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CONTENTS

CONSUMER CREDIT RISK ANALYSIS VIA MACHINE LEARNING ALGORITHMS

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This project is an attempt to assess the creditworthiness of individuals through machine learning algorithms and is based on regulatory data provided by the second-tier banks to the central bank. The assessment of borrower creditworthiness can allow the central bank to examine the quality of loans provided by the second-tier banks and predict potential systematic risks.

In this project, two linear and six non-linear classification methods were developed (linear models – Logistic Regression, Stochastic Gradient Descent, and nonlinear - Neural Networks, k-Nearest Neighbor (kNN), Decision Tree, Random Forest, XGBoost, Naïve Bayes), and the algorithms were compared based on accuracy, precision, and several other metrics. The non-linear models illustrate more accurate predictions in comparison with the linear models. In particular, the non-linear models such as the Random Forest and kNN classifiers on oversampled data demonstrated promising outcomes.

Key Words: consumer credits, machine learning, bank regulation, stochastic gradient descent (linear model), logistic regression (linear model), kNN (neighbors), random forest classifier (ensemble), decision tree (tree), gaussian NB (naïve bayes), XGBoost, Neural network (MLP classifier).

JEL-Classification: G21, G28, E37, E51.

1. Preamble

The expansion of consumer loans is the main factor behind the growth of retail loans in recent years. An issuance of consumer loans may lead to economic growth in the country, but at the same time, it should be noted that excessive financing by banks can cause the emergence of systemic risks. The rapid growth of consumer lending can be explained by the emergence of accurate data and instruments to assess the credit risk of individuals as well as a stabilization of the economic situations and noted increase in the well-being of the population.

The rapid expansion of consumer lending carries a number of systemic risks, which are associated, first of all, with the growing level of debt burden on certain segments of the population. In case of a drop in the real income of the population, the banking system may deal with massive defaults on consumer loans. As a consequence, it can lead to a decline in aggregate demand in the economy. Such a development of events might significantly negatively affect the state of the economy.

Reviewing studies of other scholars on applying machine learning algorithms, we can conclude that the most popular method of analyzing the credit risks of consumer loans on big data set is the employment of non-linear models such as Neural Networks, kNN, Decision tree, Random forest, XGBoost, Naïve Bayes and models such as Logistic Regression, Stochastic Gradient Descent. It should also be noted that the majority of authors used data from credit bureaus and second-tier banks, however, this research was conducted based on regulatory data collected by the central bank. Consequently, there might be some discrepancies in the approaches that might give minor differences.

The first section is a review of the literature, in which similar works by other authors are reviewed. The second section describes the methodology of the study, as well as a list of predictors used. Next comes the discussion section of the results, in which the authors describe the results of the assessment. The findings of this study are the final section of the work.

2. Literature Review

Grier (2012) stated that 5 parameters must be considered for consumer credit analysis. The first parameter is a character that refers to the applicant's reputation. Nowadays, credit managers have access to credit bureau report which shows the credit history of a consumer before deciding to issue a loan. The second factor is capacity which is related to the income and the existing financial liabilities of the consumer. Capital is the third parameter that indicates the down payment that the borrower can afford. The external factors such as the condition in the job market and general economic conditions are considered as the fourth factor. The last parameter is collateral.

Credit scoring techniques estimate the probability of repayment of consumers using the information in a credit bureau report and the credit application (Grier, 2012). It estimates the probability of repayment of customers. Application scoring is the first type of credit scoring model that evaluates the application of new consumers based on the parameters, such as capital, capacity, and so on. Another model such as the behavior scoring model assesses the repayment ability of consumers, warning about the potential delinquent accounts.

One of the goals of using the credit scoring technique is to decrease credit losses in the future. Besides traditional techniques, banks recently started to integrate machine learning (ML) algorithms in credit scoring. Henley and Hand (1996) compared machine learning techniques such as kth nearest neighbor (kNN) classification method with traditional credit scoring techniques such as linear, logistic regression, and decision tree. The algorithms were tested for bad debt risk and the technique with the lowest result was considered as the best method. In spite of the insensitivity of kNN classification to the parameters, it gave the best result. In addition, it takes a few seconds to assess the consumer and provide justifications for refusing to issue a loan (Henley and Hand, 1996).

