **The Herfindahl-Hirschman Index (*HHI*)** as the optimal indicator. It is advisable to select the regular HHI that comprehensively measures the level of concentration in the banking system as the target indicator to measure concentration. The AMCU should borrow from the NBU's experience in using *HHI* as the key concentration indicator. In turn, the NBU should, jointly with the AMCU, agree on the regulatory parameters for high, moderate, and low concentration limits and determine the corresponding minimum values for an *HHI* increase, below which a bank would have no sense applying for a merger permit.

- **All other indicators are supplementary**. The CRn concentration indexes and inequality indicators should be used in the course of monitoring as supplementary informational indicators that better explain dynamics of particular concentration drivers, such as uneven natural growth of a group of large banks, a declining number of market participants, and dynamics of overall or bank group-specific inequality.

- **Harmonization of Ukraine's antimonopoly legislation with EU's legislative framework**. Considering the international experience in regulation of horizontal mergers, we recommend setting limits for concentration levels that would be uniform for all industries. At this stage, a separate calculation of national concentration norms for the banking market will not conform with the world practice of inter-industrial unification of requirements for regulation of horizontal mergers. Taking into account the course of reforms in Ukraine toward European integration, Ukrainian law should be adapted specifically to EU requirements. In particular, a free M&A regime without the need to apply for permits or go through complex approval procedures at the AMCU and NBU should be introduced for markets (including the main banking products markets) with low concentration (*HHI* < 1,000). M&A agreements on these markets do not require additional in-depth analysis. For markets with moderate concentration (1,000 < *HHI* < 2,000), an HHI increase by up to 250 points should not be viewed as threatening from the viewpoint of competition, and the limit for markets with excessive concentration (*HHI*>2,000) should be set at 150 points in accordance with *EC (2004)*. Exceptional situations not covered by an *HHI* increase should include: mergers of banks that are important innovators and whose market power cannot be measured by market share; cases of substantial cross-ownership of stocks in merger participants; when merger participants were involved in oligopolistic collusions in the past; etc. The *HHI* limits may be used as primary indicators of the absence of threats to competition. However, they should not be viewed at as a presumption of the existence or absence of threats.

- **Continuous monitoring of concentration**. Concentration of the banking system and dynamics of market organization in terms of key banking products should be regularly monitored to adjust the strictness of preventive antimonopoly measures depending on the concentration level. Monitoring of current concentration levels in comparison with historical dynamics is an indispensable condition for understanding the banking sector's development trends, and is widely used by the ECB and Federal Reserve System. In our case, monitoring provides a basis to determine how standard or extreme the present and future concentration indicators are from a retrospective viewpoint and given the pace of global changes. We suggest publishing banking concentration monitoring reports as thematic working papers and as part of the NBU's regular analytical reports in sections covering the structural dynamics of the banking market's development.

- **Focusing on retail and payments market.** At present, a monitoring system should be focused on the retail banking products market, especially the banking payments segment, considering both the relatively higher concentration and higher social significance of these products that determine public trust in the banking system's participants.

- **Focusing on market leaders.** Regulatory authorities should concentrate their efforts on monitoring the natural growth rates and consolidation activities of the largest, including systemically important, banks. At the same time, attention should be devoted to heterogeneous organization of the group of banks with the largest market potential. Because of substantial differences in bank sizes, various tightening approaches should be used in macroprudential and antimonopoly monitoring of bank mergers depending on the market share of consolidation participants: from the maximal liberalization of agreements between small banks to restrictions on mergers of the largest banks, if detailed testing of the *HHI's* sensitivity will show that normative limits on particular banking products markets were exceeded.

- **Free merger of microbanks.** The requirements of antimonopoly and banking laws that prevent consolidation and capitalization of banks from groups III and IV per NBU classification should be loosened in view of the insignificant effect that reorganization of small banks has on the level of systemic risk and competition.

- **Cluster approach.** When monitoring banking concentration, it is desirable to abandon a formalized approach to determination of market shares de-facto not independent financial institutions and pay closer attention to factors such as owners or related beneficiaries for certain bank groups, which increases the risk of collusion and strategic alliances among them.

If we are to calculate the aggregate market shares for de facto related banks, we could obtain more accurate concentration indexes. In this context, bank clusters based on an ownership criterion must be additionally analyzed. Special attention should be devoted to the effect on the formation of market organization of certain clusters of public, foreign, and Ukrainian private banks that have common related parties.

VII. Concluding remarks

The structure of Ukraine's banking market is far from ideal in view of the performance of its key function – efficient redistribution of credit resources. A low amount of equity in most banks, a large percentage of related party lending, a declining volume of deposit base due to the lowering public confidence in potentially insolvent banks – these are the problems that, if we are to overcome them, require, in particular, certain optimization of the banking market's structural characteristics.

The NBU's policy toward further consolidation and capitalization promotes transformation of the banking system by increasing the financial potential and reducing individual risks of Ukrainian banks. On the other hand, this process leads to the growing concentration of the banking sector, the consequences of which are debatable and attributed by many theoreticians to the threats of increasing monopolization and financial instability.

However, our empirical analysis proves that excessive concentration of Ukraine's banking market in 2016 is unlikely. At the same time, because of the differences in capitalization rates and continuing consolidation processes, the banking system may rise from a low to a moderate concentration level, which requires closer attention on the part of regulators to M&A agreements involving systemically important banks, if they generate a high *HHI* increase. At the same time, concentration on the retail banking services (including payment) market requires closer monitoring, too.

The low effect of the inequality factor on concentration growth since the beginning of 2014 suggests the loosening of regulatory requirements on the reorganization of small and medium banks. Since the factor of the declining number of banks became the most essential for concentration, a decreasing number of defaults in the post-crisis period will help slow down the concentration rate. Moreover, even mass defaults or mergers of small banks will have an insignificant effect on the increase of concentration indexes, something that cannot be said about systemically important banks whose consolidation can generate structural changes on a much greater scale.

We consider the following as prospective areas of further studies: 1) detailed empirical assessments of the effect of concentration on the structure, effectiveness and systemic risk of Ukraine's banking market; 2) using the cluster approach for calculation of concentration on the basis of affinity of related parties; and 3) analysis of key motives and consequences of mergers of Ukrainian banks using historical financial data.

A precise assessment of the effect of capitalization, consolidation, and concentration processes on the dynamics of the banking market's organization will help implement a complex set of antimonopoly and macroprudential measures to help formation of a banking market with an optimal combination of financial effectiveness and systemic risk indicators.

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Annexes

Table 1. Dynamics of asset concentration in Ukraine's banking system from 1 January 1998 to 1 October 2015

Date	CR3	CR4	CR5	CR10	CR25	CR50	HHI	Gini	RS	Atkin-son	Theil	Variation coef.	GE
01.01.1998	35.0	42.0	48.9	68.8	82.1	90.6	**639.2**	0.83	0.69	0.59	1.73	3.27	1.45
01.01.1999	29.8	36.7	42.4	60.8	78.1	88.0	**486.0**	0.78	0.64	0.52	1.43	2.74	1.23
01.01.2000	25.6	32.9	38.6	57.0	73.6	85.8	**409.9**	0.74	0.59	0.46	1.22	2.41	1.06
01.01.2001	26.3	32.5	38.3	55.8	71.9	84.2	**400.6**	0.71	0.56	0.42	1.11	2.28	0.95
01.01.2002	28.8	35.1	40.8	55.1	71.3	84.3	**425.4**	0.70	0.55	0.42	1.11	2.34	0.94
01.01.2003	27.5	34.3	39.5	54.2	71.3	84.4	**407.4**	0.71	0.55	0.42	1.12	2.31	0.96
01.01.2004	27.3	32.9	38.1	53.7	71.7	85.3	**394.5**	0.72	0.56	0.43	1.12	2.28	0.99
01.01.2005	27.7	32.9	37.2	53.1	72.0	85.7	**394.4**	0.72	0.57	0.44	1.13	2.30	1.00
01.01.2006	26.1	31.2	36.2	53.8	73.5	87.0	**389.4**	0.74	0.60	0.46	1.18	2.31	1.06
01.01.2007	24.7	30.2	35.3	52.4	74.3	87.7	**372.8**	0.75	0.61	0.47	1.21	2.30	1.09
01.01.2008	23.1	28.3	33.1	49.7	75.2	88.2	**346.2**	0.76	0.62	0.49	1.21	2.23	1.13
01.01.2009	22.0	28.0	33.3	52.0	76.4	89.3	**354.0**	0.78	0.64	0.52	1.30	2.33	1.22
01.01.2010	23.3	29.5	34.8	53.2	77.1	90.0	**375.0**	0.79	0.65	0.53	1.33	2.39	1.25
01.01.2011	26.1	31.9	36.8	53.9	75.9	88.6	**407.3**	0.77	0.63	0.51	1.30	2.48	1.19
01.01.2012	27.9	32.8	36.6	52.8	74.6	87.1	**426.5**	0.76	0.61	0.49	1.28	2.54	1.15
01.01.2013	30.7	35.0	38.6	52.7	74.7	87.0	**470.6**	0.76	0.61	0.50	1.31	2.69	1.16
01.01.2014	32.3	36.6	40.0	54.3	76.0	87.5	**517.4**	0.78	0.63	0.51	1.39	2.88	1.21
01.01.2015	34.8	39.4	43.4	59.7	82.0	92.0	**564.5**	0.80	0.66	0.56	1.48	2.81	1.33
01.04.2015 *	40.9	45.8	50.2	67.5	86.6	94.7	**729.5**	0.82	0.68	0.58	1.58	2.95	1.42
01.07.2015 *	42.6	47.2	51.4	68.7	87.8	95.6	**778.9**	0.83	0.69	0.59	1.60	2.98	1.45
01.10.2015	44.6	49.2	53.6	71.1	88.7	96.1	**836.0**	0.83	0.70	0.60	1.64	3.05	1.48
Number of values	19	19	19	19	19	19	**19**	19	19	19	19	19	19
Period's average	28.6	34.3	39.2	56.0	75.8	87.8	**453.5**	0.76	0.61	0.49	1.30	2.52	1.15
Standard divergence	5.3	5.1	5.1	5.6	4.4	2.9	**118.8**	0.04	0.04	0.06	0.18	0.30	0.16
Median	27.5	32.9	38.3	53.9	74.7	87.5	**407.4**	0.76	0.61	0.49	1.28	2.39	1.15
Minimum	22.0	28.0	33.1	49.7	71.3	84.2	**346.2**	0.70	0.55	0.42	1.11	2.23	0.94
Maximum	44.6	49.2	53.6	71.1	88.7	96.1	**836.0**	0.83	0.70	0.60	1.73	3.27	1.48
Asymmetry	1.4	1.3	1.3	1.6	1.3	1.0	**1.9**	0.18	0.16	0.39	0.97	1.05	0.49
Excess	1.9	1.6	1.3	1.5	1.3	0.9	**3.1**	-1.00	-1.00	-0.83	0.04	-0.13	-0.71
Standard error	1.2	1.2	1.2	1.3	1.0	0.7	**27.3**	0.01	0.01	0.01	0.04	0.07	0.04

*data for 1Q and 2Q 2015 are for reference purposes only and were not included in calculation of descriptive statistics
Source: NBU, authors' calculations

Table 2. Factor analysis of asset concentration increase from 1 January 2014 to 1 October 2015

Indicator	1 January 2014 (market's actual)	1 January 2014 (hypothetically for banks that avoided default)	1 October 2015 (market's actual)	Effect from decline in the number of banks, %	Effect from internal structural changes in the subgroup of healthy banks, %	Total effect on indicator's increase, %
CR4	36.61	47.31	49.18	85.17	14.83	100
CR5	40.01	51.78	53.62	86.48	13.52	100
CR10	54.28	68.66	71.12	85.38	14.62	100
CR25	76.02	86.03	88.67	79.15	20.85	100
HHI	**517.38**	**835.70**	**836.03**	**99.90**	**0.10**	**100**
Gini	0.78	0.81	0.83	57.09	42.91	100
RS	0.63	0.67	0.70	56.45	43.55	100
Atkinson	0.51	0.56	0.60	55.04	44.96	100
Theil	1.39	1.54	1.64	58.97	41.03	100
sd	1.61	2.51	2.49	102.03	-2.03	100
var.coeff	2.88	3.02	3.05	82.75	17.25	100
entropy	1.21	1.35	1.48	53.80	46.20	100

Source: NBU, authors' calculations

Table 3. Concentration of banking services markets in Ukraine as of 1 October 2015

Concentration / inequality indicator	Banking market (in asset terms)	Retail deposits	Corporate deposits	Retail loans	Corporate loans
CR3	44.6	52.6	39.2	49.5	43.8
CR4	49.2	56.8	45.3	57.4	51.0
CR5	53.6	60.3	50.6	63.7	57.6
CR10	71.1	75.0	67.7	79.5	72.6
CR25	88.7	90.8	88.7	95.0	89.9
CR50	96.1	97.7	97.0	99.1	96.4
HHI	836.0	1457.1	683.3	1161.9	957.6
Gini	0.83	0.87	0.83	0.89	0.84
RS	0.70	0.72	0.69	0.76	0.71
Atkinson	0.60	0.69	0.61	0.74	0.63
Theil	1.64	1.93	1.55	1.96	1.71
Variation	3.05	4.11	2.72	3.65	3.28
GE	1.48	1.76	1.51	1.95	1.57

Source: NBU, authors' calculations

Table 4. Simulated forecast of concentration levels of Ukraine's banking system due to banks' exit from the market, under the condition of a declining number of financial institutions in 2016 *

All banks under exit risk, k=100												
Simulation set	mean.hhi	sd.hhi	min.hhi	median.hhi	q.099.hhi	max.hhi	mean.cr5	sd.cr5	min.cr5	median. cr5	q.099.cr5	max.cr5
1	1008.61	132.81	463.46	1012.80	1321.32	1653.67	57.99	4.08	38.64	58.42	66.07	71.21
2	1007.28	130.64	476.65	1011.55	1328.77	1596.42	57.96	4.06	38.76	58.35	66.17	71.10
3	1006.53	133.14	458.29	1011.89	1324.86	1743.05	57.91	4.11	38.68	58.30	66.33	71.86
4	1007.02	131.42	472.37	1012.49	1321.01	1613.26	57.94	4.10	38.67	58.37	66.22	71.24
5	1007.44	129.97	477.43	1011.62	1324.76	1634.22	57.99	4.01	39.26	58.35	66.22	71.32
mean	**1007.38**	**131.60**	**469.64**	**1012.07**	**1324.15**	**1648.12**	**57.96**	**4.07**	**38.80**	**58.36**	**66.20**	**71.35**
sd	0.77	1.36	8.43	0.55	3.16	57.28	0.03	0.04	0.26	0.04	0.10	0.30
Small banks under exit risk, k=100												
Simulation set	mean.hhi	sd.hhi	min.hhi	median.hhi	q.099.hhi	max.hhi	mean.cr5	sd.cr5	min.cr5	median. cr5	q.099.cr5	max.cr5
1	858.76	3.18	847.95	858.71	866.19	872.49	54.35	0.10	54.00	54.35	54.59	54.79
2	858.71	3.15	849.21	858.61	866.25	871.23	54.35	0.10	54.04	54.35	54.59	54.75
3	858.70	3.15	848.80	858.64	866.23	870.90	54.35	0.10	54.03	54.35	54.59	54.74
4	858.74	3.16	848.43	858.65	866.37	870.16	54.35	0.10	54.02	54.35	54.59	54.71
5	858.73	3.16	848.48	858.67	866.19	871.28	54.35	0.10	54.02	54.35	54.59	54.75
mean	**858.73**	**3.16**	**848.57**	**858.65**	**866.25**	**871.21**	**54.35**	**0.10**	**54.02**	**54.35**	**54.59**	**54.75**
sd	0.02	0.01	0.47	0.04	0.07	0.84	0.00	0.00	0.01	0.00	0.00	0.03
Small and medium banks under exit risk, k=50												
Simulation set	mean.hhi	sd.hhi	min.hhi	median.hhi	q.099.hhi	max.hhi	mean.cr5	sd.cr5	min.cr5	median. cr5	q.099.cr5	max.cr5
1	983.13	10.10	947.41	983.43	1004.32	1013.51	58.21	0.31	57.11	58.22	58.85	59.12
2	983.27	9.98	944.32	983.67	1004.54	1014.78	58.22	0.30	57.02	58.23	58.86	59.16
3	983.34	10.06	944.12	983.61	1004.35	1013.28	58.22	0.31	57.02	58.23	58.85	59.12
4	983.25	10.06	947.58	983.52	1004.72	1015.99	58.21	0.31	57.12	58.22	58.86	59.20
5	983.43	9.99	950.22	983.62	1005.11	1013.82	58.22	0.30	57.20	58.23	58.87	59.13
mean	**983.28**	**10.04**	**946.73**	**983.57**	**1004.61**	**1014.28**	**58.22**	**0.30**	**57.10**	**58.23**	**58.86**	**59.14**
sd	0.11	0.05	2.55	0.10	0.32	1.11	0.00	0.00	0.08	0.00	0.01	0.03

*Five sets of Monte Carlo simulations (1 set = 10,000 scenarios of bank exits and corresponding changes in concentration indexes).

