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The Methodology of Stress Tests for the Kazakh Banking System

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The Methodology of Stress Tests for the Kazakh Banking System[*] Project Paper

Abstract

In this paper, we describe the results for the section "Stress Testing Methodology for Kazakh Banking System" which is part of the "Development of an Early Warning System for Kazakhstan" project. The participating Kazakh institutions are the National Bank of Kazakhstan (NBRK), the Financial Supervisory Agency (FSA) and the National Analytical Centre of the Government and the National Bank of Kazakhstan (NAC). In this section, we apply different methodologies for developing stress testing tools for the Kazakh banking system: the "bottom-up" and "top-down" approaches. The "bottom-up" approach is based on questionnaires we have transmitted to Kazakh banks asking them to calculate their own risk positions under stress. The collected results and the analyses show that banks tend to underestimate the decline in real estate prices and to overestimate currency devaluation. In the "top-down" approach, we apply methodologies for portfolio and macro stress tests to raw data collected by FSA and estimate the impact of the external macroeconomic shocks on the expected losses of financial institutions. In the portfolio stress test, the change in the expected losses under stress ranges between 34 percent and 86 percent relative to the unconditional expected losses. In the macro stress test, we find an average change of 26 percent in the ratio of bad loans to total loans under stress scenario 1 and an average change of 80 percent under scenario 2 relative to the baseline scenario.

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The opinions expressed in this paper are those of the authors and do not necessarily represent the views of the Deutsche Bundesbank, the National Bank of the Republic of Kazakhstan, the Financial Supervisory Agency or the National Analytical Centre. We are, of course, responsible for any remaining errors.

CONTENTS

LIST OF ABBREVIATIONS

NBRK	National Bank of the Republic of Kazakhstan
FSA	Financial Supervision Agency of the Republic of Kazakhstan
FSAP	Financial Stability Assessment Program
IMF	International Monetary Fund
LLP	Loan Loss Provisions
NPL	Non-Performing Loans
UK	United Kingdom
GDP	Gross Domestic Product
ROA	Return on Assets
ROE	Return on Equity
IFS	International Financial Statistics
GLS	Generalized Least Squares
CPI	Consumer Price Index
NiGEM	National institute Global Econometric Model
LGD	Loss Given Default
PD	Probability of Default
FE	Fixed Effects Estimation
RE	Random Effects Estimation
GMM	Generalized Method of Moments
KASE	Kazakhstan’s Stock Exchange Index

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1. Introduction

Recent developments in the financial markets have underscored the importance of suitable risk management instruments not only for detecting and assessing vulnerabilities in the financial system as a whole but also for identifying specific risks to financial institutions. Accordingly, individual banks as well as central banks and supervisory authorities have found stress testing to be an indispensable tool for quantifying the risk exposure and resilience of the financial system. Stress testing has therefore been declared a fundamental part of the financial stability instruments in the Financial Sector Assessment Programs (FSAPs) conducted by the IMF and the World Bank.

In the field of stress tests, two different approaches are employed depending on the institutional and computational responsibilities.

First, in the "bottom-up" approach, individual banks carry out stress test analyses and transmit the results to the central bank. This approach serves to create a more precise picture of the risks to an individual bank using internal risk models. At the same time, it fails to generate a comparable risk evaluation for all banks when aggregated, as each bank applies different risk models. Second, in the "top-down" approach, the central bank conducts its own stress tests using micro data on financial institutions, thereby ensuring greater comparability of results yet at the price of estimating individual banks' risk less accurately.

A further distinction is that stress test methodologies are adapted to market risk, liquidity risk and credit risk. As credit risk constitutes a crucial risk component of a bank, credit risk stress tests have gained in significance for individual banks as well as for central banks and supervisory authorities. Credit risk is defined in a narrow sense as the risk that a borrower will default on his financial obligations. In a broader sense, credit risk is defined as a spread risk in the event of deterioration in the borrower's credit rating.

Currently, the Agency of the Republic of Kazakhstan for the regulation and supervision of financial market and financial organizations (FSA) regularly applies a "top-down" approach, which is based on a sensitivity analysis. For this purpose, the agency calculates capital adequacy indicators from data contained in regulatory reports. This calculation is performed for several stress scenarios, such as currency depreciation, falling real estate prices etc. Since the existing indicator-based approach does not incorporate a feedback mechanism between the banking sector and the macro economy, we decide to develop, first, an empirical macro approach and, second, a two-stage approach which integrates a macro perspective of the economy with the micro perspective of the individual bank and involves two different models.

We adapt both “top-down” approaches to credit risk exclusively and find that the change in the expected losses under stress ranges between 34 percent and 86 percent relative to the unconditional expected losses in the portfolio stress tests. We also identify an average change of 26 percent in the ratio of bad loans to total loans under stress scenario 1 and an average change of 80 percent in scenario 2 relative to the baseline scenario in the macro stress test. In the framework of this project, the participating National Analytical Centre (NAC) developed the “bottom-up” approach, which encompasses the preparation of questionnaires, their transmission to the banks and the evaluation and interpretation of the submitted stress-tests results. The collected results and the analyses in the “bottom-up” approach show that banks tend to underestimate the decline in real estate prices and to overestimate currency devaluation.

Our results from both the “bottom-up” and the “top-down” approaches are useful to risk managers, central banks, or supervisors alike. They give information about the resiliency of a major part of the Kazakh banking system and provide an empirical implementation of the stress testing methodology. The change in the banks’ regulatory equity capital ratios may represent useful supervisory information.

In the following section, we describe the related literature. In section 3, we illustrate the “bottom-up” approach. Section 4 consists of two tests, the portfolio stress and the macro stress test. The last section summarises and concludes.

2. Related Literature

Various studies have been carried out in this field, usually based on portfolio credit risk models or panel data regressions, in order to evaluate the influence of macroeconomic variables on different measures of credit risk.

A series of studies examine the macroeconomic determinants of loan loss provisions (LLP) or non-performing loans (NPL). Pesola (2001) concentrates on the Nordic countries, Kalirai and Scheicher (2002) on Austria, Pain (2003) on the United Kingdom, Hadad et al. (2004) on Indonesia, Virlonainen (2004) on Finland, Quagliariello (2004) on Italy, and Jakubík and Schmieder (2008) on the Czech Republic and Germany.

Pesola (2001) employs an econometric model based on panel data to assess the relationship between the dependent variables, the ratio of banks’ loan losses and enterprise bankruptcies per capita, and macroeconomic variables as well as surprise variables based on macroeconomic forecasts. His findings suggest that high corporate and household indebtedness, combined with negative macroeconomic shocks, such as a rise in interest rates above its expected value or a fall in gross domestic product (GDP) below its forecasts, contributed to the banking crisis in the Nordic countries.

Kalirai and Scheicher (2002) model the impact of key macroeconomic variables, such as indicators of general economic activity, price stability, households' and corporate sectors' situation, financial market and external events, on aggregated loan loss provisions (LLP) using a linear regression model and a sensitivity analysis for macro stress testing. Short-term interest rates, GDP growth rates, the stock index and industrial production are found to influence LLP. Furthermore, changes in LLP generated by a sensitivity analysis based on historical "worst case" scenarios are set against the risk-bearing capacity of the Austrian banking sector.

In contrast, Virolainen (2004) applies a macroeconomic credit risk model for Finland linking a set of macroeconomic variables and industry-specific default rates instead of aggregate loan loss estimates. He finds GDP, interest rates and corporate indebtedness to be good predictors of industry-specific default rates.

Hadad et al. (2004) estimate univariate and multivariate regressions based on pooled least-square fixed-effects techniques in order to measure the effects of macroeconomic developments on LLP in Indonesia. The authors claim that price stability indicators play an essential role in explaining credit risk in the univariate as well as multivariate cases having significant long-run effects. At the same time, only univariate regressions show oil prices to be significant for credit risk.

Pain (2003) investigates the impact not only of aggregated variables but also of bank-specific factors, such as the loan portfolio, on banks' LLP in the United Kingdom. His empirical results suggest that the evolvement of banks' LLP can be tracked by macroeconomic variables, such as GDP growth, real interest rates and lagged aggregate lending or some bank-specific variables such as increased lending to riskier borrowers.

Quagliariello (2004) estimates static fixed effects and dynamic models with the aim of understanding the movements of LLP, non-performing loans (NPL) and the return on assets (ROA) over the business cycle and conducts simple stress tests on the impact of macroeconomic shocks on banks' balance sheets. His empirical results confirm the pro-cyclical behaviour of the profitability and riskiness measures as well as the significance of bank-level indicators.

Jakubík and Schmieder (2008) employ a Merton-type one-factor credit risk model for the corporate and household sectors of the Czech Republic and Germany in order to test the effects of macroeconomic variables on NPL as a measure of the default rate. They conclude that key macroeconomic determinants, such as interest rates, exchange rates, inflation, GDP growth and the level of indebtedness, can meaningfully model corporate default rates for both countries but not household default rates. Moreover, macro stress tests reveal that the effect of macroeconomic shocks is considerably greater for the Czech Republic than for Germany, on both the macro and micro levels.

All in all, the studies confirm the assumption that key macroeconomic factors affect measures of credit risk, such as LLP and NPL. Above all, most studies show GDP growth rates, interest rates and different measures of indebtedness to be the main drivers of credit risk. As a result, policymakers and monetary authorities alike can use macro stress tests as a method of assessing the consequences of macroeconomic shocks for credit risk and of sustaining financial stability.