Addo, Gueran, and Hassani (2018) applied logistic regression, random forest and gradient boosting classifier, and deep learning model for credit risk analysis of companies. Various data sets were used, and then 10 most important features were chosen and the same techniques were used to compare the results. The best algorithm is supposed to show the highest area under the curve (AUC) and the least root means square error (RMSE). Binary classifiers outperformed deep learning models, and the best performance belongs to the gradient boosting classifier.

Regression models of machine learning are also used to evaluate consumer credit applications. Munkhdalai et al. (2019) compared machine learning algorithms with human-expert-based models such as the FICO credit scoring system. Survey of Consumer Finances (SCF) data was used as a data set and various machine learning regression methods were applied to the data set. The result demonstrated that the credit losses would be lower if the lending institutions started to use machine learning from 2001. Additionally, deep neural networks and xgboost algorithms showed higher accuracy.

Brown and Mues (2012) tested the suitability and accuracy of classification techniques, such as logistic regression, neural network, decision tree, gradient boosting, least-square support, and random forest, to imbalanced loan data set. The undersampling method was applied to the data set, and then the imbalance of the data set was increased progressively to assess machine learning classification techniques. The result indicates that random forest and gradient boosting classifiers dealt well with imbalanced data, while decision tree, quadratic discriminant analysis (QDA), and kNN classifier performed worse than other methods.

There are also several algorithms in machine learning besides the abovementioned models. Baesens et al. (2003) tested kernel-based support vector machine and least-squares support vector machine, and also other popular machine learning classifiers to real-life credit scoring data sets including Benelux and UK financial institutions' data sets. The result indicates that the neural network classifier and kernel-based support vector machines performed very well. The author also mentioned the good performance of linear discriminant analysis and logistic regression. 41 classifiers including novel credit scoring methods applied to the same data sets (Lesmann, Baesens, Seow, and Thomas, 2015). The result of the research shows that artificial neural networks (ANN) performed better than extreme learning methods (ELM), random forest (RF) better than rotation forest (RotFor). However, the methods cannot give insightful explanations of the model and future researches should be done to achieve this goal. Random Forest classifier was chosen as a benchmark as it has the capability to provide explanatory insights for fundamental analysis.

Tsai and Chen (2010) developed four hybrid machine learning methods to compare with simple classifiers. A hybrid algorithm is a combination of two machine learning methods. In this research, classification and clustering methods were chosen and four different methods were selected. The result indicates that the combination of logistic regression (LR) and neural networks showed the highest prediction, while 'clustering + clustering' was the least accurate algorithm.

In 2015, the participants implemented XGBoost in 17 out of 29 Kaggle challenge winning solutions. The algorithm was implemented for store sales prediction, web text classification, customer behavior prediction, malware classification (Chen & Guestrin, 2016). In this research, the algorithm will be used for credit analysis and compared with other methods.

In this project, two linear and 6 nonlinear classification methods were applied to the dataset that will be described in the next section. The algorithms were compared based on accuracy, precision, and several other metrics.

3.Research Methodology and Data

Machine learning algorithms were used for the analysis of the consumer credit portfolios of Kazakhstani banks. The data was obtained from the Credit Register provided by second-tier banks to the National Bank of Kazakhstan (NBK). The loan with missing and unreliable parameters was cleaned out. In addition, loans with late payments of no longer than 90 days were removed from the data. If the delinquency of loan payment is more than 90 days, the loan is declared as a non-performing loan (NPL). Performing loans has no payment delinquency from the consumer side.