Legend:

K – total number of banks on the market after exit

Mean – mean value of HHI or CR4

Sd – standard divergence

Min – minimum value

Median – value distribution median

q.0.99 – 0.99 distribution quantile

Max – maximum value

Table 5. Mergers and acquisitions of Ukrainian banks from 1998 to 2015

No	Acquiring bank	City	Target bank	City	Merger / acquisition year
1	Mriya (present-day VTB Bank)	Kyiv	Ros	Bila Tserkva	1998
2	Zorya	Rivne	Paritet	Donetsk	1998
3	Aval (present-day Raiffeisen Bank Aval)	Kyiv	Ternopil Credit	Ternopil	1998
4	Ukrgazbank	Kyiv	Service	Shostka	1998
5	Avtokrazbank	Poltava	Ukruniversalbank	Bila Tserkva	1999
6	Stolychnyi	Kyiv	Armand	Odesa	1999
7	Nadra	Kyiv	Slobozhanshchyna	Sumy	2000
8	Nadra	Kyiv	Kyivo-Pecherskyi	Kyiv	2000
9	Ukoopspilka	Kyiv	Podillia	Khmelnytskyi	2000
10	Ukrgazbank	Kyiv	Ukrnaftogazbank	Kyiv	2000
11	Investbank	Odesa	Arkadia	Odesa	2000
12	International Commercial Bank (present-day Piraeus Bank MKB)	Kyiv	Tavria	Theodosia	2001
13	Ukrgazbank	Kyiv	People's Bank	Kyiv	2002
14	Aval (present-day Raiffeisen Bank Aval)	Kyiv	Etalon	Kyiv	2002
15	Ukrainian Bank for Trade Cooperation (later Inprombank)	Kharkiv	Innovative-Industrial Bank	Kyiv	2003
16	Industrial Bank	Zaporizhia	MT Bank	Kremenchuk	2005
17	United Commercial Bank (later European Bank for Development and Savings)	Simferopol	European Bank for Development and Savings	Kyiv	2006
18	Unikreditbank	Lutsk	HVB Bank Ukraine	Kyiv	2007
19	VTB Bank (Mriya)	Kyiv	Vneshtorgbank	Kyiv	2007
20	SEB Bank (present-day Fidobank)	Kyiv	Factorial Bank	Kharkiv	2009
21	Swedbank (later Omega Bank)	Kyiv	Swedbank Invest	Kyiv	2009
22	PUMB	Kyiv	Dongorbank	Donetsk	2011
23	Bank Credit Agricole	Kyiv	CIB Credit Agricole	Kyiv	2012
24	Fidobank	Kyiv	Fidokombank	Kyiv	2013
25	Ukrsotsbank (Unicredit Bank)	Kyiv	Unikreditbank	Kyiv	2013

Visnyk of the National Bank of Ukraine, 2015, No. 234, pp. 39-51

THE NBU APPROACH TO STRESS TESTING THE UKRAINIAN BANKING SYSTEM

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ABSTRACT

This paper gives a review of the stress testing methodology developed by the National Bank of Ukraine (NBU) in cooperation with the International Monetary Fund (IMF) for assessing the robustness of the Ukrainian banking sector, following one of the largest economic downturns in Ukrainian history. It starts with a brief summary of stress testing approaches and methods used throughout the world, their classifications, and key features. It then moves on to give an overview of the stress testing approach applied by the NBU, concluding with remarks as to the specificity of this approach and avenues for further development.

JEL Code: G280
Keywords: banking supervision, stress-tests, capital adequacy, credit risk

I. Introduction

"Risk comes from not knowing what you're doing"

— Warren Buffett

All banking regulations were born of blood. Predominantly in response to crises – either huge ones, sending economies tumbling down into squalor and despair, or less destructive ones, forcing people to tighten their belts – have new banking rules been developed. Think of the origins of Basel or the Dodd-Frank Act, to name a few. Stress tests are children of the same parents. With Ukraine being hit by the worst economic crisis in its history, it is time to get to know them better.

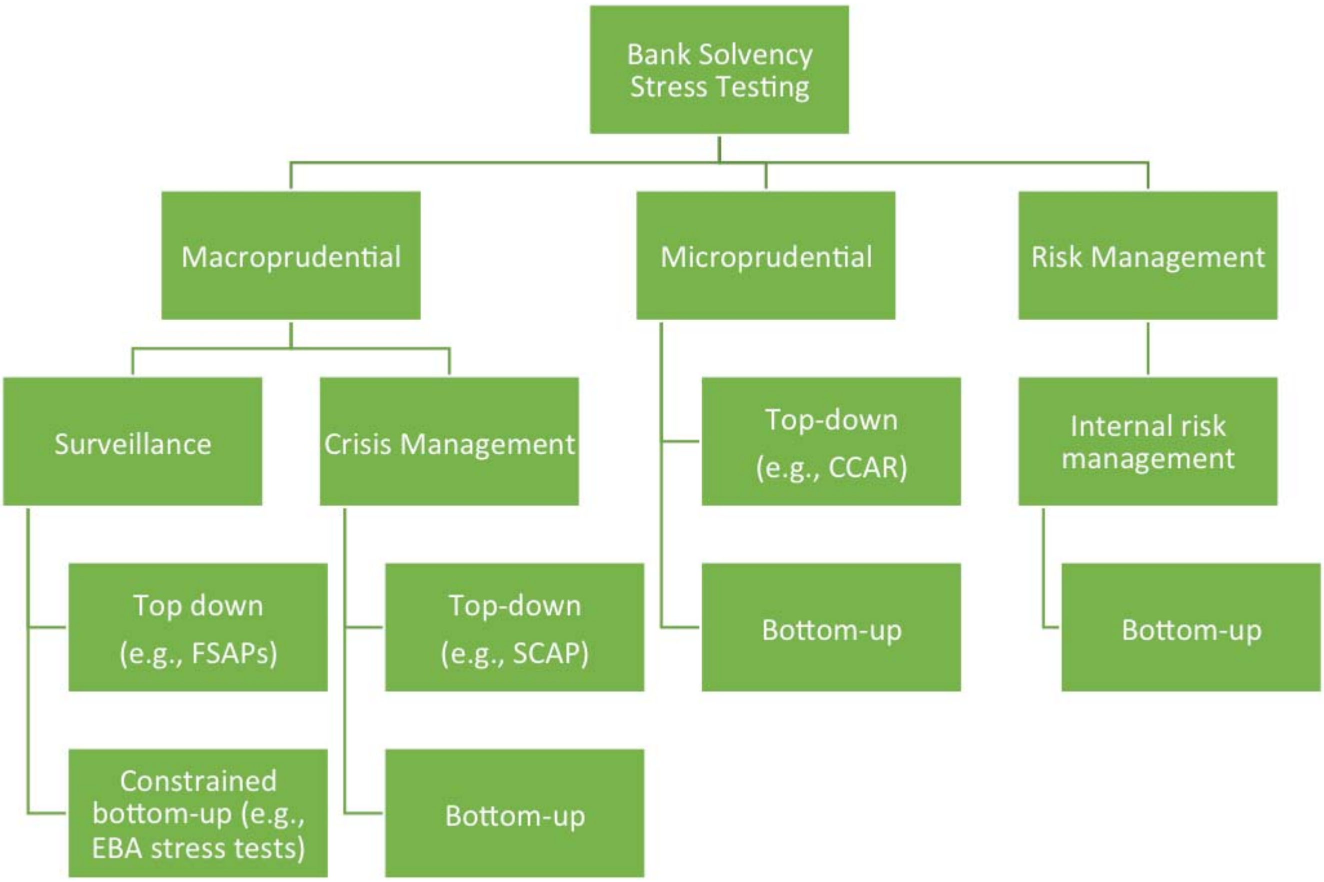
Stress testing is an exercise directed at measuring the resilience of a particular bank or the whole banking system to "exceptional but plausible shocks" (Čihak and Ong, 2014).

Early stress tests, used primarily as risk management tools, date back as far as the 1990s, but have come to the forefront following the financial crisis, when authorities around the world undertook measures to stabilize the financial system and increase the resilience of the banking sector. The severity of the crisis led many to question the adequacy of stress tests used prior to the crisis, as well as their ability to assess the true magnitude of risks and potential vulnerabilities. Financial Sector Assessment Programs (FSAP) conducted by the IMF and the World Bank (WB) have largely promoted the use of stress tests (Foglia, 2009). FSAPs, aimed at analyzing the resilience of the financial sector, the quality of regulatory and supervisory frameworks, and the capacity to manage and resolve crises, include stress tests as part of their toolkit (IMF website). Basel 2 requires banks to conduct their own stress tests as an important risk management tool, alerting bank management to adverse unexpected outcomes related to various risks and estimating capital that may be needed to weather a storm (BIS Working Paper, 2009). The Basel Committee on Banking Supervision (BCBS) calls for banks using an internal models-based approach for meeting market risk capital requirements to adopt comprehensive stress testing programs (Blaschke et al., 2001). The European Banking Authority (EBA), together with the European Central Bank (ECB), the Federal Reserve System (FRS), as well as various European national regulators have conducted periodic stress tests over past years.

  https://doi.org/10.26531/vnbu2015.234.039

Stress tests are forward-looking in the sense that they aim to measure the sensitivity of a portfolio, financial institution, or the whole system to adverse shocks, which could have a significant negative impact should they occur. The aim of a stress testing exercise is thus to assess the potential effect of those shocks on banks' capital adequacy and the need for corrective action to increase resilience. Over time, stress tests came to be recognized as a powerful tool not only in risk management, but also in macroprudential and microprudential policies (see Figure 1 below). The FSAPs mentioned earlier are a good example of a macroprudential application. The IMF stress tests tend to focus on severe hypothetical scenarios, testing the financial systems' vulnerability to a major deterioration of the macroeconomic environment. The results of such tests generally do not require action on the side of the banks' management, but are used to inform the authorities of the systemic risks present (Jobst et al., 2013). Microprudential stress tests are typically conducted to examine the soundness of individual financial institutions and can result in recapitalization requirements or even bank restructuring (Jobst et al., 2013). For example, in 2010 the Federal Reserve launched the Comprehensive Capital Analysis and Review (CCAR) program to evaluate capital adequacy and internal capital planning processes of large banking groups (FRS website).

Figure 1: Bank solvency stress tests*



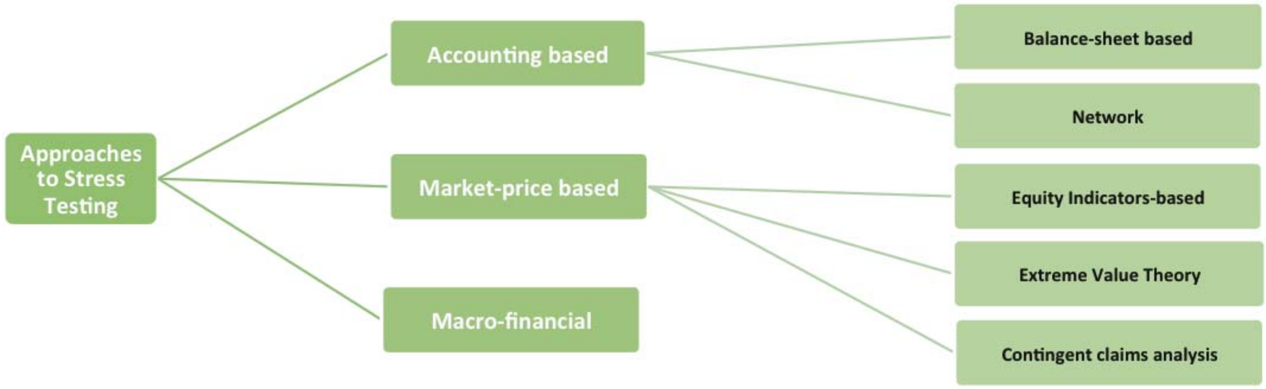
** Adapted from Jobst et al (2013).*

II. Stress testing approaches: literature review

We shall give a brief overview of the existing approaches to banking system stress testing before moving on to discuss the methodology applied by the NBU. Numerous approaches to conducting stress tests have been developed over the years, and various classification schemes exist. Regulators across countries have come up with their own stress testing designs, built on international best practices with local variations catering to country-specific idiosyncrasies (for an example, see Table 1).

When it comes to particular types of risks, solvency remains at the forefront of the stress testing exercises, although more and more attention is being given to developing models for testing liquidity, market, and systemic risks, as well as dynamic interaction between various types of risks. A stress test may estimate the effect of a single risk factor or model the impact of a group of risks acting simultaneously. The first approach is in essence a sensitivity analysis, the second – a scenario analysis. The scenarios selected may be based on historical data, statistical analysis, or be purely hypothetical (Blaschke et al., 2001).

Figure 2. Approaches to stress-testing (IMF methodology)



The IMF provides the following broad classification of stress testing approaches, dividing them into three categories: accounting-based approaches (including the balance-sheet approach), market-price based approaches, and macro-financial approaches (Čihak and Ong, 2014; Schmieder and Schumacher, 2014).

The *accounting-based approach*, as the name suggests, uses accounting data from financial statements of individual institutions or systems (Čihak and Ong, 2014). One of its most widely used variations is the *balance-sheet approach*, which relies on information obtained from financial statements, such as the income statements and off-balance sheet reports, as well as the balance sheet itself. This method is popular due to input data availability, financial statements being prepared regularly and usually publicly disclosed (Čihak and Ong, 2014). Additionally, financial statement information is quite standardized, which allows for peer comparison and system-wide application. Due to the granularity of the data, it is possible to use both top-down and bottom-up approaches, identifying risk drivers at the level of particular institutions as well as for the system overall (Schmieder and Schumacher, 2014). The *network approach* allows for tackling vulnerabilities that arise from systemic linkages between financial institutions operating in either domestic or global financial markets. Network analysis is best combined with regular stress testing exercises in order to complement the assessment of the vulnerabilities of a particular institution with analysis of the relationships between institutions and possible contagion effects (Espinosa-Vega and Sole, 2014).

As popular as they are, accounting-based stress tests have drawbacks stemming from differences in accounting standards, risks of financial statement manipulation, and the backward-looking nature of the reports (Chan-Lau, 2014). An alternative approach relies on the market's perception of risks, as reflected in the prices of financial instruments rather than accounting figures (Čihak and Ong, 2014). The *Equity indicators-based approach* uses information gauged from security prices in secondary markets. Although bonds and credit default swaps are a preferred source of information, their prices being more directly reflective of the issuer's creditworthiness, equities are more commonly used due to their higher liquidity and coverage. Credit default probabilities estimated from security prices can be used to assess losses under various stress scenarios (Kapinos and Mitnik, 2015). The *Extreme value theory (EVT) approach* focuses on identifying extreme events (tail risks) that could have an adverse impact on the financial system or separate institutions. EVT uses statistical and econometric models to assess spillover effects during a tail-risk event (Mitra, 2014). *Contingent claims analysis* is an approach based on a combination of balance-sheet information and forward-looking information from equity markets. It estimates credit risk based on the impact of changes in asset values related to payments on debt liabilities (Gray et al., 2014).

The *Macro-financial approach* promotes a holistic view on financial stability, incorporating individual institutions' soundness, their interactions between each other, and the overall economy. This method considers the links between the financial and the nonfinancial sectors of the economy and can be implemented based on both accounting and market-based data (Čihak and Ong, 2014; Maechler, 2014).