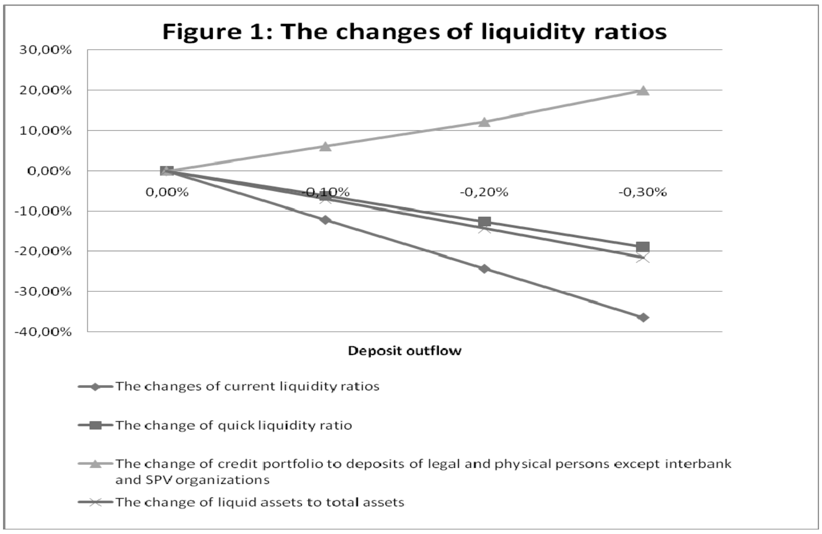
The portfolio stress testing model tested in the project is based on the methods of the Deutsche Bundesbank. In particular, we use the methodology of Duellmann and Erdelmeier (2009) and Duellmann and Kick (2009) to develop the two-stage approach for Kazakhstan. In the former, Duellmann and Erdelmeier (2009) stress-test credit portfolios of 28 German banks based on a Merton–type multifactor credit risk model. The stress scenario is an economic downturn in the automobile sector. They end up finding a 70–80 percent increase in expected loss under the stress event. Duellmann and Kick (2009) test the impact of a global credit crunch on the credit portfolios of 24 large German banks. In the following section, we describe the "bottom-up" approach.

3. Bottom-Up Approach

In the "bottom-up" approach, the financial institutions calculate their risk positions using their own methodology upon a request by the supervisory authority, which specifies uniform stress scenarios. The supervisor then collects and analyzes the submitted results.

In our project, NAC acts as an initiator in conducting "bottom-up" stress-testing methodology, which encompasses the development of questionnaires and specification of the following stress scenarios: a run on deposits, a drop in real estate prices and a devaluation of the Tenge. The first scenario assumes deposit outflows of 10 percent, 20 percent and 30 percent. The change in the real estate prices implies a drop of 25 percent, 35 percent and 50 percent. The devaluation rates are 10 percent, 20 percent and 30 percent. By design, each stress event happens suddenly; financial institutions are therefore unable to make corrections in their portfolios. The questionnaires contain 20 indicators of banks' financial stability, such as bad loans to credit portfolio, return on equity, liquid assets to total assets, provisions to credit portfolio etc. All indicators cover the following classification: capital adequacy, asset quality, risk concentration, earnings and profitability, and liquidity. The financial sustainability indicators and their classification are given in Appendix 1. The participants were asked to calculate the change of given indicators under stress relative to the baseline scenario.

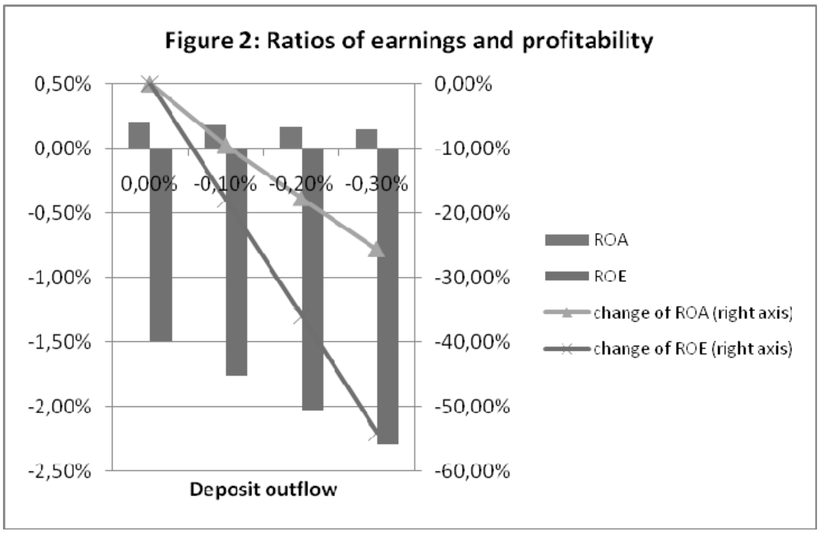
According to the submitted results, the stress scenario – a run on deposits – causes negative changes in liquidity ratios and in ratios of earnings and profitability.[3] Figure 1 shows the change of liquidity ratios, which ranges between 20 percent and –40 percent. Figure 2 illustrate the change of profitability ratios (ROA, ROE) under stress events. For other indicators of financial stability, deposit outflow has an insignificant impact.

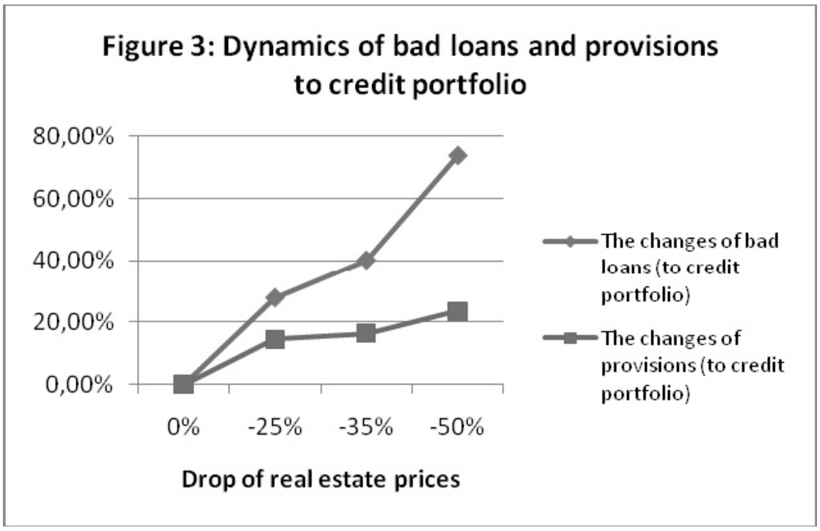


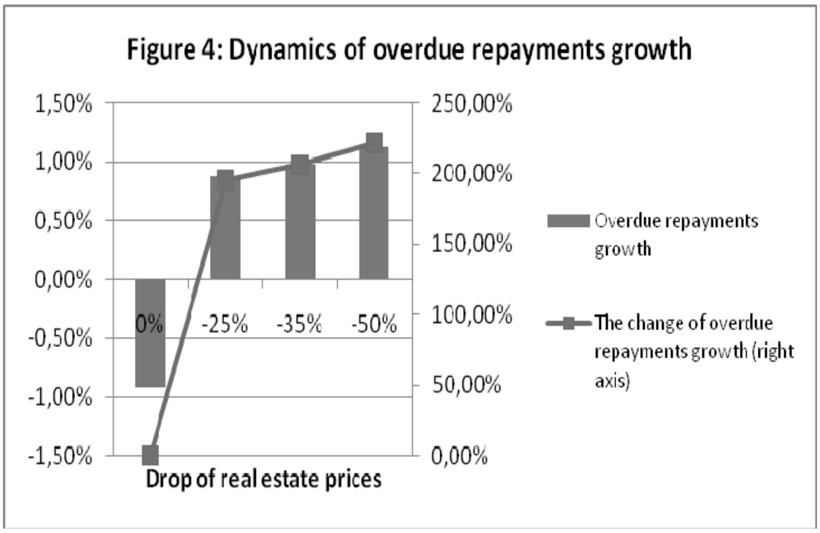
Source: based on the authors' calculations.

The "drop in real estate prices" stress scenario influences all indicators. However, a high sensitivity to this scenario is observed in indicators of asset quality and profitability ratios. Figures 3, 4 and 5 illustrate the extent of conditional changes. For example, a 50 percent drop entails a 73.96 percent change in the NPL ratio (Figure 3). The profitability ratios such as return on assets (ROA) and return on equity (ROE) decreased at high rates (Figure 5). Furthermore, a major threat of an increase in overdue repayments exists, shown in Figure 4.

[3] The results were submitted by 8 banks, which represent some 22 percent of the whole Kazakh banking system, which consists of 37 banks. These 8 banks account for a combined 53 percent of total assets.