Table 1

Data

Parameters	Type
Region	Nur-Sultan, Almaty and 15 regions
Currency	KZT, RUB, USD and EUR
Type	Personal loan and credit card
Reason	Consumer credits and auto loans
Gender	Male or female
Citizenship	Local or Foreigner
Interest Rate	Ranges from 0% to 56%
Credit amount	Ranges from 10 000 to 15 million KZT
Age	Ranges from 18 to 99 years

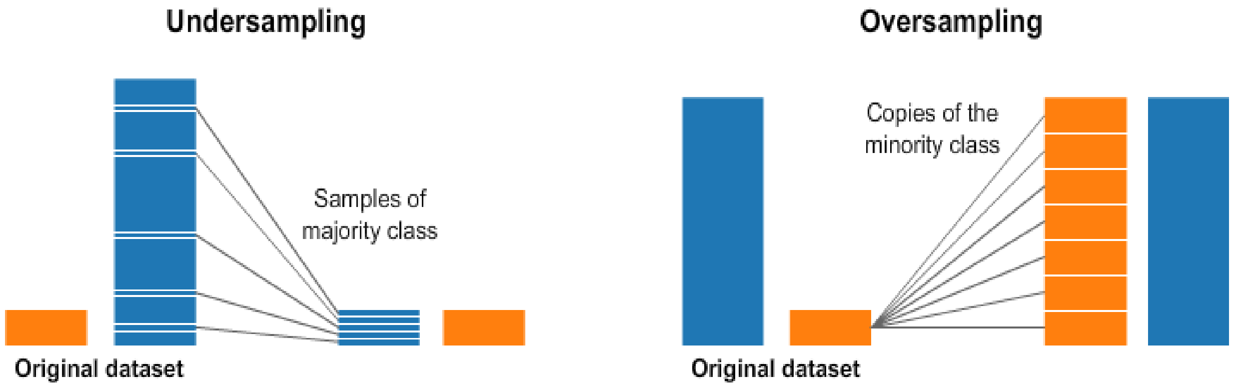
Source: National Bank of Kazakhstan

Resampling techniques for imbalanced data

In order to improve the accuracy of applied machine learning algorithms, resampling techniques such as undersampling and oversampling were utilized. Since the number of good loans was considerably more than the non-performing loans, the data was balanced and two techniques were compared.

Graph 1

Resampling strategies for imbalanced datasets



Source: Alencar, 2017

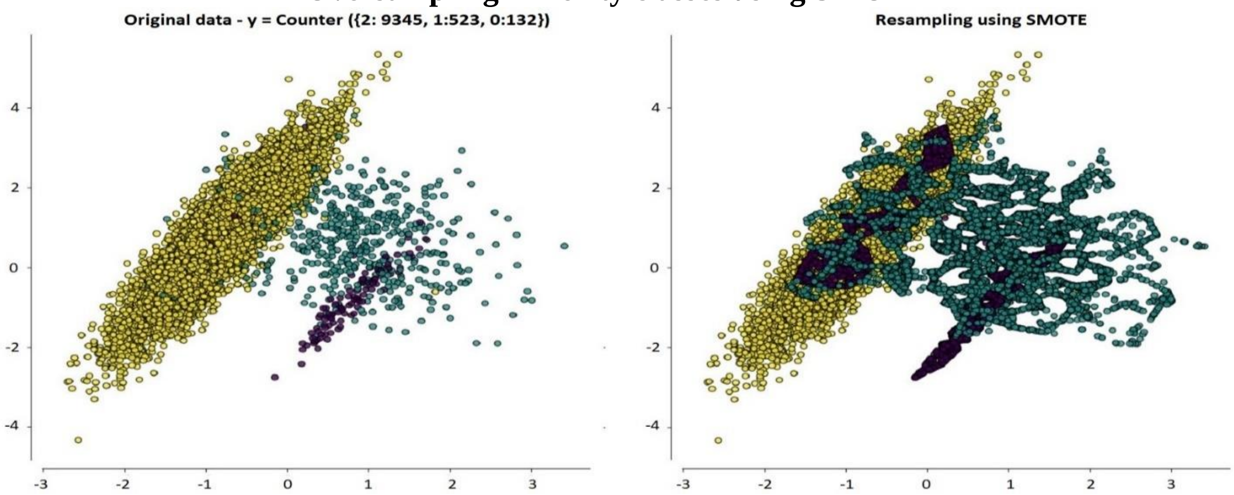
Random undersampler and oversampler are the most popular and simplest resampling strategies. The first strategy creates a new class with an equal size of minority class taken from the majority class, whereas the second strategy duplicates the minority class several times until the length of majority and minority classes will be equal. The drawback of a random undersampler is the loss of information. However, it is the only suitable undersampling strategy for a dataset that consists of categorical and continuous variables. Random oversampler leads to overfitting as it copies the minority class (Alencar, 2017). Therefore, another appropriate resampling method was selected.