Stress tests can be performed using either a bottom-up or a top-down approach. A bottom-up approach assumes that banks perform their own stress-tests, with the supervisor (regulator) providing guiding principles and verifying results. According to the IMF, with banks having better knowledge of their own exposures, the results of a bottom-up approach are more informative as to the risks and vulnerabilities faced by the financial institutions (Blaschke et al., 2001). When the regulator uses a centralized approach to stress testing, performing the analysis based on a single methodology and data submitted by banks, the approach is top-down. Mandatory stress testing as a regulatory requirement is relatively novel and the lack of formal prescriptions for stress test design has led to the proliferation of scientific research on this topic, with the majority of studies focused largely on the top-down approach and with bottom-up methods receiving less coverage (Kapinos and Mitnik, 2015).

The stress testing framework usually consists of several models –a major one complemented with auxiliary satellite models. As was demonstrated by the global financial crisis, the stress testing methodologies previously used were not adequate for evaluating the financial system's stability and robustness. In order to overcome the exposed weaknesses, new techniques were introduced, among them a heuristic proposed by Taleb et al. (2012) which allows assessment of how vulnerable a bank (or government) is to underestimation of tail risks. According to Taleb et al. (2012), missing convexities or non-linearities in outcomes may lead to underestimation of the impact of adverse shocks, and hence create serious fragilities in the financial system. Hence, the authors propose a heuristic that measures the sensitivity of the outcome (gains/losses) to a change in the stress applied. A financial institution would then be deemed fragile to higher volatility if the relationship between the increase in the shock applied and the losses is found to be non-linear, which is often the case for complex and interconnected markets (Taleb et al., 2012).

Table 1. Select stress testing approaches: comparison table

Country	USA	EU	UK
Timing	2015	2014	2015 (ongoing)
Program	DFAST	EU-wide stress test (EBA)	Bank of England stress test
Scope			
Bottom-up	NA	EBA developed the stress testing methodology, banks ran the tests, local regulators provided support and monitoring.	Banks submit their projections, BoE uses those submissions as a starting point for the stress test, making its own adjustments. Going forward, BoE intends to give more weight to its in-house models (top-down approach).
Top-down	Supervisory stress testing*	NA	
Coverage criteria	BHCs** with total consolidated assets of $50 billion or more and nonbank financial companies designated by the FSOC.	Sample of banks covering at least 50% of the national banking sector in each EU Member State in terms of total consolidated assets (as of the end of 2013).	Include all PRA-regulated banks and building societies with total retail deposits greater than £50 billion.
Institutions	31 BHCs	123 banking groups from 22 countries	7 major UK banks and building societies
Scope of consolidation	Bank holding company	Banking group.	At the highest level of UK consolidation

Country	USA	EU	UK
Data source	Data collected by the Federal Reserve on regulatory reports and proprietary third-party industry data.	Data collected by the national authorities (regulators).	Bank data, BoE data, and third-party analytics.
Stress testing horizon	9 quarters (4th quarter 2014 to 4th quarter 2016)	3 years (2014-2016)	5 years
Scenarios	Baseline, adverse, severely adverse	Baseline, adverse	Baseline scenario, annual cyclical scenario, and an additional scenario intended to probe the resilience of the system to risks that may not be neatly linked to the financial cycle (biennial exploratory scenario)****.
Description of the stress testing approach	Calculated projections of a BHC's balance sheet, risk-weighted assets (RWAs), net income, and resulting regulatory capital ratios under stress scenarios. The four regulatory capital ratios in DFAST 2015 are common equity tier 1, tier 1 risk-based capital, total risk-based capital, and tier 1 leverage.	Assessed the impact of risk drivers on the solvency of banks (focus on solvency and market risks) in terms of Common equity tier 1 capital ratios.	Uses the EBA proposed framework with certain adjustments, including the following: • Static balance sheet assumption (EBA) vs. evolution of the size and composition of the balance sheet throughout the scenario (BoE). • Income caps and expense floors (EBA) vs. no such constraints (BoE). • Use of additional models and analysis: BoE's stress test uses a set of analytical tools in addition to participating banks' own projections to assess the impact of scenarios on banks' profitability and capital ratios.
Disclosure	Detailed disclosure of individual bank results (required under the Dodd-Frank Act)***.	Disclosure of aggregate results by country (EBA). Each local regulator discloses reports on individual bank results.	Detailed disclosure of aggregate bank results (consolidated for the whole banking sector), capital-ratio data on individual banks.

** Under the Dodd-Frank Act, select financial institutions are also required to conduct annual/semi-annual company-run stress tests.*
*** BHC – Bank holding company.*
**** The Dodd-Frank Act also requires BHCs to disclose summaries of their company-run stress test results.*
***** All banks are also required to run a broad range of stress tests and scenario analyses relevant to their business models as part of their ICAAP (the results are not made public).*
Sources: Bank of England (2015), Bank of England (2014), FRS website, EBA (2014), EBA (2015), FRS (2015)

III. NBU approach to stress-testing Ukrainian banking system

On 24 April 2015, the NBU initiated a diagnostic study of the Ukrainian banking system as a mandatory part of the Ukraine-IMF cooperation program under the Extended Fund Facility (EFF) agreement. The goal of this study was to evaluate the quality of banks' asset portfolios and estimate their potential capital needs over the three-year period of 2015-2017. The first part of the exercise consisted of an asset quality review (AQR) laying the foundation for the second part – the stress test. Data obtained from on-site teams (inspections) was used as a major input for the stress tests, along with data from NBU registers and the banks themselves.

Design of the stress test

The NBU stress test was focused primarily on assessing Ukrainian banks' solvency under the stress scenario applied, evaluating credit risk (including on- and off-balance sheet exposures, positions on the banking and trading books), and interest rate spreads risk, currency risk and risk of large exposure concentration in loan portfolios.

The stress test covered the 20 largest Ukrainian banks and was run at the highest level of domestic consolidation, the scope of consolidation being the perimeter of the banking group. The exercise included domestic exposures, with special attention given to large banking and trading book positions. All data inputs were fixed as of the date 31 March 2015 and projections were made for the three-year forecast period of 2015-2017. Unlike the more common multi-scenario approach, the NBU used a single baseline macroeconomic scenario, which was developed in cooperation with the IMF. The rationale behind the decision to give up adverse stressed scenarios was the fact that Ukraine was already at the nadir of an economic crisis, thus making application of additional macroeconomic shocks an unrealistically severe scenario. The baseline scenario used assumed a gradual recovery of the Ukrainian economy starting in 2016.

Projections of some of the key variables are presented in the table below. Approaching the end of 2015, it is clear that the macroeconomic projections for the relevant year were in line with actual developments.

Table 2. The baseline scenario

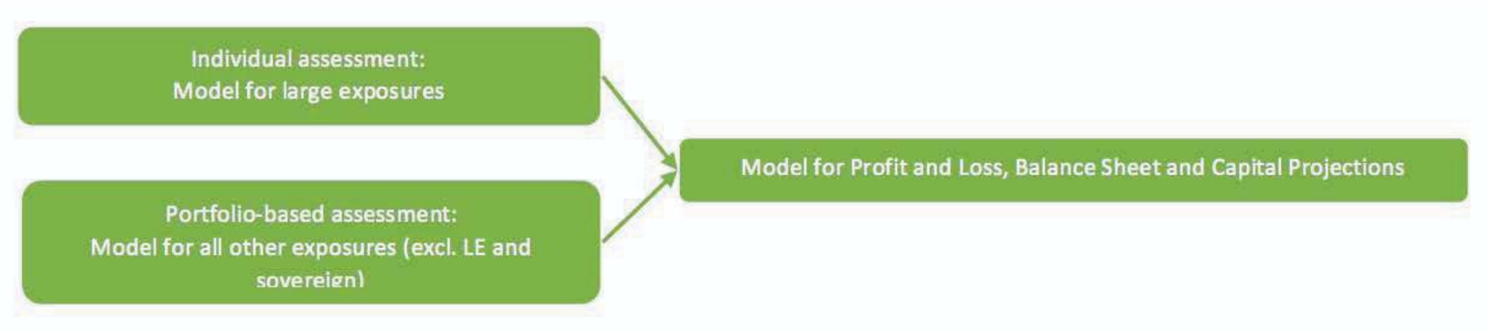
		2014	2015E	2016E	2017E
1	Real GDP, chg. YOY	(6.8%)	(9.0%)	2.0%	3.5%
2	GDP deflator, YOY	14.8%	39.0%	12.0%	9.9%
3	Nominal GDP, chg. YOY	7.0%0	26.4%	14.2%	13.7%
4	Interbank UAH/USD, EOP	15.8	23.5	24.4	24.9
5	Interbank UAH/USD, AFP	12.0	22.0	24.1	24.7
6	CPI inflation, YOY	24.9%	45.8%	12.0%	8.0%
7	Core CPI inflation, YOY	22.8%	35.0%	8.5%	6.1%
8	PPI inflation, YOY	31.8%	31.8%	12.5%	10.9%
9	Credit interest rate, UAH	17.2%	21.1%	15.8%	13.7%
10	Deposit interest rate, UAH	11.7%	12.9%	9.3%	7.6%
11	Credit interest rate, FX	8.7%	8.3%	8.4%	8.5%
12	Deposit interest rate, FX	6.7%	6.5%	5.8%	5.5%
13	Monthly avg. wage, UAH	3,480	4,256	4,958	5,628
14	Real wage, chg. YOY	(6.5%)	(18.5%)	2.0%	3.3%
15	Unemployment rate (ILO)	9.3%	11.5%	11.0%	9.4%

The expected result of the exercise consisted of estimating the need for additional Tier 1 capital and total regulatory capital for the 2015-2017 period for each of the 20 banks, with subsequent submission of capitalization plans.

Model framework

The NBU used a balance-sheet stress testing approach, relying on information provided by banks, adjusted following the AQR stage and on-site reviews. The framework consisted of three models. Two of them were essentially satellite models – the large exposures (LE) model and the portfolio-based model – providing inputs into the main bank balance sheet (BS) model. Relationships between the models are illustrated in the figure below.

Figure 3: Relationship between the three stress test models



The difference of the current NBU approach as compared to the stress tests conducted in 2014 was the separation of all exposures into three categories: sovereign and parastatals, large exposures, and the remaining exposures. Large exposures were defined as those above UAH 200 million or 5% of the bank's regulatory capital (RC), whichever was smaller. All loans of the bank, as well as its positions in fixed income securities satisfying the aforementioned size criteria, excluding sovereign exposures, were analyzed by means of a separate excel model. Financial performance of the bank's large borrowers was modelled over the forecast period of 2015-2017. Loan migrations to/from the non-performing (NPL) category and the corresponding change in loan loss provisions were then estimated. All other exposures that did not qualify as large were modelled on a portfolio basis, using econometric techniques to forecast loan migrations and changes in provisions. The practice of analyzing large exposures on an individual basis is not common among national regulators, partly due to significant resource and time requirements. Conducting individual stress-testing of large exposures by the NBU was important due to:

1. High concentration of large exposures in banks' portfolios;
2. Concerns about lending to related parties;
3. Differences in borrowers' credit ratings and overall loan quality across banks;
4. Low level of ownership structure transparency.

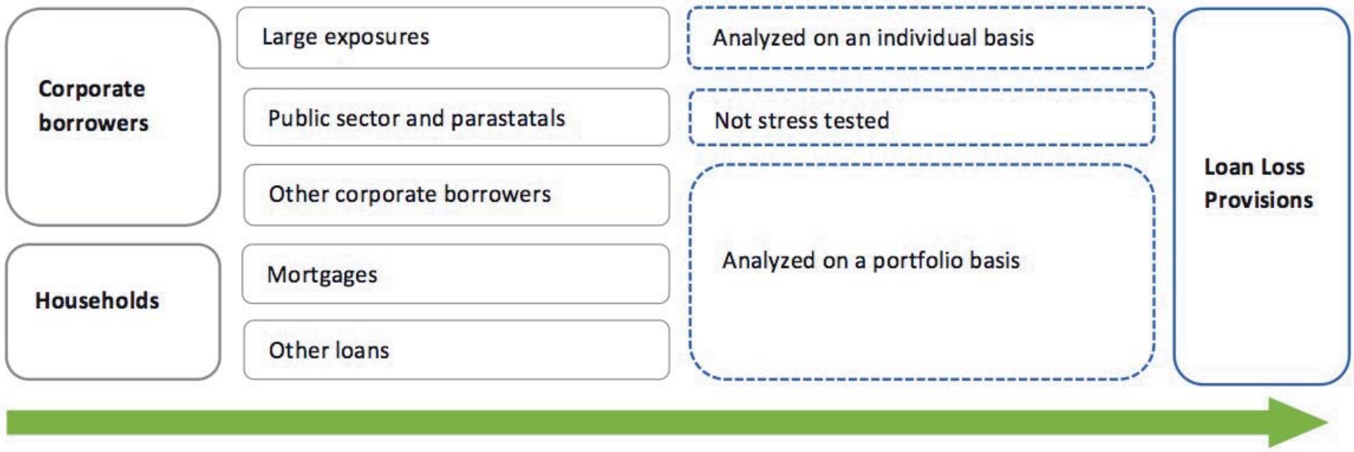
Modelling large exposures on an individual basis allowed accounting for disparities in asset and collateral quality across Ukrainian banks.

Exposures stress tested on a portfolio basis

In order to compose relatively uniform groups of borrowers with similar characteristics, the loan portfolio was structured into sub-portfolios according to the diagram below.

Exposures to the public sector and parastatals were not stress tested. Loans to other corporate clients (not classified as large) and households were stress tested on a portfolio basis.

Figure 4: Stress testing approaches to loan portfolio components



The NBU used multi-factor ordinary least squares linear regression models to forecast changes in NPL shares for each of the six exposure segments (UAH/FX; other corporate/mortgages/other retail). Change in share of NPLs was the dependent variable and changes in macroeconomic indicators – the explanatory variables. The macroeconomic factors used included real GDP, CPI, credit and deposit interest rates in national and foreign currencies, UAH/USD exchange rate, nominal wage, and unemployment rate. Regression parameters were estimated based on quarterly data collected over the 2006-2014 period. Projections of NPL share changes for each segment were then applied to the actual levels of NPL shares at each bank. For loans having migrated into the NPL category, historical provisioning levels (as confirmed or re-estimated by the AQR) were used, but not less than specified minimal levels (55%-70%).

Stress testing large exposures

The framework for stress testing large exposures was determined by NBU regulations, based on Basel principles, as well as international practices in stress testing.

According to NBU regulations, there are five credit quality categories, with the fourth and fifth categories deemed non-performing. Based on the AQR, large exposures were first classified as either performing (going concern) or non-performing (gone concern). Only loans that fell into the first to fourth categories were stress tested, with loans from the fifth category retained as part of the loan portfolio throughout the 2015-2017 period with adjustments for exchange rate changes. According to Resolution No. 23,[1] a failure to meet certain regulatory requirements (e.g., timely submission of financial statements) may result in a downgrade of a going concern loan to the fourth category. This way, the fourth category was also stress tested so as to avoid exclusion of essentially performing loans.

According to NBU regulations, a loan's probability of default (PD) is determined by its credit quality category, taking into account forward looking qualitative and quantitative factors which define the borrowers' ability to repay debt during the loan contract. The credit quality category in its turn is determined by a combination of two criteria – the financial class of the borrower and its debt service discipline. The financial class of the borrower is based on its financial state (represented by relevant financial ratios). Debt service discipline is determined by registered timeliness/delinquency in interest and principal repayments as well as ability to service debt.

Projecting the borrowers' financial state over the 2015-2017 period implied assigning them to one of nine classes based on the value of their integral indicators (estimated as a linear combination of certain financial ratios) within the ranges specified for each industry and borrower size. In order to calculate the financial ratios used to arrive at the integral indicator, the borrowers' financial performance was modeled based on data for the 2013 and 2014 full fiscal years and the first quarter of 2015. The following major assumptions were made:

[1] NBU Resolution №23 (25.01.2012) on loan loss provisioning.

• Changes in the financial performance of borrowers are largely driven by changes in macroeconomic factors. For example, revenue projections are linked to nominal output growth, approximated by GDP, and CPI/PPI.

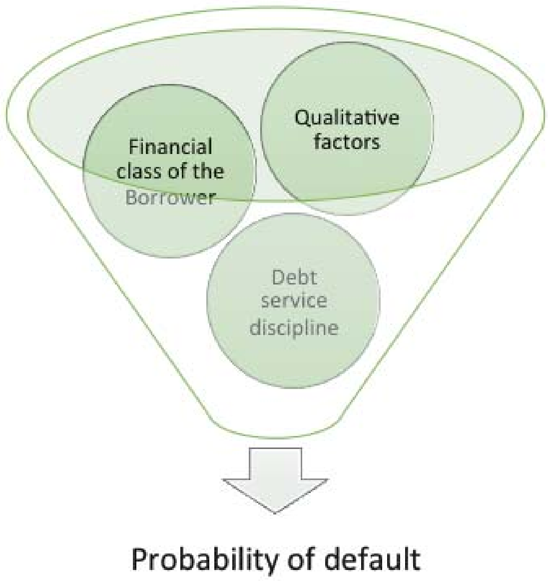
• Changes in balance sheet items are driven by relevant income statement items.