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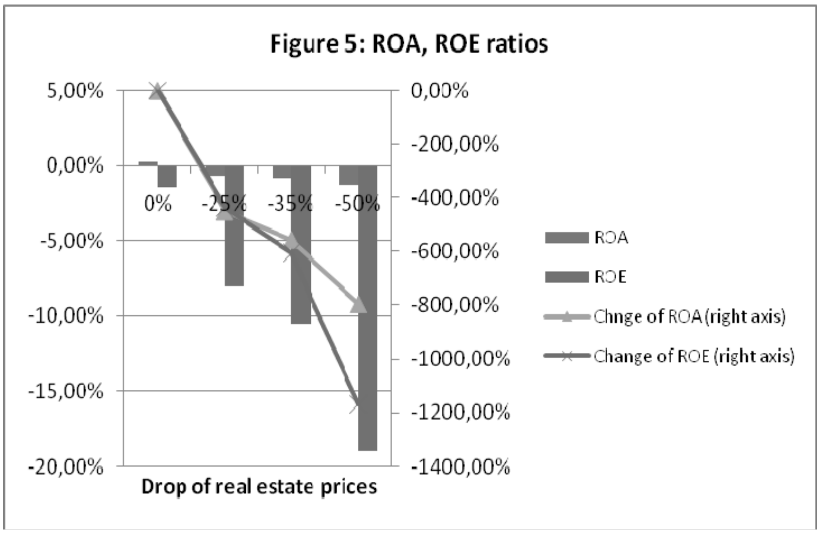
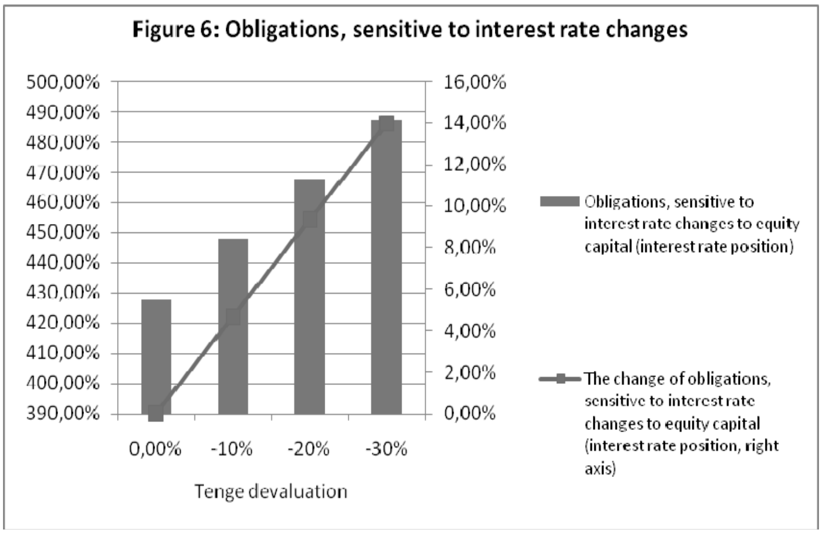
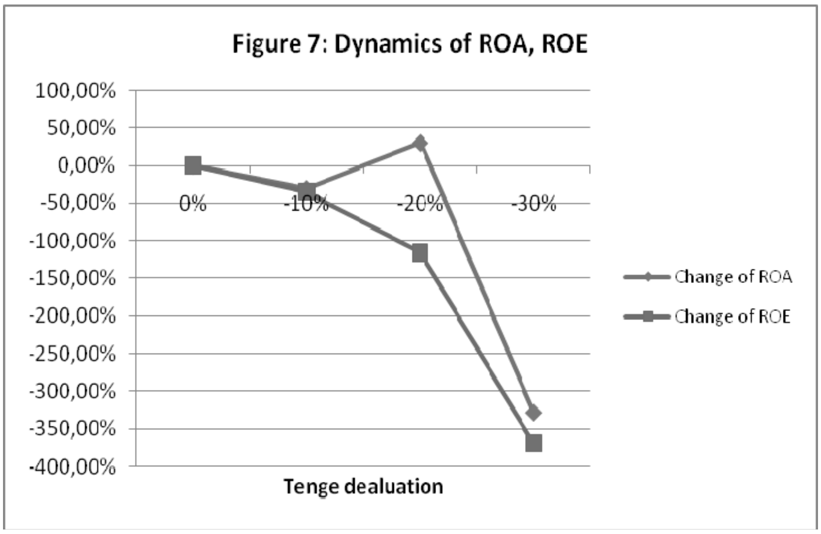






Source: based on the authors' calculations (all figures).

The indicators in the third stress scenario which are affected the most are risk concentration (Figure 6) and earnings and profitability (Figure 7).

The survey results show that the deposit outflow significantly affects the liquidity ratios. The drop in real estate prices impacts asset quality and the last stress scenario, currency devaluation, influences the ratio of sensitive obligations to interest rate changes. In all three scenarios a decrease in the ratios of earnings and profitability can be observed.

In Table 1 we summarize indicators which show significant changes under stress. These results will support the development of more optimally designed questionnaires in the future.

Table 1: Important Financial Indicators for Stress Scenarios

Scenarios	**Financial Indicators**
Deposit outflow	**Liquidity ratios:** current liquidity ratio, quick liquidity ratio, credit portfolio to deposits of legal and physical persons except inter-bank and SPV organizations, liquid assets to total assets. **Ratios of earnings and profitability:** ROA, ROE.
Drop in real estate prices	**Asset quality ratios:** overdue repayments growth, bad loans (or NPL) to credit porfolio, provisions to credit portfolio. **Ratios of earnings and profitability:** ROA, ROE.
Tenge devaluation	**Risk concentration ratios:** obligations, sensitivity to interest rate changes. **Ratios of earnings and profitability:** ROA, ROE.

Since all three stress scenarios specified at the beginning of 2008 happened at the end of 2008 and in 2009, NAC compares the real changes in the indicators with hypothetical changes in the same indicators calculated previously by the banks.[4] Particularly, deposit outflows took place as a consequence of unstable financial conditions of some banks at the end of 2008 and beginning of 2009. The real estate prices have been decreasing over an entire year starting from 1 February 2008. Lastly, the Tenge devaluation took place on 4 February 2009.

Owing to the difficulty of gathering the data for comparison in the scenario 1 (deposit outflow), NAC compares two scenarios: the drop in real estate prices and the currency devaluation.

In the last year the drop in real estate prices was around 30 percent. So the comparison in this scenario refers to the hypothetical 35 percent drop. Table 2 provides the comparison results. For both the increase in the NPL ratio and overdue repayments growth, the financial institutions which participate in the survey underestimate the impact of the stress scenario. The capital adequacy ratio does not decrease as much as the institutions expected.

The currency devalues by 25 percent. NAC compares this situation with the changes in the indicators under a 20 percent Tenge devaluation. The comparison results are given in Table 3.

[4] The real changes in the indicators were obtained from the FSA database.

Here, the financial institutions overestimate the increase in the NPL ratio and the overdue repayments growth and predict almost perfectly the change in the capital adequacy ratio.

Table 2: Drop in Real Estate Prices*

	Capital Adequacy Tier 1 (K1)	**NPL to Loan Portfolio**	**Overdue Repayments Growth**
Prediction	-2.17	40.17%	206.04%
Real Change	0.08	166.66%	366.60%
Comparison	2.25	126.49%	160.56%

Table 3: Tenge Devaluation*

	Capital adequacy Tier 1 (K1)	**Non-performing loans to loan portfolio**	**Overdue repayments growth**
Prediction	-0.19	84%	124.22%
Real Change	-0.15	50%	28.57%
Comparison	0.04	-34%	-95.65%

* Comparison of the stress testing results with real changes

The results show that banks tend to underestimate the decline in real estate prices and to overestimate currency devaluation.

By comparing the stress testing results with real changes, the supervisory authority can assess the ability of financial institutions to estimate the risk impact on their balance sheet indicators. However we have to take into account the fact that the real drop in real estate prices does not happen suddenly. The relatively large differences between the hypothetical size of change in the indicators may be caused by differences in the character of the real and hypothetical stress events. Hence, the power of the comparison is doubtful.

The implementation of bottom-up methodology is a dynamic process. It requires permanent improvement of the questionnaires along with further development of stress events. In addition, the accuracy of the predicted change in the indicators depends on the methodology used by banks, the experience of the experts who complete the questionnaire and the success of communication between the bank and the supervisory authority. At this point of view we successfully start the process of implementation of "bottom-up" stress testing methodology.

In the next section we describe two different "top-down" approaches – portfolio and macro stress tests.

4. Top-Down Approach

In the "top-down" approach, the central bank usually collects the raw data and calculates the risk positions.[5] The advantage of the "top-down" approach is that it allows a broader selection of scenarios such as a decline in certain macroeconomic variables. On the other hand, institution-specific risks are captured less accurately. In our further steps, we present "top-down" approaches exclusively for credit risk.

4.1. Portfolio Stress Test for the Banking System of Kazakhstan

The purpose of the portfolio stress test is to explore the impact of abrupt changes in the macro-economic environment on the credit portfolios of Kazakh banks.

The quantitative framework encompasses the macro-perspective of the economy and the micro-perspective of the individual bank. The framework consists of two different models: a macro-econometric model and a multifactor portfolio model. Figure 8 illustrates the portfolio stress testing methodology. The first model is used to forecast the impact of an economic downturn on three production sectors in Kazakhstan: industry, construction and agriculture. We forecast a decline in production levels in a deteriorating macroeconomic environment, such as a decrease in oil prices. The impact of the economic multi-sector downturn (primary effects) is then captured by the CreditMetrics-type portfolio model with sector-dependent unobservable risk factors as drivers of the systematic risk. The spill-over effects to the remaining production sectors (Figure 9) are also captured (secondary effects) through the inter-sector correlations. Furthermore, the model takes into account sector concentration, identified as a major source of credit risk.

The following description consists of several parts: data, the methodology of the macroeconometric forecast model, the portfolio model, and the mapping between two models, results, summary and shortcomings.

4.1.1 Data Sample

The data sample for the macroeconometric model consists of quarterly data from 1994 to 2007. The production indices for the business sectors as our dependent variables are obtained from the Statistical Agency of Kazakhstan. The data which we use as exogenous variables in the macroeconometric model came from the IMF International Financial Statistics (IFS) and

[5] In our project the raw bank-specific data were colleted by FSA.

DataStream. The quarterly bank-specific data we generally use for the multifactor portfolio model are from September 2005 to September 2008. The information about the credit portfolios of Kazakh banks is obtained from the FSA. In our analysis we use 11 banks which account for a combined 90 percent of the total assets of the Kazakh banking system. The credit information is available only at sector level and not borrower level. Figure 9 below demonstrates the aggregated loan exposures by sector. The agriculture, industry and construction sectors represent 40 percent of the aggregated loan exposures.

Given that our data sample contains no information on the credit quality of sectoral credit exposures, we have to calculate the sectoral probability of default approximately using the ratio of NPL to total loans for each industrial sector. The inter-sector correlations are estimated from the sectoral return on equity.[6] We aggregate two sectors, transport and communication, into one in order to make the classification of sectoral credit exposures conform with the sectoral return on equity.