SMOTE (Synthetic Minority Oversampling Technique) is another popular oversampling method that draws new samples of minority classes using its existed data. It draws the lines between an example and the nearest 5 neighbors and creates a new sample along that line. Graph 2 illustrates how new samples were created, thereby providing additional information to the machine learning model (Brownlee, 2020).

SMOTE cannot be applied to the above mentioned dataset as it does not handle categorical features. Therefore, Synthetic Minority Oversampling Technique-Nominal Continuous (SMOTE-NC) is selected as the oversampling method. It works as a SMOTE method for a continuous dataset, and the categorical variable of the new sample is the value of the majority of the k-nearest neighbors (Chawla, Bowyer, Hall and Kegelmeyer, 2002).

Graph 2

Oversampling minority classes using SMOTE



Source: Lemaitre, Nogueira, Oliveira and Aridas, n.d.

Preprocessing

Preprocessing is important task to make the data readable. Six parameters of dataset are categorical data and it has to be converted to numerical using encoder. Scikit-learn library (Python) provides techniques that convert discrete features to one-hot numerical array. It also has models which split the data into training and testing dataset (du Boisberranger, n.d.).

The next important part of preprocessing is feature scaling of the dataset. Machine learning algorithms commonly use Euclidean distance measure; thus it is sensitive to magnitudes of parameters. For instance, the algorithms neglect other parameters in the dataset because of large values of credit amount. Therefore, feature scaling is required to normalize the dataset. It also decreases the cost: credit scoring techniques analyze the normalized dataset faster. Abovementioned python library provides standard feature scaling techniques that normalize the dataset through the formula:

$$z = \frac{x-\mu}{\sigma} \text{ (du Boisberranger et al., n.d.)}$$

whereas, μ is mean and σ is standard deviation of the data.