• Change of forecasted debt amount is determined by debt amortization and funding needs (estimated as short-term loans).

• Projections are solely based on historic data, excluding any future income/expenses related to implementation/ termination of business projects, optimization initiatives and/or new client acquisitions.

A borrowers' debt service discipline for 2015-2017 was estimated based on the projected cash flows for each period and scheduled amounts of debt repayments. In case of estimated cash flow deficiency, debt service discipline was expected to deteriorate, but not more than 1-2 notches below the current level: one notch-for regular borrowers, two notches for high-risk profile borrowers.

Figure 5: Probability of default estimation



In estimating default probabilities, the following qualitative factors were also taken into account: the availability of audited financial statements, risk profile, and history of business activity. When evaluating the risk profile of a borrower, measures such as debt to sales ratio and the number of employees were considered.

Following Resolution No. 23 and Basel principles, Loan loss provisions (LLP) were estimated at the level of expected losses (EL) from credit operations, determined by the size of exposure at risk, probability of the borrower defaulting, and the amount and quality of collateral pledged.

$$EL_i = EAD_i \times PD_i \times LGD_i = PD_i \times (EAD_i - Collateral\ value\ adj._i)$$

Where $LGD_i = 1 - RR_i = 1 - \frac{Collateral\ value\ adj._i}{EAD_i}$

EAD_i – Exposure at Default,

PD_i – Estimated probability of default;

LGD_i – Loss given default;

RR_i – Recovery rate;

Collateral value adj. – collateral value adjusted for liquidity risk and expenses for collateral enforcement and selling.

The stress testing methodology allowed the use of consolidated financial statements for borrowers which were part of larger business groups, moving toward a broader understanding of the risks pertinent to those borrowers.

Under the NBU stress testing approach, credit quality and default probability of a corporate borrower were largely influenced by the borrower's financial standing, as is the typical practice in stress testing exercises. This way, the regulator analyzed the company's ability to internally generate cash flow for debt servicing purposes, rather than simply recognize the timeliness of payments (debt service discipline).

Bank model: BS and Profit and loss projections

For the purpose of stress-testing, forecasts of banks' financial statements (balance sheet and P&L statement) were made covering three years – 2015, 2016, and 2017. A key assumption underlying the stress testing methodology was that of the fixed balance sheet and business mix. Both the asset structure and the funding structure of the banks would remain unchanged over the time horizon of the exercise. It was assumed that assets and liabilities that matured within the forecast period would be replaced with similar financial instruments in terms of type and credit quality. Thus, balance sheet changes would only be driven by:

- Exchange rate changes (Assets, Liabilities);
- Asset quality changes (Assets);
- Irrevocable off-balance sheet credit facilities drawdown for large (Assets) borrowers;
- Retained earnings changes from income/loss in the period (Equity).

It was assumed that over the stress testing horizon, the banks would refrain from paying out dividends to their shareholders and/or repaying their subordinated debt.

The income statement forecast included loan loss provisions charges, estimated using the satellite models (individually for large exposures and on a portfolio basis for all other exposures), as well as other income/expense items. An adjustment for interest rate sensitivity gap, interest rates pass-through effect, and corrections for one-off items were made. Incorporating the pass-through effect in the model allowed accounting for differences in interest rate movements across various assets and liabilities. Application of a gap model accounted for the risks arising from a mismatch in the rate sensitivity of the bank's assets and liabilities.

The gap effect was taken into account for assets and liabilities which matured (fixed rate instruments) or whose interest rates were repriced (floating rate instruments) over the short-term horizon of one year. All interest sensitive assets and liabilities were allocated to separate "time buckets" depending on their maturity/time of repricing (Blaschke et al (2001)). The projected interest rate income reflected repricing effects (changes in interest rates) for the new positions and changes in the reference rates for the floating rate items. A simplified formula for calculating adjustment for interest rate sensitivity gap ($\Delta \mathrm{NII}_t^g$) is presented below.

$$\Delta NII_t^g = \sum_{i=1}^{k}((A_{i,t} \times \Delta R_{a,t} - L_{i,t} \times \Delta R_{l,t}) \times (\frac{start_i + end_i}{2 \times 360}))$$

$\mathrm{R}_{a/l,t}$ - Effective interest rate on asset a (liability *l*) class for the time period *t*;

$\Delta\mathrm{R}_{a/l,t}$ – Change in weighted average effective interest rate on assets/liabilities assuming a parallel shift in loan and deposit interest rates;

$\mathrm{A}_{a,t}$, $\mathrm{L}_{l,t}$ – Average interest-sensitive asset/liability class for the time period t;

$\frac{start_i + end_i}{2 \times 360}$ – Maturity adjustment factor (period midpoint) defined according to table 3.

Table 3. Interest rate sensitivity structure

Maturities	Start	End	Adjustment factor
Demand	0	0	0.000
0-1 months	0	30	0.042
1-3 months	30	90	0.167
3-6 months	90	180	0.375
6-12 months	180	360	0.750
above 12 months	360	NA	1.000

Bank model: estimating capital requirements

For each forecast period the amount of Tier 1 capital was estimated as the sum of Tier 1 capital from the previous period and net income in the current period, with certain adjustments. If Tier 1 ratio in any given period fell below the required threshold, a capital gap was identified.

Table 4. Estimating capital gap in 2015-2017

2015	2016	2017
Tier 1 capital (Q1 2015, after AQR-based adjustments)	Tier 1 capital (2015, EOP)	Tier 1 capial (2016, EOP)
+	+	+
Operating profit	Operating profit	Operating profit
-	-	-
Loan loss provisions change	Loan loss provisions change	Loan loss provisions change
+/-	+/-	+/-
other adjustments	other adjustments	other adjustments
÷	÷	÷
RWA(after AQR-based adjustments)	RWA (2015, EOP) + Changes in RWA	RWA (2016, EOP) + Changes in RWA
=	=	=
Tier 1 ratio (2015)	Tier 1 ratio (2016)	Tier 1 ratio (2017)

Total regulatory capital was estimated as the sum of Tier 1 and Tier 2 capital, minus deductions. According to Ukrainian banking regulations, the amount of Tier 2 capital included in the regulatory capital should not exceed Tier 1 capital (Tier2 ≤ Tier 1). Many Ukrainian banks satisfy Tier 2 requirements through issuance of subordinated debt. Over the forecast periods, the amount of subordinated debt was fixed at the level reported as of 1 April 2015, adjusted for changes in foreign exchange rates (for debt denominated in foreign currency) and amortization schedules (according to Ukrainian regulations).

If the results demonstrated that Tier 1 capital and total regulatory capital were not sufficient to absorb the shocks under the stress testing scenario, the NBU requested banks to submit recapitalization plans to meet minimum capital requirements. The schedule for submission of such plans and their implementation was developed by the NBU in accordance with the IMF memorandum.[2] Minimal capital requirements and milestones under this agreement are outlined in the table below.

[2] The agreement under the current EFF program between Ukraine and the IMF.

Table 5. Minimal capital adequacy ratios

	2016	2017
Tier 1 capital	4%	6%
Regulatory capital	5%	7%

IV. Future developments

The current NBU stress testing methodology allowed execution of a thorough multilateral analysis of the largest Ukrainian banks' financial resilience, based on which action would be taken to strengthen capital adequacy. As economic conditions evolve, the stress testing methodology will need to be updated and improved.

One area of further development is the addition of adverse macroeconomic scenarios. In 2015, Ukrainian banks were stress tested based on a baseline scenario, which is in essence a projection of the current state of the economy into the forecasted period. In the future, it will be necessary to introduce more scenarios, including adverse and severely adverse scenarios, as well as to test the financial system for specific shocks, the impact of which could be material.

Inclusion of other types of risks (liquidity, market, etc.) into the stress testing exercise, either together with the solvency test or as separate exercises, would be highly beneficial for a more comprehensive understanding of financial institutions' resilience to potential shocks.

The specificity of Ukraine's financial system, which is characterized by a relatively small interbank market, practically non-existent securities markets, and a high concentration of banks' asset portfolios in traditional lending to corporate and retail clients, has influenced the design of the stress test. As the system evolves, more sophistication will be required within the stress testing models.

As Ukraine moves towards higher transparency and convergence with international banking standards, more disclosures regarding stress testing methods, as well as stress test results, will be required. Those issues remain sensitive for the banking community and the transition would need to be gradual and prudent.

V. Conclusions

This paper gives a review of the stress testing methodology that has been developed by the NBU in cooperation with the IMF for the purpose of assessing robustness of the local banking sector. The stress testing framework incorporated experiences and practices of foreign regulatory authorities and supranational organizations responsible for financial stability. Building on the large body of scientific research covering various aspects of the stress testing process, NBU adapted its methodology for idiosyncrasies present in the local economic and business environment. Being forward-looking by design, it focused on estimating expected losses on large exposures portfolios. Moreover, in certain aspects the stress testing approach allowed analysis of consolidated financial statements for borrowers which were part of larger business groups, thus moving towards a broader understanding of the risks pertinent to those borrowers.

Under the NBU stress testing approach, credit quality and default probability of a corporate borrower were largely influenced by the borrower's financial standing. This way, the regulator analyzed the company's ability to internally generate cash flow for debt servicing purposes, rather than simply recognize the timeliness of payments. Such an approach allowed to focus on the viability and sustainability of the borrower's business and proved more reliable in terms of evaluating credit quality.

In order to account for borrower characteristics influencing credit risk, the methodology broadened the use of qualitative factors. Factors evaluated included the borrower's staff size, years operating, and audit of the financial statements.

The decision to stress test large borrowers of banks on an individual basis proved justified. Modelling the borrowers' financial performance over a 3-year horizon allowed assessment of their capacity to service and repay their loans, thus giving a more realistic picture of a particular bank's NPL rate across a large exposures portfolio.

These, and other additions and modifications to the current NBU stress testing methodology, helped improve the quality of the analysis and subsequent recommendations. But it is a work in progress; as the Ukrainian financial system evolves, stress testing models and approaches will need to be further updated. Economic ups and downs are inevitable, adverse shocks are unpredictable, and no tool, however sophisticated, can fully guard against them. Despite these facts, stress tests represent a reliable compass for navigating us towards the safe shores of financial stability. They are well worth befriending.

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Visnyk of the National Bank of Ukraine, 2015, No. 234, pp. 52-72

NATIONAL BANK OF UKRAINE ECONOMETRIC MODEL FOR THE ASSESSMENT OF BANKS' CREDIT RISK AND SUPPORT VECTOR MACHINE ALTERNATIVE

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ABSTRACT

Econometric models of credit scoring started with the introduction of Altman's simple z-model in 1968, but since then these models have become more and more sophisticated, some even use Artificial Neural Networks (ANN) and Support Vector Machine (SVM) techniques. This paper focuses on the use of SVM as a model for default prediction. I start with an introduction to SVM as well as to some of its widespread alternatives. Then, these different techniques are used to model NBU data on banks' clients, which allows us to compare the accuracy of SVM to the accuracy of other models. While SVM is generally more accurate, I discuss some of the features of SVM that make its practical implementation controversial. I then discuss some ways for overcoming those features. I also present the results of the Logistic Regression (Logit) model which will be used by the NBU.

JEL Codes: C45, C51, C52, C53
Keywords: machine learning, svm, credit risk, scoring model

I. Introduction

Credit risk is the probability that a given counterpart will fail to honor its obligation to pay back a loan to the provider of the loan. The Basel Committee on Banking Supervision attaches a lot of importance to the development of a proper framework for quantifying this risk and promotes an Internal Rating Based (IRB) approach encouraging banks to develop their own internal models in order to score their clients properly to make sure banks have enough capital to cover expected losses.

In order to estimate credit risk, however, the NBU imposes the use of a particular econometrics model to all banks. The reason for this is that many Ukrainian banks do not yet have well-developed credit processes based on a commonly accepted statistical approaches. Large international groups do have such processes, however, they differ widely across banks. In addition, some of them use models provided by their international headquarters that are not necessarily adapted to the specific characteristics of the Ukrainian economy.

In Directive No. 23 (2012), which previously regulated credit risk assessment, the role of such a model was not crucial – the financial risk identified by the model was then adjusted by the days past due, meaning that even if the model assigned the company a high credit risk, the absence of days past due would allow banks to assign relatively low provisions to it.

  https://doi.org/10.26531/vnbu2015.234.052

The new Directive on credit risk assessment will abolish the adjustment - provisioning will be mostly[1] determined by the company's financials. That's why the choice of an appropriate model has become much more important. In this paper, using Ukrainian data, I analyze and compare the predictive accuracy of three models: Linear Discriminant Analysis (LDA) model, Logit model, and SVM model.

II. Theoretical summary

2.1. Linear Discriminant Analysis (LDA)

Edward Altman proposed the use of LDA for default prediction in 1968. Since then, this method has been very popular mainly due to its simplicity and its relatively accurate results in terms of default prediction. It is currently used by the NBU as the main credit risk model according to a regulation that is going to be suspended (Directive No. 23).

LDA can be used for multiple classification; however, within the framework of default prediction we have only two classes - solvent and insolvent companies. Let π_i be the prior probability of class i, and $p\ (x|i)$ be the conditional distribution of explanatory variables x. Then the posterior probability distribution can be written as:

$$p(i|x) = \pi_i p(x|i)$$

It is assumed that the distribution $p(x|i)$ is a multivariate normal $p(x|i) = N(x|\mu_i, \Sigma)$, where μ_i is a vector of conditional means of the variables and Σ is covariance matrix. Note that Σ is without subscript i. This is because it is assumed that it is equal for both classes.[2]

Since we have just two classes, we denote them as i = 0 and i = 1. Then, assuming linearly separable data, $\pi_0\ N(x|\mu_0,\Sigma) \neq \pi_1\ N(x|\mu_1,\Sigma)$ (note that we can also write π_1 as $(1 - \pi_0)$). We would assign x to class 0 if $\pi_0 N(x|\mu_0, \Sigma) > \pi_1 N(x|\mu_1, \Sigma)$, and to class 1 otherwise. Based on this, we can define the decision boundary as:

$$\ln\left(\frac{\pi_1 N(x|\mu_1,\Sigma)}{\pi_0 N(x|\mu_0,\Sigma)}\right) = 0.$$

It can be shown that this decision boundary can be presented as a simple linear equation of the form $w^T x + w_0 = 0$, where w are weighting coefficients to be estimated.

Consider the illustrative example from Figure 1. Red points are solvent companies and blue ones are insolvent companies. We observe that their conditional means are quite different. Normal distributions are overlaid around these means. We clearly see that at the point of the distributions' intersection, i.e., where the probability of getting to each category is equal, the decision boundary is located. If the point falls to the left of the boundary, the probability of being solvent becomes higher than insolvent, therefore the point is classified accordingly.

It is argued,[3] that the model performs poorly when the abovementioned underlying assumptions do not hold, and this is usually the case – financial ratios are rarely distributed normally (for example, because such variables cannot have negative values), and it is not likely that solvent and insolvent companies have similar covariance matrices across ratios, because, intuitively, companies with completely different solvency statuses can have different relations across variables.

2.2. Logistic Regression

While LDA is a linear parametric model, Logit is a non-linear parametric model. Compared to LDA, Logit does not use the assumptions of multivariate normality and equivalence of covariance matrix that were made in LDA case, but instead assumes a logistic distribution of the output variable.