The reference data for the calculation of expected losses is the end of the year 2008. In the next section, we describe the methodology of the macroeconometric forecast model.

4.1.2 Methodology of the Macroeconometric Forecast Model

We begin by modelling the relationship between the production indices and three risk factors identified as major sources of macroeconomic risk. For each production sector, we run Generalized Least Squares (GLS) regressions with Prais-Winsten transformation based on the time series data as follows:[7]

$$Y_t = \alpha_t + \sum_{i=1}^{n} \beta_i X_{i,t-k} + \mu_t \qquad (2)$$

where:

Y_t : dependent variable (Production Volume)

X_{t-k} : lagged macroeconomic variables (Tenge/US$ exchange rate, gas and oil price index, Russian GDP)

α_t, β_i : constant and regressions coefficient

[6]The Financial Stability Department of the National Bank of Kazakhstan computes sectoral return on equity (ROE) and sectoral return on assets (ROA) quarterly. These indicators are available from 2004 Q1 to 2009 Q4.
[7] The Prais-Winsten Transformation makes it possible to include the first observation in the estimation, which is lost in a GLS estimation.

Figure 8: Methodology of Portfolio Stress Testing

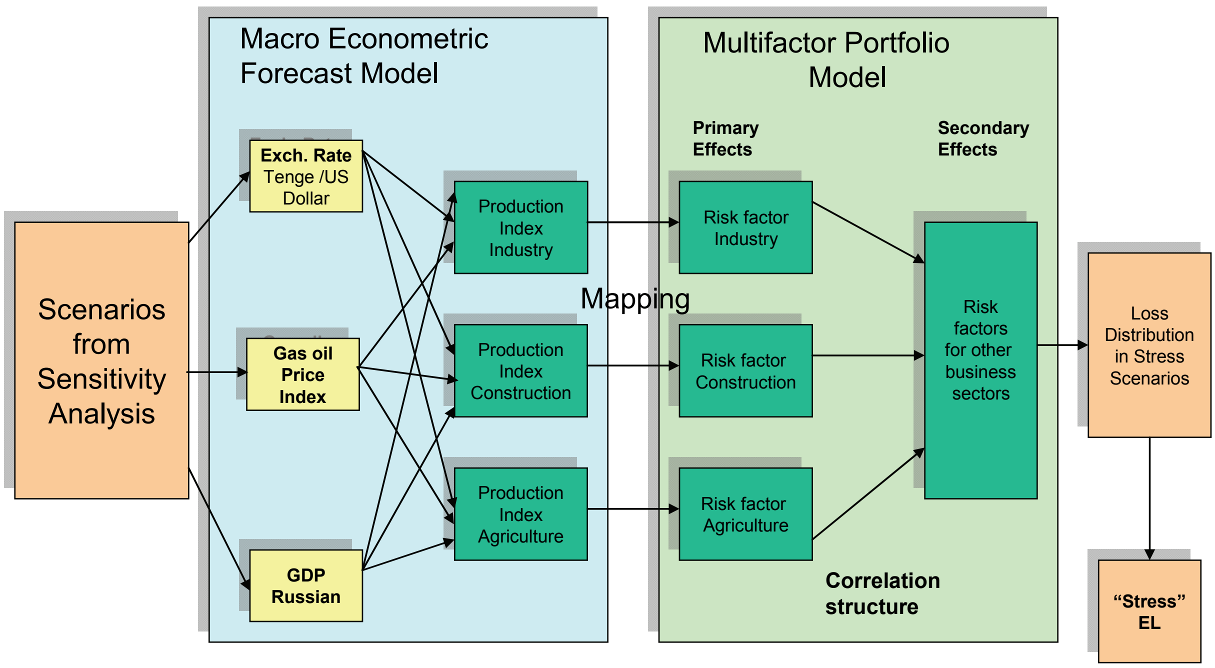
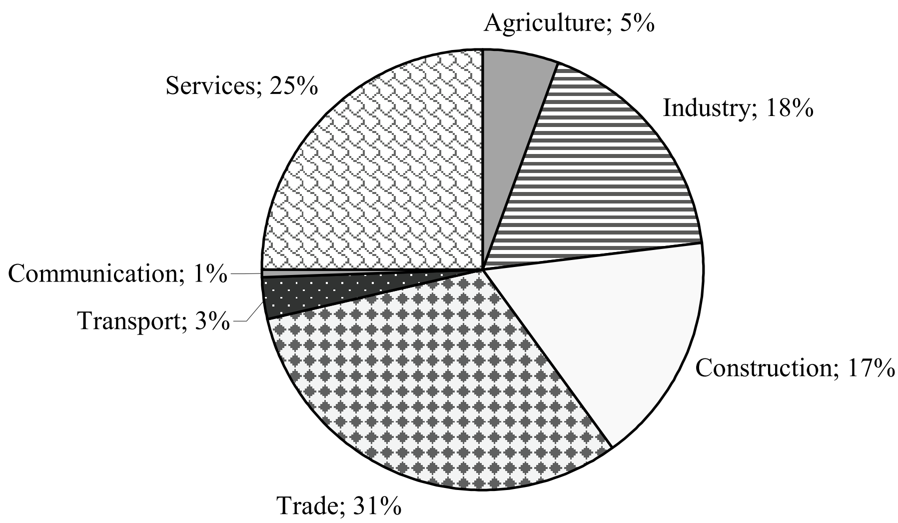


Figure 9: Aggregated Credit Exposures by Sectors (2008)



Sources: FSA data and authors’ calculations.

μ_t : residuals, where $\mu_t \sim N(0,\sigma^2)$.

The dependent variable is a sectoral production volume expressed in Tenge. We calculate real values of the dependent variable using the Consumer Production Index (CPI) for Kazakhstan.

Next, we seasonally adjust the variable using the Census12 method and, finally, calculate growth rates of quarter t to quarter t-1 in order to detrend the variable.[8] The exogenous variables are the exchange rate (Tenge/US$), the price index for gas and oil, and Russian GDP. For the lattermost variable, we calculate real values using CPI for Russia and then seasonally adjust it using the Census12 methodology. All three variables are transformed into growth rates. The Dickey-Fuller test shows that all transformed variables do not contain a unit root.

All of the exogenous variables are external indicators that can impact Kazakhstan's production. We expect a positive sign for the oil and gas price index in the industry sector owing to the fact that this sector "produces" oil and gas and profits by increasing prices.[9] The agriculture sector obviously consumes oil and gas and so we therefore tend to expect a negative sign. The relationship between the production level in construction and the gas and oil prices is ambiguous. Though a consumer of oil and gas, this sector has a built-in order from oil firms, which profit from increasing gas and oil prices. Russia is a neighbour and one of Kazakhstan's biggest trading partners. Consequently we expect the variable "Russian GDP" to have a positive sign in all three sectors. The impact of the exchange rate is dubious. The depreciation of the domestic currency stimulates exports and therefore leads to increased production levels. This situation is reversed if the majority of production costs are in foreign currency. Accordingly, the depreciation of domestic currency may lead to a decline in the level of production. Table 5 presents the GLS estimation results.

With the empirically chosen lag structure of up to three lags, all of the coefficients of the exogenous variables show plausible signs.[10] The variable "gas and oil price" has the negative sign in the agriculture and construction sectors, but is not significant. As expected, this variable has a positive impact on the production level in the industry sector. The variable with the greatest predictive power is the exchange rate, and it has a negative sign. Hence, the

[8] There is also an another reason for expressing the production volume in growth rates. In the second part of this approach, we will map the decline in the production to the systematic risk factor of the multifactor portfolio model. This risk factor is assumed to be standard normally distributed. In order to make the mapping between two models work, the referring variable in the macro model has to be approximately normally distributed. In our case the growth rates in production are more normally distributed then the production levels.

[9] Exports of oil and gas account for approximately 70 percent of the whole export volume of Kazakhstan.

[10] We test within a univariate regression the influence of the exogenous variables with different lags. We refer to the usual criteria to chose the right lag (statistical significance, R^2).

positive effect of simulated exports is quite small. The variable "Russian GDP" is positive and significant in all three sectors. The predictive power of the models measured by R^2 is relatively high considering that we explain growth rates and not production levels. The industry sector therefore has the best fit with an R^2 of 57 percent.

Table 4: Regression Results

VARIABLES	IND GROWTH	AGRA GROWTH	CONST GROWTH
EXCH GROWTH (1)		-0.72***	
		(-6.95)	
EXCH GROWTH (2)			-0.29***
			(-7.69)
EXCH GROWTH (3)	-0.15***		
	(-12.23)		
GASOIL GROWTH			-0.09
			(-0.98)
GASOIL GROWTH (2)	0.07**	-0.19	
	(2.31)	(-1.41)	
GDP_RUS GROWTH		1.10***	
		(3.16)	
GDP_RUS GROWTH (2)			0.94***
			(4.22)
GDP_RUS GROWTH (3)	0.30***		
	(3.62)		
Constant	-1.40**	-1.19	0.06
	(-2.40)	(0.62)	(0.04)
Observations	52	53	52
R^2	**0.57**	**0.33**	**0.40**

t-statistic in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the estimation results for each of three production sectors. The dependent variable is the corresponding growth of production. The exogenous variables are expressed in growth rates as well. The numbers in parentheses ranging from 1 to 3 are referred to the time lag.

Following the estimation of the model, we now turn to measuring the impact of various adverse macroeconomic events. The selection of the magnitude of the stress to the macroeconomic variables is based on the comparison of the baseline scenario to a 1-standard-deviation change in the variable as a hypothetical stress event and to a 2-standard-deviation change in the variable as a hypothetical shock event.[11] The lattermost is approximately comparable with the extreme values experienced by Russian and Kazakhstan in the 1990s.