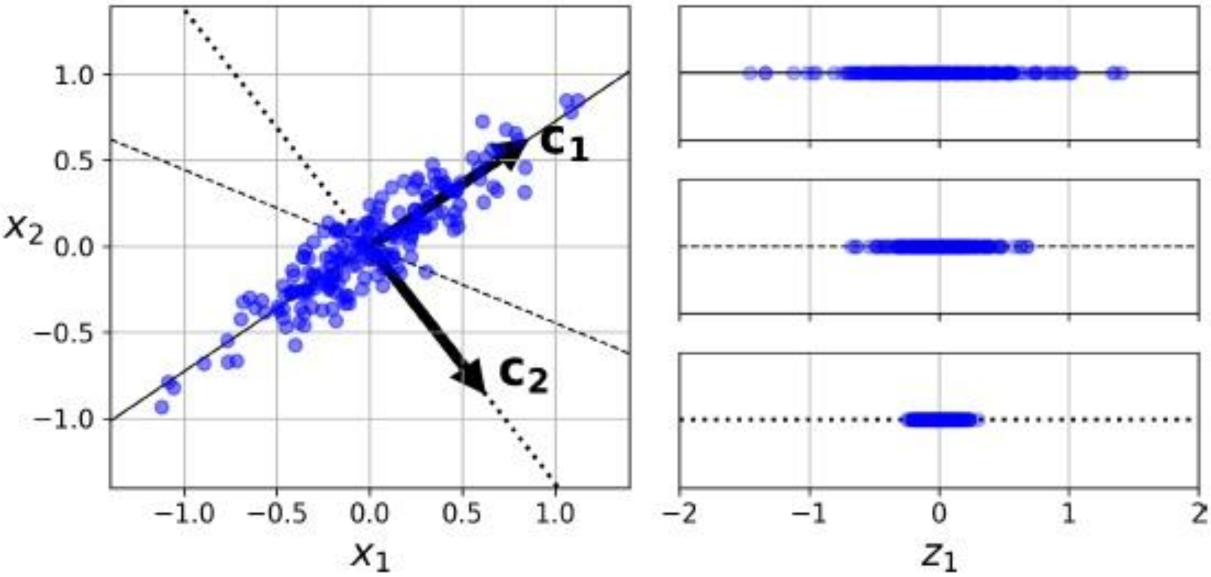
Principal component analysis

Principal component analysis (PCA) is one of the well-known dimensionality reduction techniques. It helps to decrease the dataset dimension with minimal loss of information (Mueller & Guido, 2017). Consequently, it will decrease the computation time of an algorithm.

The algorithm selects the right hyperplane and projects the data onto that hyperplane. After the projection, the variance of the data is computed based on each new axis called the principal component. The first component preserves maximum variance, while the last component - least variance.

Graph 3

Principal component analysis

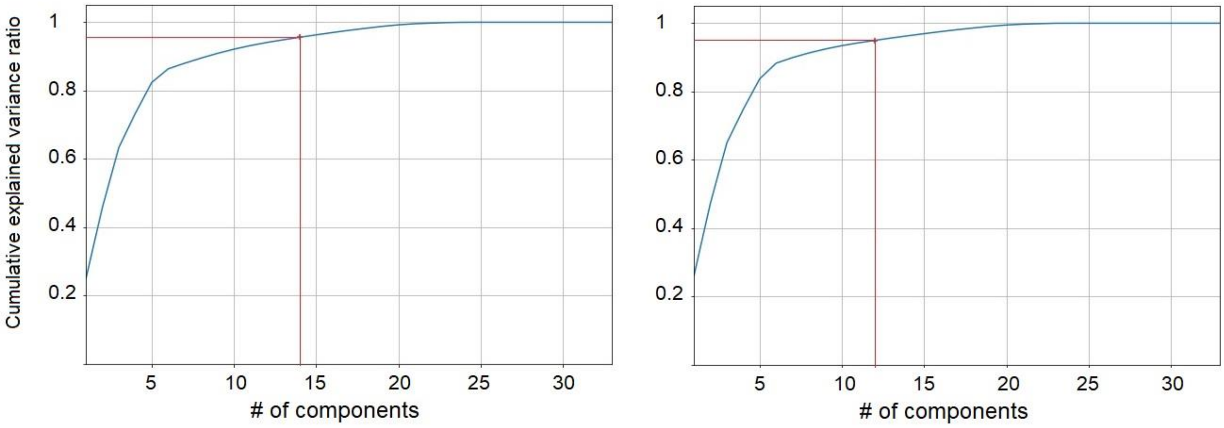


Source: Geron, 2017

Principal component analysis performed on both balanced datasets. The result of the undersampled dataset indicates that the first 14 components (columns) are enough to capture the 95% of the total variance of the dataset and the other 19 components can be erased. It is enough to use only 12 components of an oversampled dataset to capture 95% of the total variance.

Graph 4

Cumulative explained variance ratio of PCA



Source: compiled by the author

In this research, two linear and six nonlinear machine learning methods were applied to the dataset. The main goal to find out which algorithm outperforms others. In addition, the research helps to compare and contrast linear and nonlinear algorithms.

The feasibility of handling a large dataset is the main criteria for algorithm selection. Therefore, well-known algorithms such as linear and kernel support vector classifier (SVC) were not considered in the research. Logistic regression, stochastic gradient descent (SGD) classifier, Naïve Bayes classifier, kth nearest neighbors (kNN), decision tree classifier, random forest classifier, multilayer perceptron (MLP) classifier (neural network classifier), and extreme gradient boosting (XGB) classifier were implemented, and the results were discussed. Several hyperparameters of nonlinear algorithms will be neglected due to the inability to handle large datasets.