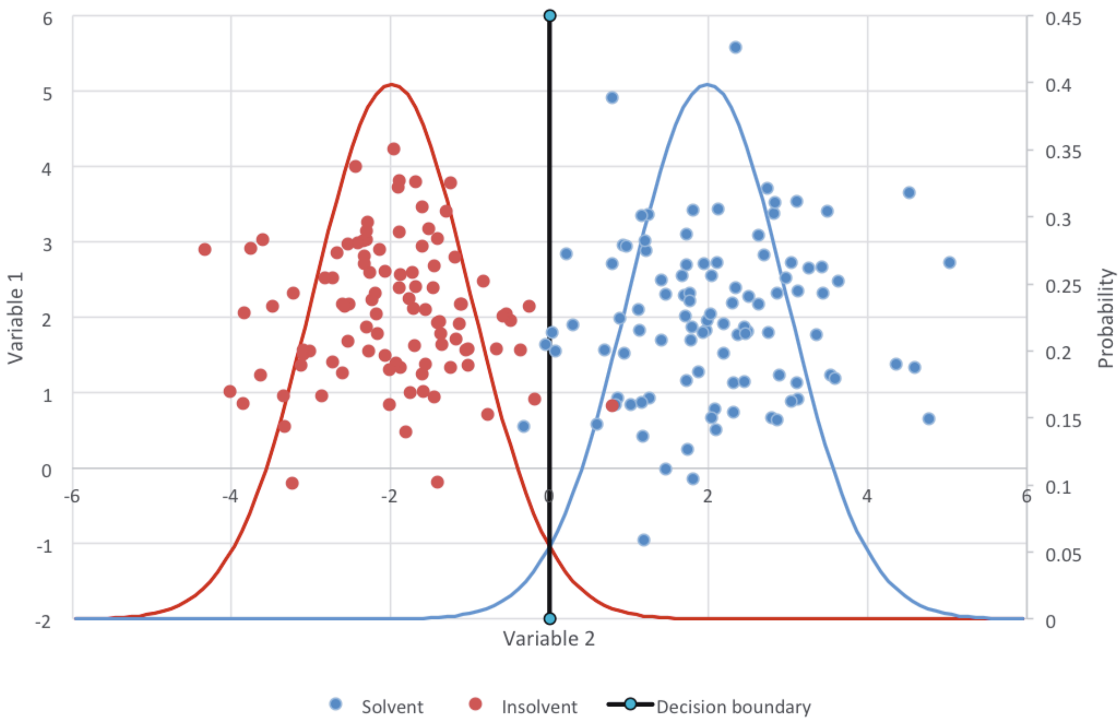
Let x be explanatory variables (in our case, financial ratios), β are coefficients for x. Suppose an equation $\beta^T x + \beta_0$ defines the value of the variable z, which then goes into a logistic Cumulative Distribution Function (CDF) $\Phi(.)$ as a parameter. Then each company i has its own probability of default (PD):

[1] There are still some qualitative triggers provided in the text of Directive No. 23 that can adjust the output of the model.

[2] The assumption is made in order to make the inference equation linear. Refer to Venables W. N. and Ripley B. D. (2002) for the complete theory.

[3] Pohar M., Blas M., and Turk S. (2004) have studied the behavior of LDA and Logit when normality condition fails.

Figure 1. Principle of LDA



$$PD(x_i) = \Phi(\beta^T x_i+\beta_0)= \Phi(z_i). \qquad (1)$$

Our obvious task is to maximize (1) for insolvent companies (denote them y = 1) and to minimize it for solvent ones (y = 0). We can write this as:

$$\max_\beta \prod_{i=1}^{n}[\Phi(\beta^T x_i + \beta_0)]^{y_i}[1 - \Phi(\beta^T x_i + \beta_0)]^{1-y_i}, \text{ where } n \text{ is the total sample size.} \qquad (2)$$

In other words, by varying β, we try to maximize the product of whether PD (for insolvent companies) or survival rate (for solvent companies), which is 1 – PD, over the sample. This procedure is called Maximum Likelihood Estimate (MLE). Usually, the logarithm of (2) is taken in order to simplify computations as taking the logarithm turns the product into the sum of logarithms.[4]

Figure 2 provides illustration of Logit (notations are the same). The variable z is located on the horizontal axis. After (2), βs are set in such a way that z is on average maximally different across classes. And the logistic CDF (black line) is generally higher at insolvent companies. However, the leftmost points are, of course, errors of the model. The same is true to the rightmost points of the solvent companies.

2.3. Support Vector Machine

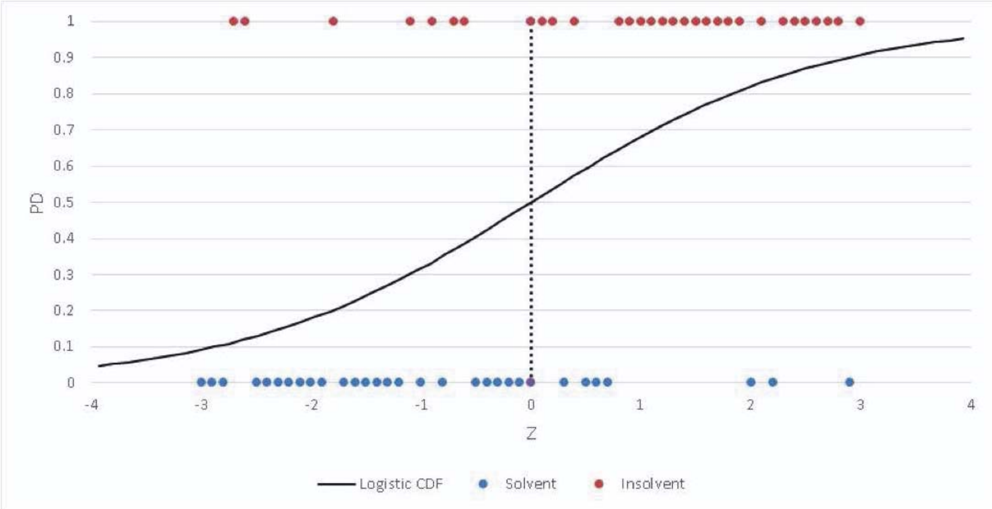
Bernhard E. Boser, Isabelle M. Guyon, and Vladimir N. Vapnik (1995) introduced SVM as highly nonlinear non-parametric machine learning algorithm for classification. Lately, it is getting increasingly popular in the default prediction scope as more and more researchers test and further develop this model. Western commercial banks and rating agencies are also interested and many of them incorporate SVM and related machine learning methods internally (McKinsey, 2015).

Regulators are also using these models. Deutche Bundesbank used SVM in credit scoring of non-financial companies up to 2012 (ECB, 2013).[5]

[4] Refer to Hosmer D. W., Lemeshow S. (2000) for deeper explanations on Logit.

[5] In 2012, the model was substituted with a more sophisticated integrated model that comprises several auxiliary models.

Figure 2. Principle of Logit



Consider the linear equation $h(x) = w^T x + b$, with x (as usual) as a vector of independent variables, w is a vector of weighting coefficients, and b is an intercept. This equation forms a separating hyperplane when it is equal to zero.

The so-called "margins" play the key role in SVM. It is essentially the distance from the point to the separating hyperplane. We can distinguish between functional margin and geometric margin. Functional margin can be formalized as:

$$y = y(w^T x + b), \tag{3}$$

Where y is an indicating variable, which takes the value of +1 if company defaulted and -1 otherwise. Therefore, we classify the company as defaulted if the value of (3) is greater than zero. The larger it is, the more we are confident in our prediction. Figure 3 illustrates a linearly perfectly separable case. The separating hyperplane is located in such a way that the margin between the closest points (support vectors) and the plane is maximal. Notice, that for the linear case, there should be at least three such points. Otherwise, the line could be drawn in an infinite number of ways. In other words, the points "support" the line. This is where the method receives its name.

However, (3) cannot be a reliable confidence measure, because, after rescaling w and b (multiplying or dividing by a number), the prediction remains the same, but the value of (3) changes (i.e. we can make it arbitrarily large, which can misleadingly provide a confident prediction).

To overcome this problem, we further introduce the notion of geometric margin. Instead of just using w *and* b, we normalize them so that they now become $\frac{w}{||w||}$ and $\frac{b}{||w||}$. It now means that the parameters are normalized to have the length of unity. And the formula (3) becomes:

$$\gamma = \frac{y(w^T x + b)}{||w||}.$$

The principle of SVM is to find the set of weights that maximizes the minimal margin of each class points to the separating hyperplane. In other words, this makes our prediction as confident as possible. It is done by formulating an optimization problem of the form[6]

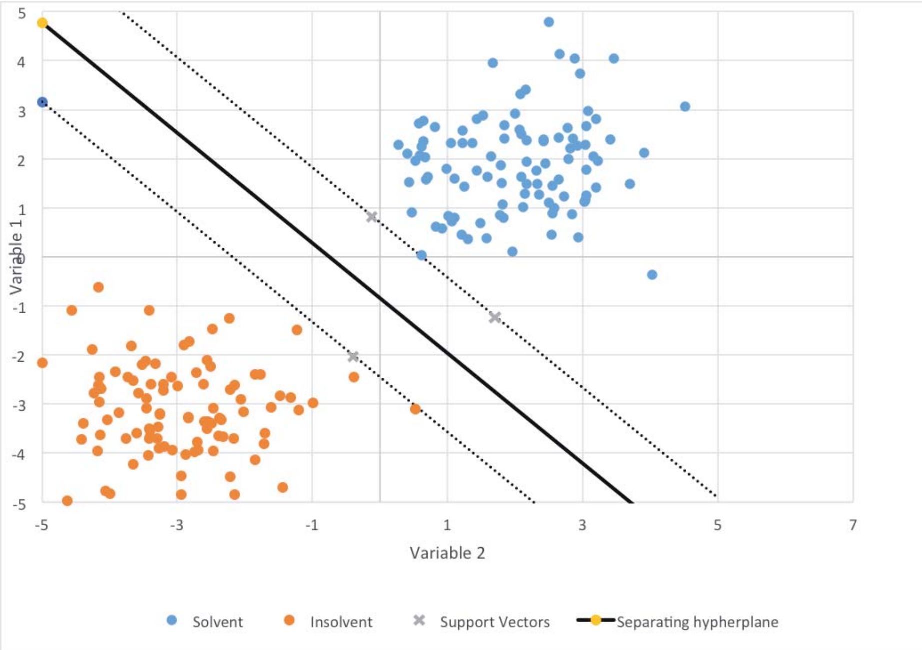
$$\min_{w,b} \frac{||w||}{2} + C\sum_{i=1}^{n} \varepsilon_i \tag{4}$$

$$\text{s.t. } y_i(w^T x_i + b) \geq 1, \quad i = 1, \dots, n$$

$$\varepsilon_i, w \geq 0, \quad i = 1, \dots, n, \ n \text{ - sample size}$$

[6] Detailed derivation is out of the scope of this paper. For in-depth theory, refer to Andrew Ng, Stanford University, CS229 Lecture notes.

Figure 3. Principle of SVM



ε_i in this formulation is the parameter, which allows some fraction for misclassification (can be regarded as an error term), C controls for the quantity of such misclassifications. If one sets C too large, then there will be less of a misclassification, while, at the same time, the risk of overfitting increases too.

What makes SVM so good is usage of Kernel functions. Kernel functions transform the functional form of the original input variables, transferring them into highly dimensional space (feature space). Transformed variables are called features. In feature space, points, which were linearly inseparable in the original space, usually can be easily separated. The principle of kernels can be best illustrated with the following example. Suppose we have only two financial coefficients that can be used for prediction (x and y). If this is the case, we operate in just 2 dimensions. Consider Figure 4 a). Let red circles be solvent companies and the blue – insolvent ones. It is apparent that no line could separate the points from one another. But, what if we don't want to limit ourselves with just 2 dimensions. Let's transform the points such that they now have another dimension with coordinate $(x^2 + y^2)$. The result of this is that the points could be separated linearly, which is illustrated on the Figure 4 b).

The next step is introduction of Lagrange duality. While the formulation in (4) is called primal form, the dual form version (already with Kernel functions) looks like the following:

$$\max_a \sum_{i=1}^{n} a_i - \frac{1}{2}\sum_{i,j=1}^{n} y_i y_j a_i a_j K(x_i, x_j); \qquad (5)$$

$$\text{s.t. } 0 \le a_i \le C, \; i = 1, \dots, n;$$

$$\sum_{i=1}^{n} a_i y_i = 0, \; i = 1, \dots, n; \; n \textit{ - sample size.}$$

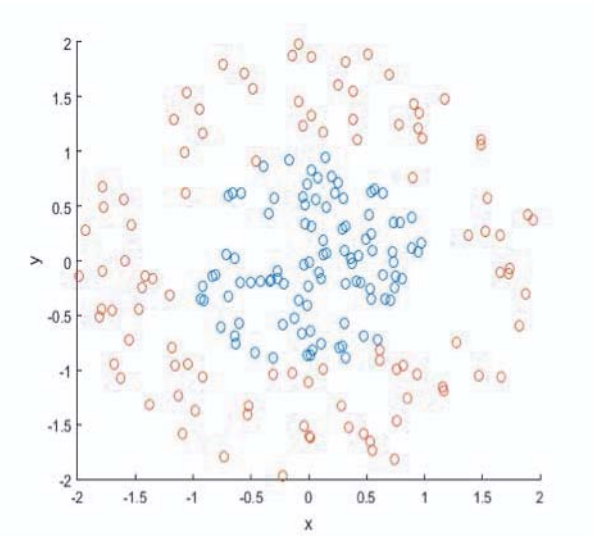
$a's$ in (5) are Lagrange multipliers from the primal form. Note that parameter C sets the upper boundary for a that's why it is also called a box constraint. During optimization the majority of $a's$ will turn to zero, non-zero $a's$ correspond to the support vectors.

Now, the formula for prediction is $h(x) = \sum_{i=1}^{k} a_i y_i K(x_i, x) + b$, where k is the number of support vectors.

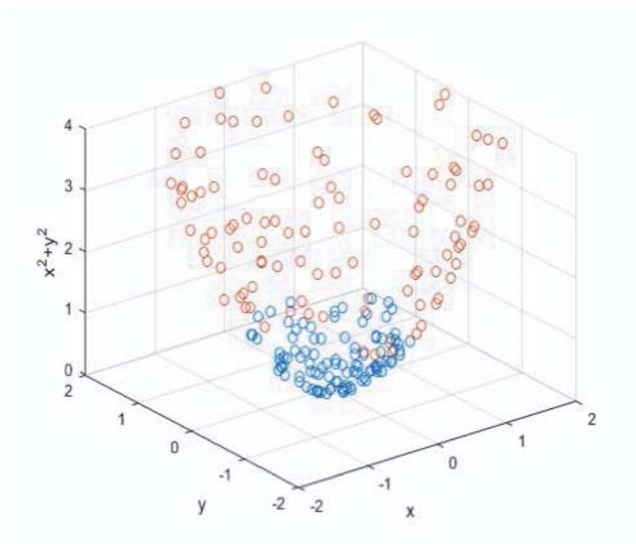
Despite its obvious advantages, SVM has some drawbacks as a credit scoring application. They will be discussed in the subsequent section.

Figure 4. Illustration of Kernel Transformation

a) Original Space



b) Feature Space



Note that parameter C from (4) is responsible for the level of misclassification. The bigger it is, the more precise the model on the training sample becomes. However, a large value of C often leads to overfitting. Therefore, one should find some trade-off between precision and overfitting when deciding on C.

In addition, one should opt for a particular type of Kernel function. In this application, the Gaussian kernel was chosen, which has the following form:

$$K(x,x') = \exp\left(-\frac{\|x-x'\|^2}{2\sigma^2}\right)$$

Gaussian kernel is probably the most popular due to its computational efficiency. The parameter σ in the formula above is called the kernel scale parameter. It is also subject to optimization. These two parameters are selected in such a way that maximize the GINI of the model.[7]

Another parameter to be tuned is prior probabilities of each class. For the present purpose, uniform probability was chosen. It means that the model puts equal weights on the observations of solvent and insolvent companies during optimization.

III. Model

In this section, the three abovementioned models are built and tested in order to reveal the optimal one.

3.1. Data[8]

NBU data from financial statements of more than 8,000 private enterprises[9] was used to build the models. The data was further refined as some companies that were suspected to be related to certain banks[10] were eliminated from the analysis.

The data was divided by the size of enterprises (large and small) and then by industry (Agriculture, Manufacturing, Trade, Others). The division by size is stipulated by different accounting standards for large and small companies that exist in Ukraine.

[7] The list of parameter values selected for each model is provided in the Appendix, Table C.

[8] I'd like to thank the NBU Risk Management Department, in particular Alexander Fostik and Dmytro Sharov, for the great help and participation in Logit model building, as well as in creating the independent variables list and breakdown to clusters.

[9] Companies located in Donbass and Crimea were eliminated from the sample, since they went bankrupt not due to economic reasons.

[10] For such companies, the Directive has a list of qualitative triggers that increase the probability of default.