[11] Here, the development of the stress scenarios is based on pure sensitivity analysis. For example, the macroeconomic stress testing tool at the Deutsche Bundesbank, developed by Duellmann und Kick (2009), is linked to the National institute Global Econometric Model (NiGEM). This macroeconomic simulation and forecast tool is based on more than 3,600 equations and historical data back to 1961. In this model, several scenarios can be simulated and specific factors can be extracted and used for stress testing purposes. Since we are not in a position to extract stress scenarios from a forecast model for Kazakh macroeconomic development, we work with historical events.

Given that the comparable events actually happened, these hypothetical scenarios are plausible enough to be given reasonable consideration by the responsible authorities.

Table 5 provides the aggregated stress scenarios for the year 2008 and Table 6 shows the quarterly values for the shock scenario. Accordingly, we assume a decline in Russian GDP of 7.56 percent in the stress scenario and 24.91 percent in the shock scenario, currency depreciation of 35.12 percent and 79.34 percent, and a decrease in oil and gas prices of 30.95 percent and 69.22 percent, respectively. We then predict the production growth under these stress scenarios (Table 7) using the regressions results of our macroeconometric model.

Table 5: Stress Scenarios for 2008

	Baseline	**Stress**	**Shock**
Russian GDP	12.63%	-7.56%	-24.91%
Exchange Rate	-0.36%	35.12%	79.34%
Gas and Oil Price Index	33.63%	-30.95%	-69.22%

Table 6: Shock Scenario for 2008

JQ	**GDP_RUS**	**EXCH**	**GASOIL**
2008q1	-8.17%	15.55%	-6.91%
2008q2	-5.93%	15.93%	-20.03%
2008q3	-7.05%	15.13%	0.64%
2008q4	-6.49%	16.29%	-58.91%

Production growth in agriculture seems to be very sensitive to the stress scenarios. The dimension of the decline in production in the agriculture sector is hard to compare with the other sectors' production growth rates owing to the different time-lag structure. The "shock" is distributed differently over quarters in every industry sector. In the agriculture sector, the stress impact evolves from the first quarter onwards, whereas in the other sectors the stress impact occurs completely at the end of the year.

Table 7: Production Growth Under Stress Scenarios

JQ	**AGRA_0**	**AGRA_2**	**IND_0**	**IND_2**	**CONST_0**	**CONST_2**
2008q1	0.87	-10.09	1.2	1.2	-1	1.95
2008q2	1.38	-21.01	-0.31	-0.31	5.45	8.4
2008q3	-2.87	-19.16	2.62	0.28	-1.21	-12.23
2008q4	0.86	-15.42	0.03	-7.79	6.38	-4.64

Note: This table provides predicted values for production growth in the sectors agriculture (AGRA), industry (IND) and construction (CONST) under the baseline scenario (0) and macroeconomic stress events (2).

The decline in the production growth conditional on the shock scenario as shown in Table 7 will later be mapped to the systematic risk factor in the multifactor portfolio model. Before we start explaining the mapping methodology, we will describe the underlying portfolio model used to measure portfolio losses from credit defaults.

4.1.3 Multifactor Portfolio Model

We measure the impact of the macroeconomic shock events on banks' credit portfolios using a Merton-type linear multi-factor model. As mentioned in the introduction, we apply the methodology developed by Duellmann and Erdelmeier (2009).

Here, the concept is based on the classic Merton model, where an obligor defaults if his asset value falls below an exogenously determined default point derived from the obligor's rating or probability of default. The change in the asset value in our model is determined by two factors, an "idiosyncratic" and a systematic factor. Since borrower-level data is not available to us, we modify the economic interpretation of the idiosyncratic factor. In our model, the idiosyncratic factor encompasses residual risk, which is not accounted for by the systematic factor.

The inter-sector correlation captures the sector interdependences. The model considers a one-period time horizon and differentiates between the default and non-default of a financial institution at the end of the one-year horizon. The following loss function captures the portfolio losses which occur due to the credit defaults:

$$L = \sum_{i=1}^{n} v_i . LGD_i \cdot 1_{\{Y_i \le c_i\}} \tag{3}$$

where L designates the total loss of the bank portfolio which is related to n sectors. In accordance with the supervisors (FSA) of the Kazakhstan banking system, the LGD_i of all sectors is set to 50 percent. The share of the sectoral credit exposures is v_i and n is set to six. The corresponding, approximated sectoral probability of default is given by PD_i.[12] The indicator function $1_{\{Y_i \le c_i\}}$ is a binary random variable which takes the value of one if a loan defaults and otherwise zero. In our case, the indicator is set to one when the complete sector

[12] As mentioned in the data description, we calculate the sectoral probability of default using the ratio of NPL to total loans of each industrial sector.

defaults and it is the case when Y_i falls below c_i.[13] Since Y_i is standard normally distributed, the default point $c_i = \Psi^{-1}(PD_i)$ can be derived directly. Here, $\Psi^{-1}(...)$ denotes the inverse of the cumulative normal distribution function. The default trigger Y_i has two components:

$$Y_i = \theta \cdot X_i + \sqrt{1-\theta^2} \cdot \zeta_i . \quad (4)$$

Both components – the systematic risk factor X_i and the "idiosyncratic" risk factor ζ_i – are pairwise independent and have a joint standardised normal distribution. Furthermore, the sector factors X_i are normally distributed. The relative weight of systematic risk factor is denoted by θ. The asset correlation of any pair of borrowers i and j is given by

$$\rho_{i,j} \equiv cor(Y_i, Y_j) = \theta^2 \omega_{i,j} , \quad (5)$$

where θ^2 is the inter-sector correlation and is the same for all sectors. To determine the parameter θ we take the average asset correlation $\bar{\rho} = 0.09$ of small and medium-sized companies[14] and the mean value $\bar{\omega} = 0.48$ of the correlation matrix Ω which is given in Table 8. With these values, θ in the formula $\theta = \sqrt{\bar{\rho}/\bar{\omega}}$ equals 0.43.

Table 8: Correlation Matrix

Sectors	Agriculture	Industry	Construction	Trade	Transport and Communication	Services
Agriculture	**1.00**	0.18	-0.01	0.72	0.47	0.30
Industry	0.18	**1.00**	0.38	0.35	0.45	0.73
Construction	-0.01	0.38	**1.00**	-0.07	0.58	0.36
Trade	0.72	0.35	-0.07	**1.00**	0.32	0.33
Transport and Communication	0.47	0.45	0.58	0.32	**1.00**	0.63
Services	0.30	0.73	0.36	0.33	0.63	**1.00**

Note: The table provides the empirical correlation between industrial sectors in Kazakhstan. The calculation is based on the quarterly observed sectoral return on equity.

The distribution of portfolio losses is obtained from Monte Carlo simulations, which requires a Cholesky decomposition of the correlation matrix Ω.

These are the steps for calculating the unconditional expected losses from credit defaults for a given bank. The determination of the stress impact on the portfolio loss requires a restriction

[13] The calculation of the expected losses is more precise if borrower-level data is available. Then the indicator is set to one if one of the borrowers defaults.

[14] We assume that the average assets correlation of small and medium-sized companies in Kazakhstan is the same as the correlation value of German companies of the same size. This assumption simplifies reality, of course, but it is currently not possible to determine the average asset correlation for Kazakh companies. See the methodology in Hahnenstein (2004) and Duellmann and Erdelmeier (2009).

of the state space of the industrial sectors stressed in the previous section: industry, construction and agriculture. The expected values of the loss distribution, which are calculated with the restricted state space of the distribution of the systematic factors, are *the expected losses under the stress scenarios*. To make this process clear, in the next section we explain in more detail the mapping of the stress impacts from the decline in the industrial production to the systematic risk factor in the multifactor portfolio model.

4.1.4 Mapping between the Macroeconometric Model and the Portfolio Model

In this step of the portfolio stress testing methodology, the forecast of the three stressed sectors (Table 7) has to be mapped to the corresponding unobservable systematic risk factors of the portfolio model. Since our reference date in the portfolio model is the end of 2008, we map the average value of the stressed production indices of the second half of the year 2008. These values are -17.3 for agriculture, -8.43 for construction and -3.76 for industry.

In conducting the mapping methodology, we first carry out the (Epanechnikov) kernel density estimation and obtain a continuous distribution of 52 quarterly growth rates of the industrial production from 1996Q1 to 2007Q4. The next step is to determine the cut-off value g_{j^*}, which has the following property:

$$\mathrm{E}[\Xi_{j^*} / \Xi_{j^*} \leq g_{j^*}] = \hat{\varepsilon}^* . \tag{8}$$

Referring to (8), the expected value of the industrial production index Ξ_{j^*} conditional on being below the cut-off point is exactly the predicted stress value $\hat{\varepsilon}^*$ of this industrial production index. We determine the probability $p(g_{j^*}) = P(\Xi_{j^*} \leq g_{j^*})$ from the (Epanechnikov) kernel density distribution for each of three industrial sectors. Then, we find the corresponding cut-off point $\Psi^{-1}[p(g_{j^*})]$ of the corresponding unobservable risk factor X_{j^*}, since the distribution of this systematic factor is standard normal. The mapping results are shown in Table 9.

In the agriculture sector, the stress forecast $\hat{\varepsilon}^*$= -17.28 which implies a cut-off point of -14.15. The probability of the stress scenario $p(g_{j^*})$ = 4.05% is relatively low in comparison to industry with $p(g_{j^*}) = 25.62\%$, which means the stress scenario is not quite severe.[15] The corresponding cut-off point of the standard normally distributed unobservable systematic risk factor is -1.75 for agriculture, -1.17 for construction and -0.65 for industry. In the next section, we describe the results of the portfolio stress test.