Therefore the information in the financial statements cannot be compared. In the previous Directive, there was more detailed breakdown by industries. The unavailability of a large enough sample dictated the decision to aggregate the breakdown. If original clusters were used, then only about a hundred companies would have remained in each cluster. The choice of the particular clusters was made after conducting a cluster analysis, which revealed similarities in the balance structure among the abovementioned clusters. It should be noted that only ratios that describe balance structure differences were used, ratios that might indicate problems with solvency were not used.

For the purpose of this paper, "default" means getting to the category of insolvent companies, according to the Directive No. 23[11] as of 1 January 2015, while the financial statements was as of 1 January 2014, i.e. with a lag of one year.

3.2. Variables

For modeling, a long list of financial ratios was initially made (Table 1). They cover various types of profitability, liquidity, turnover, and solvency measures. All variables were capped with 5 and 95 percentile. Similar variables were used by Hardle et al., (2009), they built similar model for Deutsche Bundesbank in their paper.

3.3. Efficiency criteria

The main efficiency criterion was Accuracy Ratio (AR). For Logit it was also Pseudo - R^2. These measures indicate how well the model can differentiate between solvent and insolvent companies.

Accuracy Ratio (GINI)

It is also called the GINI coefficient. In general, it shows how precise the model identified defaulted companies in relation to non-defaulted. It is derived from Receiver Operating Characteristic (ROC) curve.

Suppose you have model predictions, for instance z-values in an LDA case. Among them, there is True Positive (TP), i.e. defaulted companies that are correctly identified; and False Positive (FP), i.e. non-defaulted companies that are predicted as defaulted. Let us then simultaneously add some arbitrary value to each variable's predicted z-score and recalculate TP and FP. Repeat this step until FP takes all values in the range {0;1}. The ROC curve is formed in 2-dimensional space, where FP is on the horizontal axis and TP is on the vertical axis.

Assume further a very bad model, which gives random predictions. Theoretically, the ROC curve of such a model will be a straight line connecting points (0,0) and (1,1). AR is exactly the area between this line and the ROC curve of a given model. In other words, it is the difference between a given model and a random model. The larger the area between them, the better.

3.4. Weight of Evidence (WOE) Transformation

WOE transformation is in essence transformation of continuous variables to discrete ones. The reasoning for using such an approach is that LDA and Logit gave bad results using pure data. The GINI coefficient amounted on average to 0.2-0.3, which is not even comparable to the results produced by SVM. Unfortunately, Ukrainian financial statements are often low-quality since IFRS is not mandatory for the majority of companies and financial statements are often not audited. Therefore, there is a lot of noise in the data, which cannot be handled by LDA and Logit. By noise, I mean some sort of counterintuitive dependences that might occur due to mistakes or omissions in the financial statements. Making variables discreet helped reduce this noise. The principle is the following:

1) Each variable is divided by some number of ranges from the sample minimum to maximum. (First column of Table 2);

2) For each range, WOE is calculated by the formula.

WOE_i = ln(%$solvent_i$) - ln(%$insolvent_i$), where %$solvent_i$ is a fraction of non-defaulted companies in the range i, and %$insolvent_i$ is a fraction of defaulted companies in the range i (Columns 2 and 3 of Table 2).

[11] Typically, these are companies that are more than 90 days overdue on a loan, but there are other conditions.

Table 1. Initial Full Set of Variables

Variable	Formula	Variable	Formula
K1	*Operational Profit / Revenue*	K17	*K8 + K15 – K16*
K2	*EBITDA / Revenue*	K18	*Financial Liabilities / Shareholders Equity*
K3	*EBIT / Revenue*	K19	*Financial Liabilities / EBITDA*
K4	*Current Assets-Current Liabilities / Current Assets*	K20	*Shareholders Equity / Total Assets*
K5	*Net profit / Revenue*	K21	*Current Assets / Current Liabilities*
K6	*Net profit / Shareholders equity*	K22	*Most liquid current assets / Current Liabilities*
K7	*Net profit / Total Assets*	K23	*EBIT / Financial Expense*
K8	*Inventories / Cost of goods sold*	K24	*Financial Liabilities / Revenue*
K9	*Accounts Receivables / Revenue*	K25	*Current Assets-Current Liabilities / Shareholders Equity*
K10	*Accounts Payables / Revenue*	K26	*EBITDA / Financial Expense*
K11	*Total Assets / Revenue*	K27	*Financial Liabilities / EBTDA*
K12	*Current Assets / Revenue*	K28	*EBITDA / Short term financial liabilitie + Financil expense*
K13	*Fixed Assets / Revenue*	K29	*Working Capital / Total Assets*
K14	*K8 + K9 – K10*	K30	*Working Capital / Revenue*
K15	*Accounts Receivables for advances / Revenue*	K31	*Financial Liabilities / Net profit*
K16	*Accounts Payables for advances / Revenue*	K32	*EBTDA / Revenue*

3) IV (Information Value) for a variable is calculated by the formula $IV = \sum_{i=1}^{n} (\%solvent_i - \%insolvent_i) * WOE_i$, where n is the number of ranges. This value becomes larger when the difference between the number of solvent and insolvent companies in each range increases (bottom right cell of Table 2).

4) The number of ranges and their bounds are selected in such a way that maximizes IV.

5) WOE values (column 4) go into the model's equation.

Table 2. Example of WOE Transformation

Bounds	Solvent	Insolvent	WOE	IV
<–0.006	9	6	–1.3	0.25
<0.053	34	11	–0.57	0.12
<0.16	41	3	0.91	0.18
>0.16	42	3	0.93	0.19
Totals	126	23	Na N	0.73

It is very important from an economic prospective to have monotonic WOE. In essence, it means that with an increase of some variable WOE can only increase or decrease. It is unacceptable to have, say, Debt/EBITDA ratio, which decrease WOE at first, and then, suddenly, starts increasing, because an increase in debt burden should never entail a decrease of PD.

Of course, there is a negative in this approach – the model losses its flexibility since the variables can only take several values. Suppose a model consists of just one explanatory variable, Net Profit/Revenue, suppose further that it has just two WOE ranges – from negative infinity to 0%, and from 0% to positive infinity. Let corresponding WOEs be -1 and +1, respectively. Suppose we predict the financial stance of three companies – A, B, and C with respective values of Net Profit/Revenue of -70%, -0.1% and 0.1%. The model prediction for B and C would be antipodal, though the difference between them is just 0.2%. At the same time the prediction for A and B will be exactly the same, though the company A is obviously much worse than B. Of course, it is a simplified example, but it perfectly reflects the drawback of such an approach. Despite this, it helped to sufficiently enhance the model's efficiency in terms of GINI.[12] In essence, it makes a model a bit non-linear. Suppose we have the same variable in two separate equations with the same coefficient of 1. But, it is WOE transformed in the second equation according to an example from Table 2. Consider Figure 5. The horizontal axis is the number of variable values. Since the WOE-transformed variable (Figure 5 b)) has four ranges, it can only take four consecutive values (WOEs). An untransformed variable (Figure 5 a)), as it's continuous, can take any value, four values with equal step were picked in order to compare it with a transformed one. It is apparent that the WOE transformed variable shows non-linear behavior.

It must be noted that SVM do not need such transformation, because it shows very good results on pure data, which is an obvious plus.

3.5. Variables selection

Due to WOE transformation, the procedure for variable selection differs for Logit and LDA, and SVM.

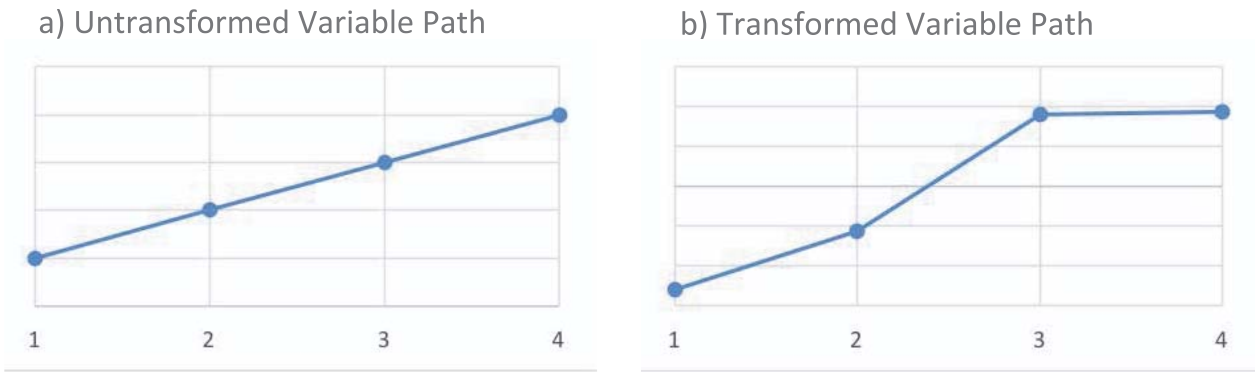
Logit and LDA

1) All coefficients are compared by IVs. Variables with the lowest IV are dropped from the analysis since they cannot discriminate between classes well;

2) The correlation matrix and economical reasoning of the sign of variable coefficients in the equation are assessed. Highly correlated or not economically justified variables are dropped;

[12] In fact, by doing this transformation we fit our input data to what we expect to see (notice, that we make WOE trend to be in line with economic intuition).

Figure 5. Illustration of WOE Transformation



3) The remaining set of variables goes to the cross-validation stage, where the efficiency of the model is assessed with these variables. Additional variables can be dropped in this stage.

SVM

For SVM, a forward selection procedure was chosen:

1) Selection starts with a model with no variables and then one variable is added to the model in turn;

2) The variable that ultimately brings the largest GINI increment is added;

3) All highly correlated variables (>|0.8|) with the chosen one are eliminated from the initial set;

4) Then the procedure is repeated with the remaining set;

5) It continues until variable addition does not lead to an enhanced efficiency.

A third step is needed to accelerate computations. Highly correlated variables presumably describe one common aspect of a borrower's financial standing. So, after the best of these variables is picked up, all others are eliminated so that they do not participate in the next lap, thereby saving computational time.

Of course, there is no possibility of trying all possible combinations of variables, so this procedure or a backward selection is commonly chosen.[13] A backward selection procedure is inverse to the forward one – the model starts with a full set of variables and then variables are deleted in turn. As you noticed, variable selection and cross-validation stages for SVM are combined in one step.

Figure 6 illustrates the GINI path in a forward variable selection process for SVM for large companies. We see that after some point (most often it is 4-6 variables) GINI starts to diminish. It is the cut-off point in variable selection for each model.

Table 3 provides information on the variables picked for each particular model, according to the selection procedure described above.[14] Don't be confused with the fact that there are not many coinciding variables in LDA & Logit and SVM. Many of them are highly correlated, therefore can be regarded as substitutes for each other. For example, in the "Manufacturing" cluster of Large companies, the K7 coefficient is absent in the equation for SVM, however this equation uses the K3 coefficient, which has a correlation of 0.78 with K7. On the other hand, LDA & Logit equation does not have the K12 coefficient, but has the K30, their correlation is 0.81. It means that despite large difference in the variables, the economic reasoning behind them is much closer than might seem.

The fact that the models are not equal in specification makes them harder to compare directly. Instead, it would be proper to say that a comparison of both the models and the variable selection procedures was made.

[13] Refer to Hardle W. K., Moro R. A., Schafer D. (2009) for an additional example of both approaches.

[14] Refer to the Appendix for the additional statistics for each variable, Tables A and B.

Figure 6. GINI Path in SVM Variable Selection Process

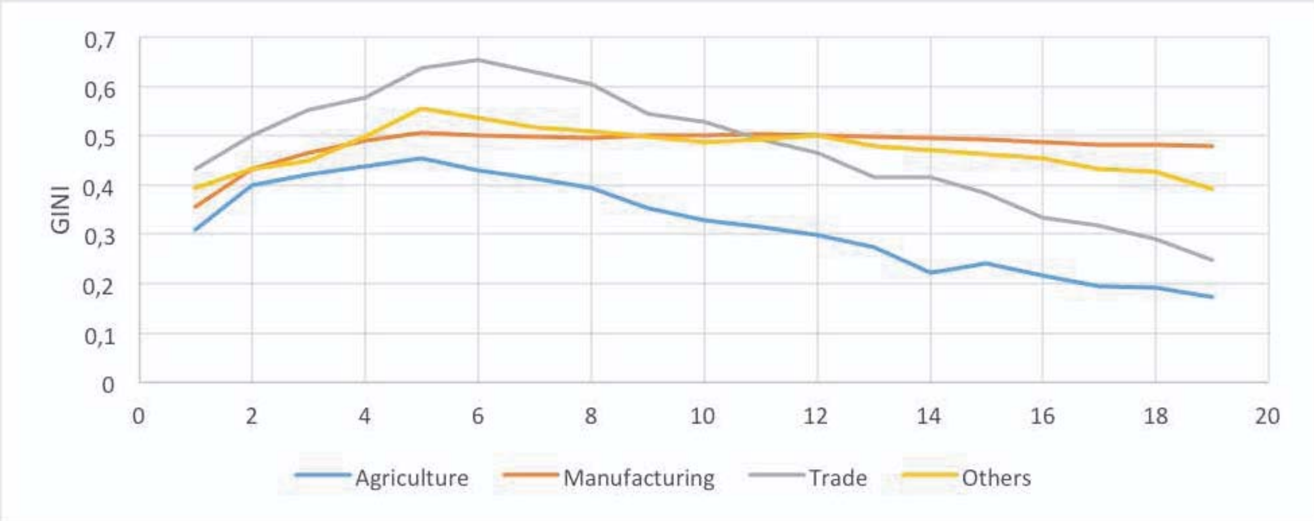


Table 3. Variables Selected for Each Model

Large Companies							
Agriculture		Manufacturing		Trade		Others	
LDA&Logit	SVM	LDA&Logit	SVM	LDA&Logit	SVM	LDA&Logit	SVM
K10	K8	K7	K3	K11	K9	K10	K10
K11	K10	K20	K12	K14	K14	K22	K12
K24	K19	K23	K16	K15	K20	K27	K21
K25	K22	K24	K24	K21	K24	K29	K32
	K24	K30	K25	K23	K25	K30	K27
	K25				K31		
Small Companies							
Agriculture		Manufacturing		Trade		Others	
LDA&Logit	SVM	LDA&Logit	SVM	LDA&Logit	SVM	LDA&Logit	SVM
K7	K7	K1	K1	K1	K8	K5	K1
K9	K11	K24	K10	K9	K13	K8	K8
K18	K21	K29	K24	K21	K18	K11	K9
K27			K27	K24	K20	K20	K12
K29				K31	K24	K31	K18
K30							K24
							K31

3.6. Cross Validation

Very rigorous validation was developed and applied for the purpose of testing:

1) Initial sample is randomly divided by training and test samples 100 times in a 70%/30% proportion;

2) Each time efficiency criteria are calculated;

3) After completion of step 2, the median values of efficiency criteria are taken.

This procedure is called 100-fold cross validation – a particular instance of k-fold cross-validation. It is a more advanced method to validate models, since single test sample efficiency may depend very much on the properties of the test sample at hand.[15] So the procedure is developed to give very close approximation of sample efficiency to a true one.

IV. Results[16]

In Table 4 you can observe the efficiency of the models based on specifications identified in the previous section.

SVM models are better in 6 out of 8 cases. It should be noted, though, that in some cases the results of the models are approximately equal.

Table 4. Accuracy Ratio (GINI) of the Models

Cluster	Agriculture			Manufacturing			Trade			Others		
Model	LDA	Logit	SVM	LDA	Logit	SVM	LDA	Logit	SVM	LDA	Logit	SVM
Large companies	0.38	0.344	0.455	0.51	0.51	0.506	0.646	0.653	0.653	0.517	0.524	0.555
Small companies	0.458	0.497	0.512	0.472	0.508	0.535	0.498	0.497	0.545	0.233	0.228	0.294

The ROC curves that correspond to the median values of GINI are presented in the Appendix.

Impediments to practical implementation of SVM

It seems that SVM is superior to its competitors in many cases. The model is more efficient than LDA and Logit, even though WOE transformation was used to foster the efficiency of the latter. Because SVM uses input variables as is, it is more flexible, which is a desirable property. However, superiority of SVM isn't so definite, since we observe that the differences in GINI are quite small in many cases.

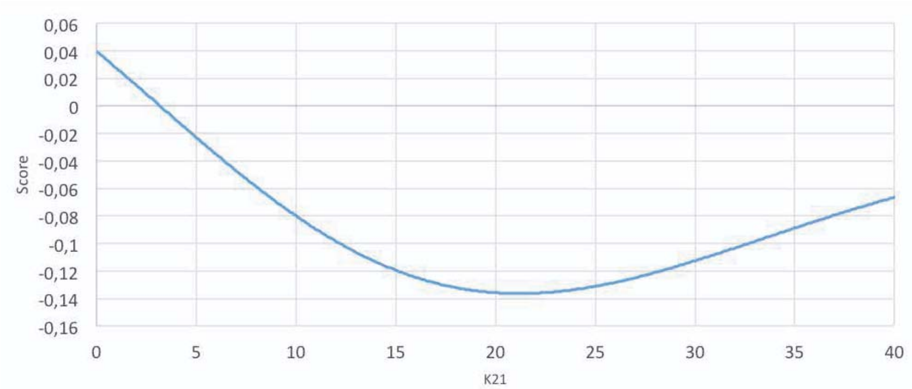
Figure 7 demonstrates another favorable feature of SVM. Because it is highly nonlinear, it is able to capture any kind of functional relationship of the input variable. We can see that, as K21[17] increases within a common range, the score decreases, which is in line with economic intuition. However, abnormally high values of the ratio might indicate some problem with the financial statements of the company, which in turn might be a sign of trouble with the very company. The model captures it, and increases the score (in other words, increases the probability of default). In a way, the model can even capture creative accounting patterns.

[15] Refer to Kovahi R. (1995) for more details on this method and its analogues.

[16] The results are not final. Therefore, the model, which will be presented to the banking system, may differ somewhat.

[17] Cluster "Others". Large companies.

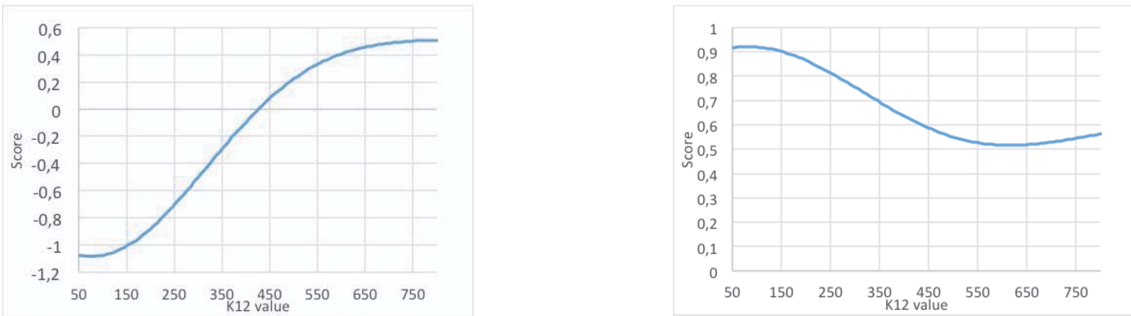
Figure 7. Dependence of Score on K21 Value of a Particular Company



However, this favorable feature sometimes causes objections from practitioners. Consider Figure 8. We can observe the dependence of the score on K12[18] for two separate companies. We can see that the relationships are totally inverse, which may be strange to many.[19] SVM catches any kind of functional dependence, as a result it losses the monotonicity of results. This happens because SVM scores depend not only on the particular variable, but also on all other variables in equation at a time. Whether it is indeed overfitting or the relationship is dictated by economic reasons cannot be easily inferred, though. The result in Figure 8 is usually possible when the set of variables' values differ very much, say, in the case when one of the companies has huge financial problems, which is reflected in very bad ratios (on Figure 8 b) it is obvious that the company has financial problems, since its score is quite high, whatever value K12 takes).

Figure 8. Illustration of Overfitting Problem

a) b)



It is not that a huge problem. Table 5 presents the percentage of monotonicity breaches for each model. It seems that on average about 20-30% of observations violate the monotonicity of results.

Table 5. Monotonicity Breaches in SVM

Large Companies			
Agriculture	Manufacturing	Trade	Others
32%	0%	29.84%	28.07%
Small Companies			
Agriculture	Manufacturing	Trade	Others
16.11%	16.72%	28.43%	34.44%

[18] Cluster "Others". Large companies.

[19] Note that counterintuitive signs were not allowed in LDA and Logit cases by construction. This might be considered a privilege for SVM in this analysis. On the other hand, LDA and Logit have a predetermined functional form, which reduces the risk of overfitting. Therefore, it is not known what effect this privilege had on the results or if it was a privilege at all.

Chosen model

At this stage, it is very important to introduce a practicable model, which would be easy to explain and understand, therefore, implementation of SVM was temporary suspended.

A Logit model is chosen for implementation since it shows slightly better results than the LDA. Besides, its statistical properties are more desirable and its use is more widespread in banking system.

Table 6 provides the most detailed information on the resulting equations, as well as t-statistics and pseudo R^2.

It seems that the “Others” cluster for small companies shows relatively poor performance. There is no surprise in this, since from practice it is known that this cluster consists of a large number of companies that are economically dependent on other businesses. For such companies, bad financial coefficients do not necessary mean a high probability of default as parent companies will likely support them. Likewise, if they lose this support, they can go bankrupt even while having nice financial ratios. For this reason, the model cannot reliably differentiate between these companies.

Table 6. Equations of Logit Models[20]

Large companies					Small companies				
Cluster	Variable	Coefficient	P-value	Pseudo R^2	Cluster	Variable	Coefficient	P-value	Pseudo R^2
Agriculture	K10	0.917	0.08	0.12	Agriculture	K7	0.613	0.05	0.19
	K11	0.564	0.27			K9	0.53	0.25	
	K24	1.11	0.01			K18	0.294	0.48	
	K25	1.084	0.12			K27	0.269	0.58	
	constant	1.875	0.0			K29	0.71	0.11	
						K30	0.524	0.31	
						constant	1.703	0.0	
Manufacturing	K7	0.366	0.2	0.15	Manufacturing	K1	0.623	0.02	0.12
	K29	0.358	0.2			K24	0.791	0.0	
	K20	0.599	0.0			K29	0.558	0.07	
	K24	0.476	0.01			constant	1.608	0.0	
	K30	0.688	0.0						
	constant	1.24	0.0						
Trade	K11	0.523	0.03	0.25	Trade	K1	0.35	0.18	0.14
	K14	0.909	0.0			K9	0.772	0.01	
	K15	0.754	0.01			K21	0.891	0.0	
	K21	0.98	0.0			K24	0.342	0.17	
	K23	0.732	0.01			K31	0.433	0.11	
	constant	2.072	0.0			constant	1.913	0.0	
Others	K10	0.652	0.03	0.18	Others	K5	0.308	0.56	0.05
	K22	0.954	0.02			K8	0.608	0.27	
	K27	0.669	0.16			K11	0.28	0.55	
	K29	0.83	0.05			K20	0.583	0.22	
		1.058	0.01				0.572	0.17	
	constant	1.544	0.0			constant	1.112	0.0	

The set presented is optimal as of now. Moreover, the model will be updated and improved as new information comes.

[20] It should be noted that some of variables are statistically insignificant by p-value. However, p-values were not the main criteria for model selection, but rather an auxiliary one. Therefore, insignificant variables were allowed in some cases.

A few words on further steps

Michael Doumpos and Constantin Zopodunis (2009) proposed a way to make SVM economically justified by introduction of so-called hints to the learning algorithm. Hints are in essence additional constraints to the optimization problem (4). Let us reformulate it so that it uses kernel transformation:

$$\min_{w,b} \frac{||w||}{2} + C\sum_{i=1}^{n} \varepsilon_i$$

$$\text{s.t. } y_i(K(x_i, X)u + b) \geq 1, \qquad i = 1, \dots, n$$

$$\varepsilon_i, w \geq 0, \qquad i = 1, \dots, n, \quad n \text{ – sample size.}$$

We want the dependence to be monotone. In other words, we want:

$$\left(K(x_i, X) - K\left(x_j, X\right)\right) u \geq 0, \tag{6}$$

where each element x_j is greater than the corresponding element of x_i. This is the additional constraint.

The formulation above implies that as x increases the score would decrease. In order to introduce this constraint, we first need to create a data set on which the model would orient. In other words, we artificially create vectors of input, thus giving the algorithm hints about what model we expect to see. In addition, since we need all variables to be monotonically decreasing [as inequality (6) stipulates], we have to flip equations for K, when necessary, such that their economic intuition would be in line with it.[21]

V. Conclusions

This paper evaluated the potential use of SVM as a methodology to measure credit risks. Using a dataset of Ukrainian companies, I have shown that SVM predicts more accurately than classical scoring models. However, the performance of SVM is only marginally better, therefore it cannot be deemed as a strictly superior choice. Rather it is very good and viable alternative, but the choice of the appropriate model is up to researcher in each particular case.

In addition, some problems with the complexity and lack of monotonicity in SVM results were discussed, and further steps to improve the model and eliminate those prohibitive properties were suggested. In particular, a learning by hints procedure can potentially be developed, which will make SVM economically intuitive and likely to reduce overfitting.

Because of SVM's shortcomings, a Logit model was adopted for now. It turned out to be somewhat more efficient than LDA. Besides, it poses more attractive statistical properties than LDA. In order to capture the most recent dynamics in the economy, the NBU plans to review this model annually.

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[21] This procedure shall circumvent the problem of monotonicity breaches caused by overfitting.

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Appendix

Table A. LDA and Logit Variables. Detailed Information

Large companies										Small companies									
Cluster	Var	Ranges	WOE	IV	Cluster	Var	Ranges	WOE	IV	Cluster	Var	Ranges	WOE	IV	Cluster	Var	Ranges	WOE	IV
Agriculture	K10	2.62	1.39	0.24	Trade	K11	0.19	1.66	0.74	Agriculture	K7	0.01	-1.3	0.73	Trade	K1	-0.02	-1.24	0.28
		66.37	-0.05				0.37	1.64				0.05	-0.57				0.00	0.00	
		146.26	-0.11				0.62	0.49				0.16	0.91				0.00	0.26	
		146.26	-0.65				0.8	0.17				0.22	0.94			K9	88.76	0.26	0.25
	K11	1.34	0.6	0.26			1.9	-0.61				0.22	0.94				162.79	-0.16	
		2.19	0.5				1.9	-0.73			K9	26.28	0.61	0.36			162.79	-1.16	
		2.51	0.11			K14	180.00	0.36	0.69			88.18	-0.51			K21	0.57	-1.41	0.44
		3.68	-0.29				250.00	-0.96				191.6	-0.69				0.9	-0.16	
		3.68	-0.56				250.00	-2.35				191.6	-0.69				1.03	-0.03	
	K24	0.47	0.36	0.29		K15	16.17	0.29	0.28		K18	0	1.07	0.44			1.42	0.16	
		1.35	-0.02				38.98	-0.24				0.1	0.86				1.42	0.61	
		1.35	-1.21				38.98	-1.21				0.16	0.17			K24	0.02	0.7	0.39
	K25	-0.52	0.93	0.12		K21	0.67	-1.26	0.32			1.66	-0.06				0.04	0.37	
		-0.03	0.11				1.01	-0.07				1.66	-1.3				0.06	0.35	
		0.59	0.06				1.01	0.35			K27	1.01	0.57	0.28			0.09	0.15	
		0.94	-0.11			K23	1.38	-0.5	0.49			1.67	0.09				0.13	0.00	
		0.94	-0.65				2.7	0.34				4.47	-0.31				0.25	-0.03	
Manufacturing		0.00	0.00		Others		2.7	1.34		Manufacturing		4.47	-0.69		Others		0.61	-0.43	
	K7	-0.11	-0.64	0.41		K10	54.47	0.65	0.46		K29	0.14	-0.51	0.51			0.61	-1.24	
		-0.02	-0.63				82.2	-0.05				0.21	-0.31			K31	1.64	0.91	0.38
		0.00	-0.3				135.6	-0.64				0.3	0.09				6.92	0.26	
		0.04	0.06				135.6	-0.9				0.36	0.17				40.71	0.07	
		0.04	1.1			K22	0.06	-0.64	0.26			0.47	0.94				100.00	-0.34	
	K20	-0.03	-0.96	0.42			0.34	-0.48				0.47	1.67				101.5	-0.65	
		0.07	-0.67				0.34	0.49			K30	0.11	0.5	0.29			101.5	-1.04	
		0.18	-0.64			K27	-0.34	-0.79	0.16			0.22	0.46			K5	-0.01	-0.53	0.1
		0.26	-0.13				0.01	-0.21				0.4	-0.31				0.02	-0.03	
		0.31	0.02				0.14	-0.05				0.76	-0.31				0.02	0.28	
		0.31	0.7				0.22	0.7				0.76	-1.01			K8	30.19	0.26	0.09
	K23	0.54	-0.59	0.43			0.22	1.06			K1	-0.07	-1.43	0.35			70.39	-0.12	
		1.11	-0.44			K29	-0.34	-0.79	0.29			0.01	0.15				70.39	-0.4	
		2.04	-0.16				0.01	-0.21				0.01	0.28			K11	0.84	0.4	0.14
		15.00	0.89				0.14	-0.05			K11	0.75	0.77	0.5			1.24	0.37	
		15.00	1.13				0.22	0.7				0.91	0.25				2.22	-0.12	
	K24	0.03	2.72	0.48			0.22	1.06				1.16	0.03				17.71	-0.28	
		0.11	0.41			K30	0.1	0.73	0.28			1.93	-0.73				17.71	-0.64	
		0.23	0.34				0.14	-0.05				1.93	-0.88			K20	-0.19	-0.64	0.11
		0.31	0.02				0.61	-0.28			K24	0.04	0.81	0.41			0.67	-0.02	
		0.42	-0.16				0.61	-0.79				0.25	-0.04				0.77	0.14	
		0.65	-0.2									0.93	-0.73				0.77	0.92	
		0.65	-0.9									0.93	-1.02			K31	0.29	1.37	
	K30	0.49	0.38	0.26							K29	-0.33	-1.02	0.29			185.00	0.28	
		1.04	-0.57									-0.11	-0.19				185.00	-0.36	
		1.04	-0.88									0.2	-0.1						
												0.54	0.5						
												0.54	1.05						

Table B. Descriptive Statistics on the Selected Variables

a) Large Companies

Agriculture

Variable	all		solvent		insolvent	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K8	210.3	157.4	219.6	155.6	148.2	158.8
K10	60.7	76.0	58.9	74.4	72.8	87.1
K11	111.7	235.9	104.4	230.9	160.8	267.2
K19	3.5	6.2	3.6	6.3	2.9	5.6
K22	0.5	0.5	0.5	0.5	0.3	0.2
K24	0.6	0.8	0.6	0.8	0.8	1.0
K25	-3.8	19.8	-4.5	21.2	0.4	0.7

Manufacturing

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K3	0.0	0.1	0.0	0.1	-0.1	0.2
K7	0.0	0.1	0.0	0.1	0.0	0.1
K12	293.4	291.5	256.9	258.3	421.3	358.7
K16	21.5	38.8	16.2	32.9	40.1	50.6
K20	0.3	0.3	0.4	0.3	0.2	0.3
K23	3.6	7.8	4.4	8.4	1.0	4.8
K24	0.5	0.8	0.4	0.8	0.8	0.9
K25	-11.1	31.7	-7.6	26.8	-23.4	42.7
K30	0.5	0.4	0.4	0.3	0.6	0.4

Trade

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K9	51.7	61.1	45.1	53.5	102.9	88.0
K11	51.0	131.5	46.7	124.0	84.8	177.6
K14	57.4	117.4	48.0	96.4	131.3	209.2
K15	13.2	28.4	11.2	24.8	28.9	45.6
K20	0.2	0.2	0.2	0.2	0.2	0.2
K21	1.5	1.1	1.5	1.1	1.5	1.4
K23	3.4	8.9	3.8	9.3	0.5	4.2
K24	0.4	0.8	0.3	0.7	0.7	1.0
K25	-9.5	29.5	-9.1	29.5	-12.4	29.4
K31	32.4	41.6	31.8	41.5	36.8	42.3