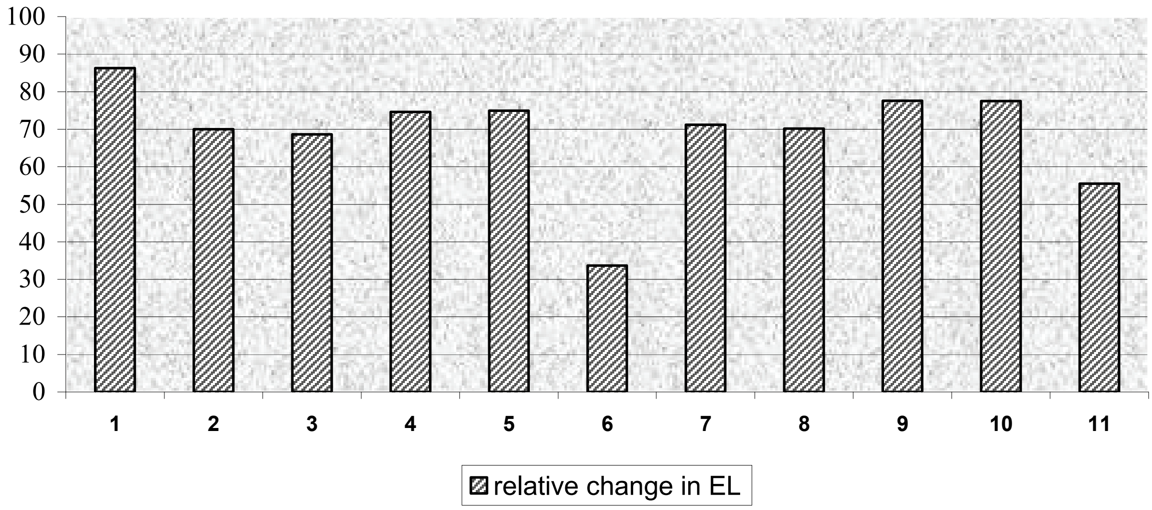
Table 9: Mapping Results

	$\hat{\varepsilon}^*$	g_{j^*}	$p(g_{j^*})$	$\Psi^{-1}[p(g_{j^*})]$
Agriculture	-17.28	-14.15	4.05%	-1.75
Construction	-8.43	-3.81	12.30%	-1.17
Industry	-3.76	-2.12	25.62%	-0.65

4.1.5 Stress Testing Results

Figure 10 shows the relative change in conditional expected losses relative to the unconditional expected losses, which we calculate for 11 Kazakh banks. The relative change ranges between 34 percent (see bank 6) and 86 percent (see bank 1).

Figure 10: Impact of Macroeconomic Stress Scenario on Expected Portfolio Losses per Bank



The relatively large change in expected losses can be explained by the fact that, first, three of six industrial sectors were stressed and, second, the correlation between the stressed and non-stressed sectors is relatively high. For example, the correlation between industry and services

[15] In the 1990s Kazakhstan and many other countries from the former Soviet Union experienced a severe recession. At this time output in the business sectors declined drastically. Since this time period is captured by our data sample, the probability of our shock scenario in the industry and construction sector is relatively high.

is 0.728 (see Table 8). Owing to these correlations, the stress event is transmitted from the original stressed sector to other sectors (secondary effect). The expected losses increase within the tested bank group in a similar range. We trace this back to the fact that the portfolio shares of industry, construction, trade, and services are relatively uniform across those banks.

In order to asses the stress impact on banking stability and therefore the impact on banks' minimum capital requirement, we analyse the equity ratios before and after the stress event.

Since the regulatory equity ratio is the ratio of regulatory equity capital to risk-weighted assets, we definite the regulatory equity ratio after stress as follows:

$$RER^{stress} = \frac{REC - \Delta EL_{\%}^{stress} \cdot CE^{sector}}{RWA} \quad , \tag{9}$$

where RER^{stress} is the stressed regulatory equity ratio, REC is regulatory equity capital, and $\Delta EL_{\%}^{stress}$ is the rise in the expected losses relative to the credit exposure of whole production sectors CE^{sector}.

Since the information on the regulatory equity ratios at bank level is very sensitive, we calculate a relative average change in the regulatory equity ratio of 0.64 percentage point.[16] It has to be mentioned that the sectoral credit portfolio covers part of a bank's entire credit portfolio. We consider the estimated change in the ratio as a minimum level of expected rise in portfolio losses.

All in all, the results show that the macroeconomic environment, particularly the negative development in the corporate sectors, induce a considerable rise in the expected losses in banks' credit portfolios, which could lead to bank failures. In the next section we describe an alternative approach to the portfolio stress testing tool presented above.

4.2. Macro Stress Tests for the Banking System of Kazakhstan

The basis of this approach is the hypothesis that credit risk is linked to the macroeconomic environment. The fluctuations in key macroeconomic and financial variables have the potential to generate endogenous cycles in credit and economic activity. These cycles, in turn, appear to involve and, indeed, may amplify financial imbalances, which can place great stress on the financial system.

[16] The change in the regulatory equity ratio differ enormous within the tested banking group.

Our empirical section of this approach consists of three steps: estimations to find significant factors, scenario analysis and consideration of risk-bearing capacity.

We model the influence of the business cycle, price indicators, interest and exchange rates on credit risk using fixed-effect estimation based on panel data. The regression coefficients capture the sensitivity of loan quality to specific macroeconomic factors. After finding the significant risk factors, we determine the dimension of stress using historical time series of the independent variables included. For each stress scenario separately, we predict the development of credit risk under a given stress scenario for 2008. The last step is to compare the risk shown by the scenario analysis with risk-bearing capacity for each bank individually.

4.2.1 Data Sample

Our sample consists of quarterly data from 2000 to 2007 and 12 Kazakh banks, which cover 92 percent of total assets. Owing to the data problems, we are unable to incorporate all 37 banks of the Kazakhstan banking system into our analysis. The data for bank-specific variables is obtained from the Kazakh Financial Supervision Agency (FSA). The data for macroeconomic variables was downloaded from the IFS. The data for oil and gas prices is from DataStream and the data for house prices in Kazakhstan from the National Bank of Kazakhstan. A weakness in our study, in addition to the data constraints, lies in the small size of our sample: we do not observe a complete economic cycle. This is a common problem in default risk modelling. In the field of stress testing, data limitations pose significant constraints on the construction of models. This is also currently the case with the Kazakh banking data.

4.2.2 Model Specification and Estimation Results

Our first step is to model the relationship between a measure of credit risk and macroeconomic factors. Since bad loans are available at single-bank level, we employ a linear regression model for panel data. We run a fixed effect estimation with a lagged dependent variable.[17,18] Our model is

[17] We examine the decision to run the Fixed Effects (FE) estimation using the Hausman test. The results show that there exists a systematic difference in the estimates between FE and Random Effects (RE), which means the assumptions on which the efficient estimator (RE estimator) is based cannot be satisfied.

$$Y_{it} = \alpha_i + \gamma_i Y_{it-1} + \sum_{j=1}^{n} \beta_j X_{j,t-m} + \sum_{l=1}^{k} \theta_l C_{l,t-p} + u_{it} \tag{10}$$

where:

Y_{it}:	transformed ratio of bad loans to total loans as a dependent variable
Y_{it-1}:	lagged dependent variable
X_{jt}:	macroeconomic variable j at time t
C_{lt}:	control variable l at time t
α_i:	individual effect for each bank
$\gamma_{i,}\beta_{j,}\theta_l$:	regression coefficients
u_{it}:	residual, where $u_{it} \sim N(0,\sigma^2)$
i:	bank
t:	quarter

As mentioned above, the dependent variable is a ratio of bad loans to total loans and therefore approximates the probability of default. Since the relationship between the probability and the independent variables is non-linear, we transform the dependent variable using a logistic transformation method as follows:

$$Y_{it} = \ln\left[\frac{R_{it}}{1-R_{it}}\right] \tag{11}$$

where:

R_{it}: ratio of bad loans to total loans of bank i at time t

The independent variables are macroeconomic variables grouped into the following categories: cyclical indicators, household indicators, price stability indicators, financial market and external indicators.

The category "*cyclical indicators*" includes variables that relate to general economic activity. The assumption is that loan quality is sensitive to the economic cycle. A deterioration in economic activity leads to falling incomes and rising payment difficulties. Then, more business failures will cause a decline in the quality of the banking books since default risk rises. As cyclical variables we include real GDP growth, the output gap and the ratio of aggregated credit in the financial system to GDP (later credit over GDP). GDP is the primary

[18] We incorporate the lagged dependent variable in order to include dynamics in our model which we use for forecasting purposes. We have to accept the Nickel Bias (the endogeneity of the lagged dependent variable with residuals can lead to biased estimation results), since our data sample does not satisfy the assumption (n > T) for using the GMM estimator which is able to reduce the bias.

measure of the state of the economy. GDP growth and the output gap, which is defined as actual GDP minus potential GDP,[19] are expected to be negatively related to the dependent variable. The credit over GDP variable measures economic activity and possible credit bubbles alike. Depending on the time lag, this variable can either be positively or negatively correlated with credit risk. In the short term, the variable is expected to be negatively correlated with credit risk due to effects of economic growth. The long-term effect is positive, showing an overheating of the economy.

In the category *"household indicators"* the variables relate to the situation of the household sector. Real consumption expenditure and the ratio of consumption to GDP are two variables that provide a measure of the development of household incomes. When households have more disposable income, overall economic conditions are favourable and loan losses are low. Thus, the variables are expected to be negatively correlated with credit risk. The next and more interesting variable of this category is "house prices" as an indicator of housing market developments. Much like the credit over GDP variable, house prices have short-term and long-term effects depending on the time lag structure. In the short term, house prices are expected to be negatively correlated with credit risk because houses are often used as collateral. The higher the price of collateral is, the lower the expected loan losses are. In the long term, the effect may be positive owing to the price bubble, indicating an overheating of the economy.

The *financial market indicators* are usually the interest rates and the stock market indices. Kazakhstan's Stock Exchange Index (KASE) is not available for the considered time period.[20] In the category "interest rates", we have only the refinancing rate and the Treasury bill rate at our disposal. Since interest rates represent the costs of borrowing, the relationship to credit risk is expected to be positive. The higher the interest rate is, the greater the cost of borrowing is, and the greater the probability of loan default as firms and households are less able to service their debt.

As a *price stability indicator*, we consider consumer price index inflation. Falling inflation pushes real interest rates higher. This is likely to be followed by an increase in loan defaults since the real cost of borrowing has increased.

[19] Potential GDP is measured as a trend using a Hodrick-Prescott filter.
[20] There is a structural break in 2002 which complicates the use of the variable in our analysis. Furthermore, the stock market indices tend to follow or lead the cyclical trends. Owing to the correlation to the cyclical variables, it is not advisable to use both variables in the regression.

The category *"external indicators"* refers to non-domestic factors that can impact Kazakhstan's domestic financial system. These are exchange rates (Tenge/US$) and the gas and oil price index. A depreciation of the domestic currency means that the borrowers must repay less than they borrowed initially. Hence, depreciation in the nominal exchange rate is expected to lead to lower loan defaults and losses. This situation is reversed if the borrowers are primarily borrowing in foreign currency. The relationship between the exchange rate and loan losses is ambiguous. Since a rise in oil and gas prices has a positive implication for the economy of Kazakhstan, we expect a long-term negative correlation between credit risk and falling gas and oil prices.

Furthermore, we employ two variables, market share and the ratio of expenses to income, to control for different bank sizes and differences in efficiency.

A summary of macro variables together with the expected sign is shown in Table 10. All nominal variables, such as GDP and house prices, were transformed into real variables using the consumer price index. The variable "GDP" was also seasonally adjusted using the Census X12 method. Besides the financial market indicators and the output gap, the variables were transformed into growth rates. The Dickey-Fuller test provides evidence of the stationarity of all macro variables.

Table 10: Descriptive Statistics of Macro Variables

Variable	Mean	Std. Dev.	Min	Max	Expected Sign
Real GDP	11.34	4.34	5.75	19.46	-
Output Gap	-0.08	0.63	-1.24	1.11	-
Credit over GDP	0.71	0.38	0.31	1.57	-/+
Real House Prices	345.94	199.47	145.69	766.76	-/+
Treasury Bill Rate	5.55	2.53	3.28	15.11	+
Refinancing Rate	9.38	2.37	7.00	16.00	+
Inflation Rate	2.20	1.50	0.13	8.85	+
Gas Oil Price Index	444.47	259.30	171.50	1275.25	-/+
Exchange Rate	136.62	11.60	120.00	154.59	-/+

Within a univariate regression we test for significance the impact of the lagged macro variables (up to four time lags). Due to the insignificance and high multicollinearity with other macro variables, we exclude real GDP (using the output gap instead), refinancing rate, inflation and the exchange rate.[21] Table 11 provides the correlation matrix of the macro variables which we chose for our final regression.

[21] The Treasury Bill rate and the refinancing rate are excluded owing to their insignificance. The inflation rate is highly correlated to the exchange rate. Both are highly correlated to GDP, the ratio of credit to GDP and gas and oil prices. We exclude both to avoid multicollinearity and, therefore, biased estimation results. We transform the ratio of

Table 11: Correlation of Macro Variables

Variables	Output Gap	Credit over GDP	Real House Prices
Output Gap (1)	1.00		
Credit over GDP (3)	-0.08	1.00	
Real House Prices (3)	-0.02	0.01	1.00
Gas Oil Price Index (4)	-0.08	-0.12	-0.02

Note: The number in parentheses is the corresponding time lag.

The regression results as shown in Table 12 indicate that the variables, lagged score (transformed ratio of bad loans to total loans using (11)) and the ratio of expenses to income are highly significant. It seems that banks with a high expenses-to-income ratio suffer from higher credit risk than more efficient banks. The variable "assets to total assets" has a negative sign but is not significant. The positive deviation of GDP from trend has a negative impact on credit risk with a one-quarter lag. As expected, favourable economic growth in Kazakhstan led to a decline in default risk. The cyclical variable with the highest predictive power relative to other macro variables is the credit over GDP gap, which has also negative impact on the ratio of bad loans to total loans with the three-quarter lag. We expect the sign to be positive, indicating overheating of the economy in the long term (five, six quarter lags). The sign changes but the variable is no longer significant. The growth rate of house prices is significant (at the 10 percent level) and has a positive impact against our expectations. We expect a negative relationship between credit risk and house prices in such a short term. As described above, the positive development in the real estate market has led to increasing collateral prices and therefore to decreasing loan losses. In a long-term perspective, the correlation is quite negative, which could indicate a price bubble. The positive impact in our case (three-quarter lag) can be traced back to our data set, which only contain the boom phase of the real estate market in Kazakhstan and not the whole business cycle. The decline in gas and oil prices has a negative impact on credit risk, which confirm the specific nature of this country as a exporter of oil and gas. All in all, the predictive power of macro variables relative to bank-specific variables is small (10 percent and 15 percent significance levels). The reason for this could be the short time period we observe. The time period from 2000 to 2007 was the boom phase[22] of the Kazakh economy, which means that the impact of our macro variables on

credit to GDP, which turns out to be insignificant, into a gap using the same methodology as for computing the output gap.

[22] The Kazakh economy was hit by the current financial crisis at the end of 2007, earlier than many other countries. Its consequences in the banking sector in terms of liquidity shortage were first visible in August of 2007. The real economy was hit by a dramatic decline in lending and a drop in commodity prices (oil, gas etc.). The reverberation from the real economy to the banking system – a rise in NPL – has been visible since the end of 2008.

the credit risk at this time is not entirely clear. In regression analysis, it is very important to observe a whole business cycle with booms and busts.

Table 12: Regression Results

Variables	Coefficient	t - statistic
Lagged Score	0.54***	-11.61
GDP GAP (1)	-0.11*	-1.61
Credit over GDP GAP (3)	-0.75**	-1.77
House Price Index (3)	0.01**	-1.69
Gas and Oil Price Index (4)	-0.004*	-1.64
Assets to Total Assets	-0.033	-1.21
Expenses to Income	0.45***	-3.68
Constant	-2.11***	-7.38

Observations 336

Number of banks 12

R^2 0.35

*** p<0.01, ** p<0.1, * p<0.15

In this table we describe the regression results of fixed-effects estimations using panel data. The house price and the gas and oil price indexes are expressed as growth rates. The dependent variable is the transformed ratio of bad loans to total loans. The number in parentheses is the time lag.

We will use these regression results in the next step, in which we forecast the transformed ratio of bad loans to total loans under the stress scenarios, which we describe in the next section.

4.2.3 Scenario Analysis

The key step in scenario analysis is the selection of the shock magnitude of the macroeconomic variables and subsequent comparison of the stress impact on the dependent variable in baseline and stress scenarios.

The scenarios are based on a decline in GDP and falling gas and oil prices in 2008. We assume a constant ratio of credit to GDP and real house prices. We first refer to a historical scenario and assess the impact of the largest shock experienced in the time series of those macroeconomic variables (scenario I).[23] Then, we create a hypothetical event based on 1 standard deviation from the historical extreme value of the variables (scenario II). Table 13 shows the extreme values of the variables and the event dates, and Table 14 shows the baseline scenario as well as the historical and hypothetical stress scenarios. The baseline scenario therefore reflects the expected development in macroeconomic variables and is a benchmark scenario.

[23] Since our sample consists of the time series until the end of 2007 with the largest fall in gas and oil prices of 30 percent, we consider the year 1998. We do not take into account the recent 54 percent fall (2009 Q1) in gas and oil prices.

Table 13: Worst Extreme Values of Variables

Variables	***Historical Largest Shock**
Real GDP	-26.95% in **1994**
Gas and Oil Prices	-29.91% in **1998**

* until the end of 2007

The stress dimension under scenario II is enormous but still plausible compared with recent developments due to the global recession. For presentation purposes, we illustrate the stress dimension on a yearly basis.

Table 14: Stress Scenarios for 2008

Variables	Scenario I	Scenario II	Baseline
Real GDP	-26.95%	-41.04%	3.67%
Gas and Oil Prices	-29.91%	-58.44%	33.63%

Our next, crucial step in scenario analysis is the incorporation of stress scenarios into macro variables and the prediction of credit risk under a given stress event.

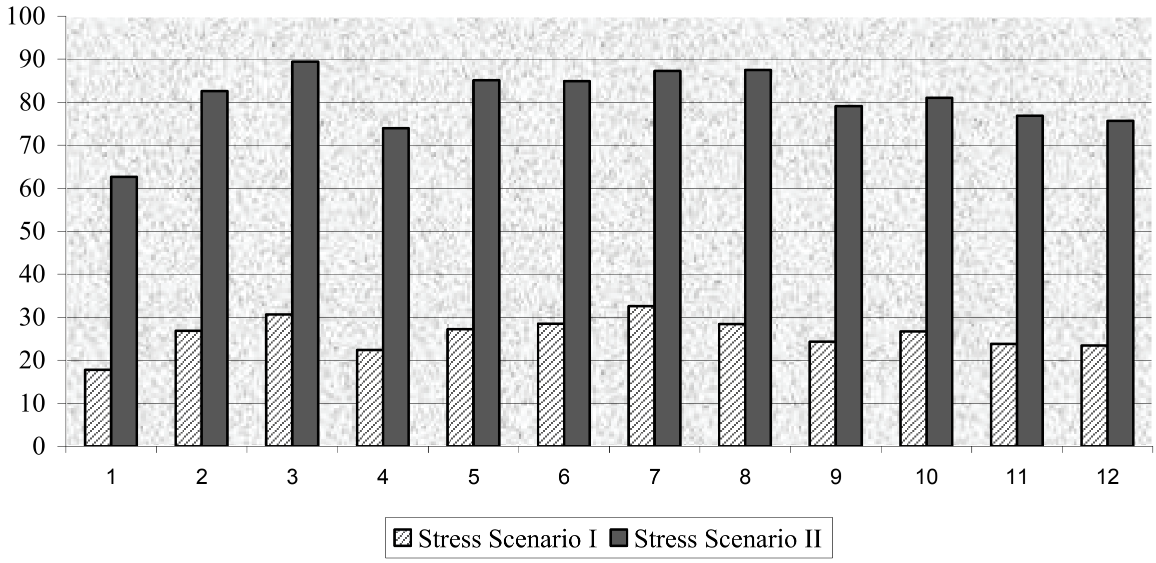
Table 15 shows predicted ratios of bad loans to total loans for 2008 for three randomly chosen banks. Owing to the lag structure of the macroeconomic variables, the stress impact spreads differently within the year 2008. There are also differences in stress impact among the banks. For banks 1 and 2, the impact in both stress scenarios is highest in the third quarter, while bank 3 suffers more in the fourth quarter.