Others

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K10	87.0	114.0	75.3	105.5	142.3	136.4
K12	291.6	334.9	266.7	330.4	409.5	335.4
K21	1.7	1.7	1.8	1.7	1.4	1.6
K22	0.6	0.6	0.7	0.6	0.4	0.4
K27	3.8	4.5	3.6	4.3	5.0	5.3
K29	0.0	0.3	0.0	0.3	-0.1	0.3
K30	0.2	0.3	0.2	0.3	0.3	0.4

b) Small Companies

Agriculture

Variable	all		solvent		insolvent	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K7	0.1	0.1	0.1	0.1	0.0	0.1
K9	64.5	121.6	56.9	114.6	105.9	150.8
K11	2.2	3.5	2.0	3.4	3.5	3.8
K18	0.7	1.5	0.7	1.5	1.0	1.5
K21	2.5	2.2	2.7	2.3	1.6	1.5
K27	3.5	9.0	3.5	9.5	3.3	5.6
K29	0.2	0.3	0.2	0.3	0.1	0.3
K30	0.3	0.3	0.2	0.3	0.4	0.4

Manufacturing

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K1	0.0	0.1	0.0	0.1	0.0	0.2
K10	138.5	184.6	126.2	171.6	201.1	231.8
K24	0.5	1.4	0.4	1.1	1.1	2.1
K27	3.4	8.6	3.4	8.1	3.4	10.6
K29	0.1	0.3	0.1	0.3	0.0	0.3

Trade

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K1	0.0	0.1	0.0	0.1	0.0	0.2
K8	40.2	112.0	35.3	104.0	73.6	152.8
K9	66.4	108.0	59.7	96.6	111.4	159.6
K13	0.6	2.0	0.5	1.8	1.4	3.0
K18	1.7	2.8	1.6	2.6	2.4	3.4
K20	0.3	0.3	0.3	0.3	0.1	0.3
K21	1.7	1.5	1.7	1.4	1.5	1.8
K24	0.4	1.1	0.3	1.0	0.8	1.6
K31	33.3	43.4	30.0	41.6	55.9	48.1

Others

	all		solvent		insolvent	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
K1	0.1	0.2	0.1	0.2	0.1	0.2
K5	0.0	0.1	0.1	0.1	0.0	0.1
K8	114.6	185.8	110.4	187.5	127.3	181.7
K9	90.1	139.0	85.4	135.8	104.5	148.4
K11	4.1	5.6	3.8	5.3	5.0	6.2
K12	1.5	2.3	1.3	2.2	1.9	2.6
K18	2.5	3.3	2.7	3.5	1.9	2.5
K20	0.3	0.3	0.3	0.3	0.3	0.3
K24	1.4	2.2	1.4	2.2	1.7	2.4
K31	46.3	47.9	42.9	47.6	56.9	47.6

Table C. SVM Generalization Parameters

Large companies			Small companies		
Cluster	Box Constraint	Scale parameter	Cluster	Box Constraint	Scale parameter
Agriculture	0.1	1	**Agriculture**	0.1	1
Manufacturing	0.1	15	**Manufacturing**	0.1	1
Trade	0.1	0.1	**Trade**	0.1	0.1
Others	0.1	1	**Others**	0.1	1

Table D. Correlation Matrices for Large Companies' Models

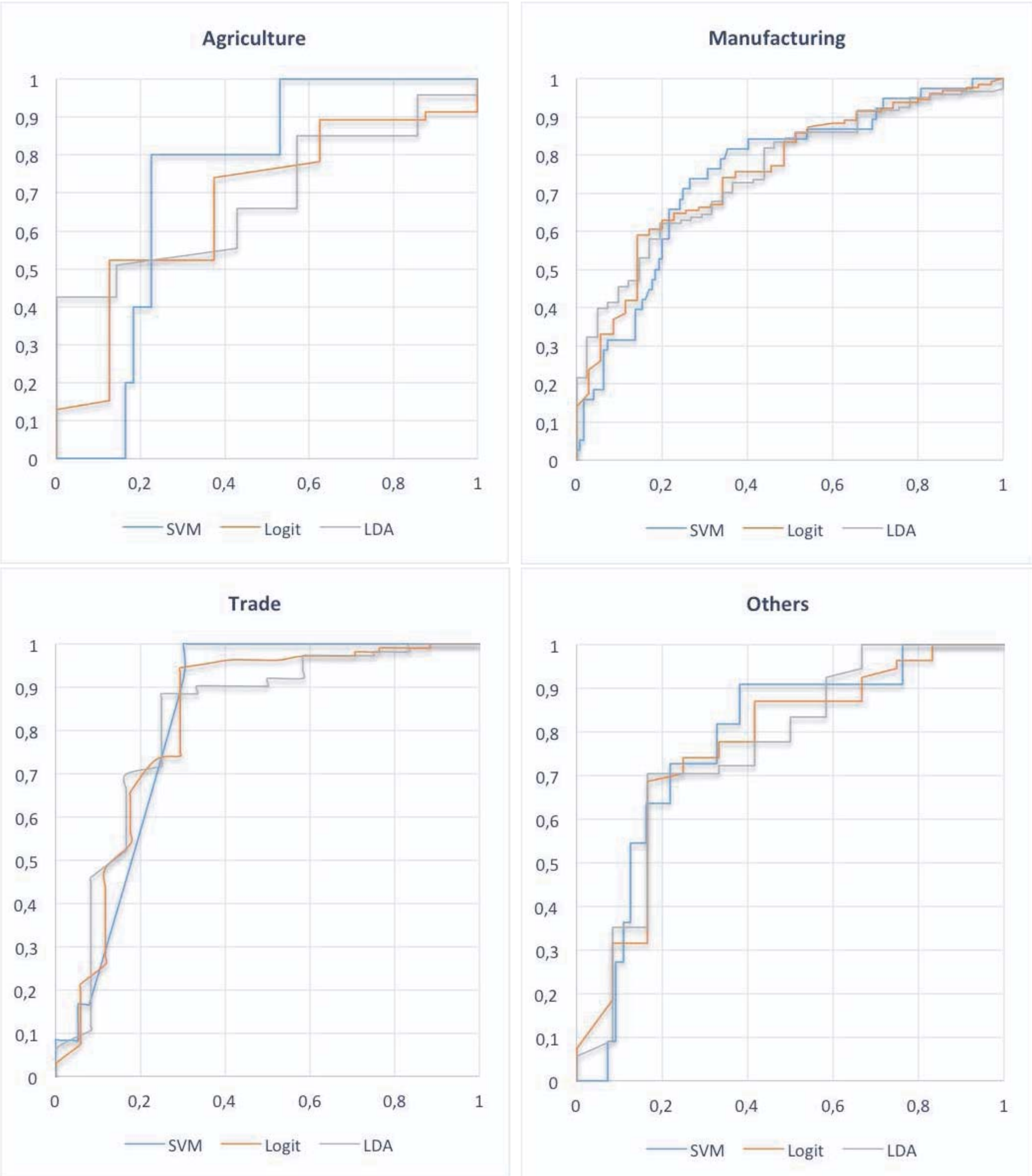
	Agriculture									
	K8	**K10**	**K11**	**K19**	**K22**	**K24**	**K25**			
K8	1.0000									
K10	0.2450	1.0000								
K11	0.1506	0.0407	1.0000							
K19	0.1612	0.0451	0.0838	1.0000						
K22	-0.0311	-0.1871	-0.1068	-0.0590	1.0000					
K24	0.0027	0.1029	0.0082	0.1488	-0.1039	1.0000				
K25	0.0846	0.0622	-0.0575	-0.1244	0.1072	-0.0660	1.0000			
	Manufacturing									
	K3	**K7**	**K12**	**K16**	**K20**	**K23**	**K24**	**K25**	**K30**	
K3	1.0000									
K7	0.7794	1.0000								
K12	-0.2502	-0.1247	1.0000							
K16	-0.1419	-0.0930	0.3819	1.0000						
K20	0.3650	0.3926	-0.2136	-0.2140	1.0000					
K23	0.4552	0.6035	-0.0603	-0.0793	0.2991	1.0000				
K24	-0.5263	-0.2653	0.5519	0.1663	-0.3617	-0.1186	1.0000			
K25	0.4348	0.3773	-0.1787	-0.1097	0.6066	0.1800	-0.3656	1.0000		
K30	-0.1712	-0.0695	0.8099	0.2797	-0.1123	-0.0400	0.3646	-0.1077	1.0000	
	Trade									
	K9	**K11**	**K14**	**K15**	**K20**	**K21**	**K23**	**K24**	**K25**	**K31**
K9	1.0000									
K11	0.1171	1.0000								
K14	0.3319	0.0826	1.0000							
K15	0.2503	0.1739	0.0472	1.0000						
K20	-0.1539	-0.0255	0.1807	-0.1379	1.0000					
K21	0.0049	0.0115	0.2624	-0.1027	0.4935	1.0000				
K23	-0.0370	-0.0596	-0.0636	-0.0825	0.1722	0.0956	1.0000			
K24	0.3188	0.3458	0.1697	0.3091	-0.1684	-0.0019	-0.0875	1.0000		
K25	0.0219	-0.0080	0.0771	-0.0032	0.4647	0.1999	0.0530	-0.2249	1.0000	
K31	0.1867	-0.1340	0.1099	0.1902	-0.2200	-0.0574	-0.4476	0.1869	-0.0506	1.0000
	Others									
	K10	**K12**	**K21**	**K22**	**K27**	**K29**	**K30**			
K10	1.0000									
K12	0.2776	1.0000								
K21	-0.0864	0.0890	1.0000							
K22	-0.0793	0.0674	0.6799	1.0000						
K27	0.2237	0.2719	0.0353	0.0081	1.0000					
K29	-0.1183	0.0849	0.7299	0.6195	-0.0203	1.0000				
K30	0.3073	0.4851	0.0271	0.0152	0.1898	0.1238	1.0000			

Table E. Correlation Matrices for Small Companies' Models

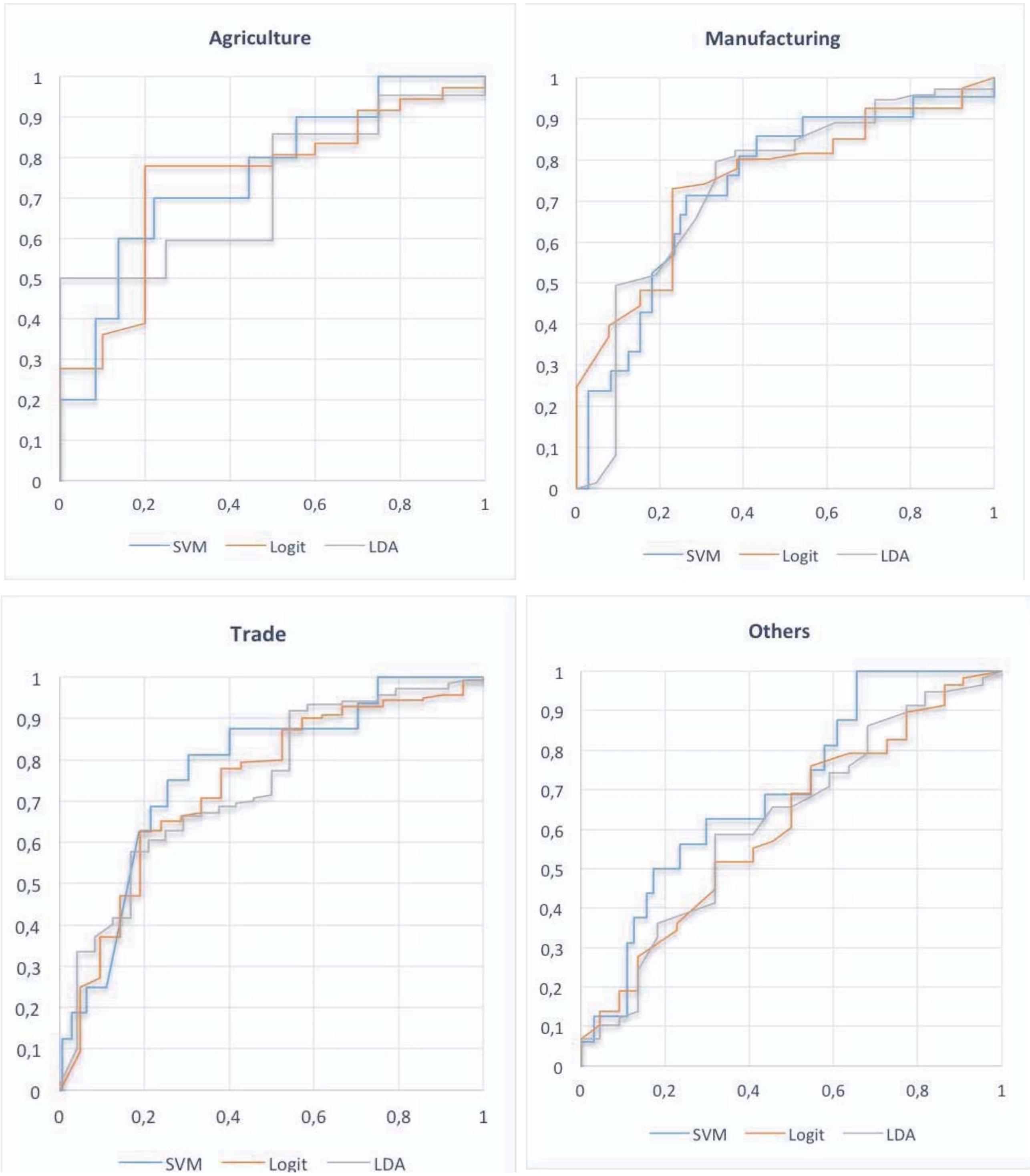
					Agriculture					
	K7	**K9**	**K11**	**K18**	**K21**	**K27**	**K29**	**K30**		
K7	1.0000									
K9	-0.2669	1.0000								
K11	-0.3357	0.6992	1.0000							
K18	-0.2583	0.2997	0.2879	1.0000						
K21	0.2622	-0.0669	-0.0518	-0.2467	1.0000					
K27	-0.2559	0.3884	0.4331	0.3724	0.0185	1.0000				
K29	0.2374	-0.0024	-0.0786	-0.2980	0.7209	-0.0086	1.0000			
K30	-0.1707	0.5054	0.3005	0.0927	0.0293	-0.0697	0.0757	1.0000		
					Manufacturing					
	K1	**K10**	**K11**	**K24**	**K27**	**K29**				
K1	1.0000									
K10	-0.0233	1.0000								
K11	-0.2497	0.4984	1.0000							
K24	-0.2153	0.4074	0.8497	1.0000						
K27	-0.0094	0.0451	0.2809	0.3079	1.0000					
K29	0.2109	-0.3764	-0.1267	-0.1141	0.0225	1.0000				
					Trade					
	K1	**K8**	**K9**	**K13**	**K18**	**K20**	**K21**	**K24**	**K31**	
K1	1.0000									
K8	-0.0403	1.0000								
K9	-0.1662	0.3918	1.0000							
K13	-0.3612	0.6052	0.5175	1.0000						
K18	0.0134	-0.0443	0.0997	-0.0300	1.0000					
K20	0.1962	0.0495	-0.1447	-0.0451	-0.4546	1.0000				
K21	0.1062	-0.0765	-0.0074	-0.1109	-0.1281	0.5316	1.0000			
K24	-0.2454	0.4573	0.5603	0.7227	0.2029	-0.1239	-0.0198	1.0000		
K31	-0.3241	0.1016	0.2027	0.2507	0.3897	-0.4279	-0.1553	0.3522	1.0000	
					Others					
	K1	**K5**	**K8**	**K9**	**K11**	**K12**	**K18**	**K20**	**K24**	**K31**
K1	1.0000									
K5	0.2968	1.0000								
K8	-0.1225	0.2013	1.0000							
K9	-0.2893	0.1582	0.3602	1.0000						
K11	-0.1231	0.1103	0.5286	0.5499	1.0000					
K12	-0.1933	0.1436	0.5958	0.6148	0.8649	1.0000				
K18	-0.0750	-0.1189	0.1097	0.0360	0.1965	0.1764	1.0000			
K20	0.2381	0.2409	-0.1872	-0.1495	-0.2661	-0.3130	-0.6378	1.0000		
K24	-0.0987	0.0315	0.5119	0.4735	0.8577	0.7859	0.4468	-0.4885	1.0000	
K31	-0.2844	-0.3901	0.2526	0.2945	0.4826	0.4088	0.3796	-0.4483	0.5397	1.0000

Figure A. ROC Curves of the Compared Models

a) Large



b) Small


Agriculture
0
0,1
0,2
0,3
0,4
0,5
0,6
0,7
0,8
0,9
1
SVM
Logit
LDA
Manufacturing
SVM
Logit
LDA
Trade
SVM
Logit
LDA
Others
SVM
Logit
LDA