Table 15: Predicted Ratio of Bad Loans to Total Loans

Stress Scenario		Baseline	Stress 1	Stress 2
Bank 1	**2008q1**	0.029	0.028	0.031
	2008q2	0.024	0.035	0.061
	2008q3	0.017	0.024	0.109
	2008q4	0.010	0.019	0.076
Bank 2	**2008q1**	0.029	0.028	0.031
	2008q2	0.023	0.035	0.060
	2008q3	0.023	0.033	0.147
	2008q4	0.018	0.034	0.128
Bank 3	**2008q1**	0.024	0.024	0.024
	2008q2	0.029	0.028	0.046
	2008q3	0.025	0.036	0.055
	2008q4	0.022	0.039	0.056

Figure 11 shows the stress impact on the ratio of bad loans to total loans for individual banks in stress scenario I and in stress scenario II relative to the baseline scenario. The calculations are based on the mean values (over four quarters) of the ratio of bad loans to total loans in the year 2008. The stress impact ranges between 17 percent and 23 percent in stress scenario I (26 percent on average) and between 62 percent and 89 percent (80 percent on average) in stress scenario II. The identification of the stress impact of macroeconomic stress scenarios on credit risk has to be compared with the risk-bearing capacity of the individual bank in order to reach an appropriate assessment of the bank's stability. In the next section, we describe the risk-bearing capacity analysis for 12 Kazakh banks.

Figure 11: Impact of Stress Scenarios on the Ratio of Bad Loans to Total Loans



4.2.4 Risk-Bearing Capacity

The bank's capital is the reserve that buffers the impact of potential losses. Such losses may be incurred as a result of borrowers defaulting or of adverse market movements. The most important measure of banks' risk-bearing capacity is the capital adequacy ratio, i.e. the ratio of capital to the bank's risk-weighted assets. The hypothetical size of stress impact for the whole banking system in terms of core capital in scenario 1 is 13.2 billion Tenge and in scenario 2 is 40.75 billion Tenge. We compute these numbers as additional capital compared with the amount of capital the banking system would need in the baseline scenario. Pursuant to the Kazakh Banking Act, the capital adequacy ratio has to be above 12 percent.[24] On an aggregated level, this ratio does not fall below 12 percent, which means that banks remain, on average, well-capitalized, while, on a disaggregated level, some banks become insolvent.[25] In

[24] We calculate the capital adequacy ratio using formula (9) on page 25. Furthermore, we weight the expected losses with the corresponding LGD, which is 50 percent.
[25] We calculate the capital adequacy ratio using data from 2008. At that time some banks were already suffering from the effects of the financial crisis.

the next section, we summarise results for both portfolio stress testing and macro stress testing and draw attention to some shortcomings of our analysis.

4.3 Summary, Shortcomings and Further Steps

In the "Portfolio Stress Tests for the Banking System of Kazakhstan" section, we first develop a macroeconometric model to forecast production decline under a macro shock in the "agriculture", "industry" and "construction" sectors. Then we transmit the stress impact from the real sector to the banking system using a state-of-the-art CreditMetrics-type portfolio model with sector-dependent unobservable risk factors and corresponding mapping methodology. We subsequently calculate the stress impact from the real economy in terms of stressed expected losses for each bank individually. In order to assess the stress impact on the regulatory minimum capital requirement, we calculate and analyse the average regulatory equity ratio before and after the stress event. Our main results are as follows.

- The production decline as an average of the third and fourth quarters of 2008 is 17.3 percent for the agriculture sector, 8.43 percent for the construction sector and 3.75 percent for the production sector.
- The relative change in the expected losses under the stress scenario (decline in the production sectors) ranges between 34 percent and 86 percent.
- The relative average change in the regulatory equity ratio is 0.64 percentage point.

We stress-test the Kazakh banking system without the "optimal" database. The detailed information about the credit exposure at borrower level and the borrower's credit quality would make the calculation of the expected losses, and therefore the stressed expected losses, more accurate. Furthermore we set the average asset correlation between small and medium–sized Kazakh companies equal to that of Germany, which is 0.09. The use of this assumption has to be examined. In our further work we have to improve the forecast power of the macroeconometric model using more appropriate models for forecasting purposes.

The purpose of the section on "Macro Stress Tests for the Banking System of Kazakhstan" has been to provide a macro stress testing tool for the Kazakh banking system by conducting three steps: identification of significant risk factors, development of stress scenarios, and analysis of risk-bearing capacity.

We identified four significant factors: the output gap, the ratio of credit to GDP gap, house prices, and gas and oil prices. Then, we developed two stress scenarios based on two macro factors and, in conclusion, we compared the results with the benchmark scenario. Finally, we analysed the risk-bearing capacity for each bank individually and for the 12 banks together and founded the hypothetical size of stress impact in different stress scenarios. Our main results are:

- the stress impact ranges between 17 percent and 23 percent in stress scenario I (26 percent on average) and between 62 percent and 89 percent (80 percent on average) in stress scenario II.
- the hypothetical size of the stress impact for the whole banking system in terms of core capital in scenario 1 is 13.2 billion Tenge and in scenario 2 is 40.75 billion Tenge.

Despite the interesting results, it has to be mentioned that our analyses possess some shortcomings which cannot be ignored. First of all, the size of our sample is quite small and we do not observe a complete business cycle. Second, there are several difficulties with our regression model, such as n<T and the Nickel bias, that we had to accept. Finally, the significance level of macroeconomic variables is not high, which means that the economic significance of macro factors for the credit risk is subject to some doubt for the observed time period.

For further research, some extensions seem important. First of all, this would involve the incorporation of the business cycle by updating the data. Second, extending the sample to include a larger number of groups would be helpful. The inclusion of other macro factors, such as interest rate spreads, could improve the predictive power of the model. Finally, as an additional robustness check, we intend to employ non-linear models instead of transformation of the dependent variable.

5. Conclusions

In this paper, we stress test the Kazakh banking system using two different approaches: “bottom-up” and “top-down”. In the “bottom-up” approach, individual banks carry out stress test analyses and transmit the results to NAC. In the “top-down” approach, we focus on credit risk and use two alternative methodologies: portfolio and macro stress tests. The results of both stress testing models show that some banks do not have enough capital to cover additional losses caused by an economic downturn.

All in all, we develop and apply methodologies in order to assess the financial stability of banking system in Kazakhstan. The accuracy of the results depends on many factors, such as data quality, plausibility of assumptions, the adequacy of the chosen stress factors, the hypothetical stress dimension, the specifics of the applied methodology. Further research, particularly on the macro stress testing model, is necessary. The tools developed and applied in the project can generally be used by the project participants (NBRK, FSA, NAC) as a method of assessing the consequences of macroeconomic shocks for credit risk, but there is still room for technical improvements. Generally speaking, the development of a well-functioning stress testing system is a dynamic process since risks are moving and the macroeconomic environment changes over time.

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Appendix

Classifications of Financial Sustainability Indicators

Financial Sustainability Indicators	Notes on Calculation
I. Capital adequacy	
Capital adequacy Tier 1 (к1)	according to prudential norms set by AFS
Capital adequacy Tier 2 (к2)	according to prudential norms set by AFS
II. Asset quality	
Bad loans to credit portfolio	according to AFS requirements to asset classification
Provisions to credit portfolio	according to AFS requirements to asset classification
Growth of past due	according to AFS requirements to asset classification
NPL net of provisions to total assets	(NPL) - 2nd, 4th, 5th category of doubtful and bad loans
NPL net of provisions to credit portfolio	(NPL) - 2nd, 4th, 5-st category of doubtful and bad loans
III. Risk concentration	
Credits to other countries to credit portfolio	according to quarterly regulatory reports. Credit portfolio includes interbank, client credits and reverse repo
Mortgage loans (backed by real estate) to credit portfolio	according to quarterly regulatory reports
Credit portfolio in foreign currency to credit portfolio	according to quarterly regulatory reports
Credits to construction sector in structure of crediting the economy	according to quarterly regulatory reports
NPL in loans to construction sector to total loans to construction sector	according to quarterly regulatory reports
Obligations sensitive to interest rate changes to equity capital (interest rate position)	according to quarterly regulatory reports
IV. Earnings and profitability	
ROA	according to bank accounting data
ROE	according to bank accounting data
V. Liquidity	
Current liquidity ratio	according to prudential norms set by AFS
Quick liquidity ratio	according to prudential norms set by AFS
Credit portfolio to deposits of legal and physical persons except inter-bank and SVP organizations	according to bank accounting data
Obligations to non-residents to total obligations	according to quarterly regulatory reports
Liquid assets to total assets	Liquid assets – assets with residual maturity of up to three months, including highly liquid assets (on an average basis in accordance with the method of calculation of liquid assets for short-term liquidity ratio of banks (k.5) prudential requirements

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