Logistic Regression

Despite its name, logistic regression is used for classification. The algorithm calculates the probability based on the training dataset according to the formula:

$$P(y=1|x) = \frac{1}{1+e^{-(w_0+\boldsymbol{W}^{\boldsymbol{T}}x)}} \text{ (Baesens et al., 2003)}$$

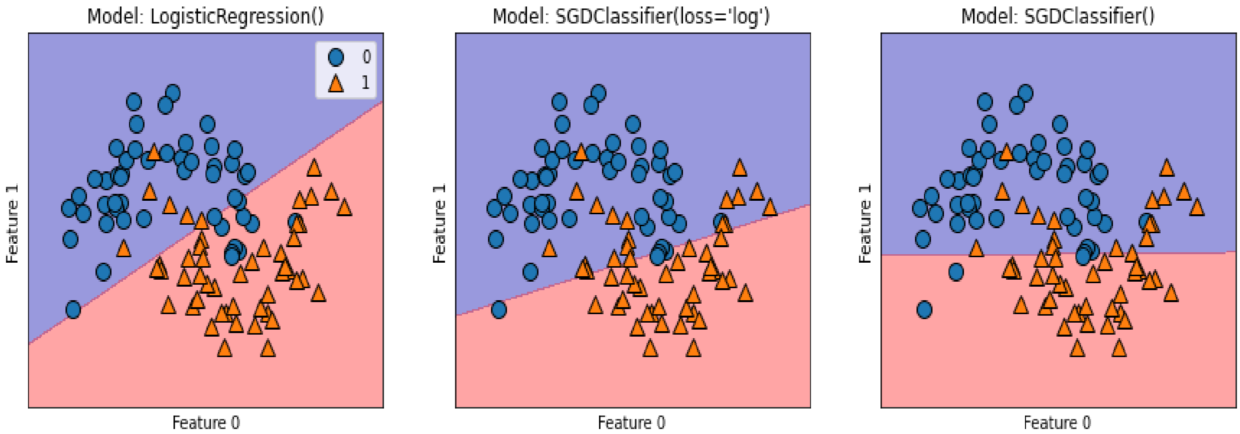
where x is input data, w0 is a scalar intercept and W is a parameter vector. If the probability is more than 50%, the input data is classified as positive.

The important hyperparameter such as solver and regularization parameters were tuned to increase the accuracy. ‘Liblinear’ solver is generally used for a small dataset, whereas ‘sag’ and ‘saga’ are a better choice for larger data analysis as it takes less time for computation (du Boisberranger et al., n.d.).

The penalty is a regularization hyperparameter used in penalization, and it has a close connection with the solver. ‘Newton-cg’, ‘sag’ and ‘lbfgs’ solvers support only ‘l2’ penalties, while only ‘saga’ solver supports ‘elasticnet’ penalty. ‘C’ is the inverse of regularization strength which must be positive. A smaller value for ‘C’ indicates stronger regularization (du Boisberranger et al., n.d.).

Graph 5

Linear classification models



Source: compiled by the authors

Stochastic Gradient Descent (SGD)

SGD classifier is one of the effective linear classification methods applied to large datasets. The algorithm uses a first-order SGD learning routine. The parameter of the method is updated iteratively over training examples according to the formula:

$$\omega = \omega - \eta[\alpha \frac{\partial R(\omega)}{\partial \omega} + \frac{\partial L(\omega^T x_i + b, y_i)}{\partial \omega}]$$ (du Boisberranger et al., n.d.)

Where α is hyperparameter which controls regularization strength, *R* is regularization term that penalizes model complexity. *L* is loss function that measures model fit, ŋ is the learning rate and b is intercept which is updated similarly without regularization.

Gradient descent is one of the important algorithms used to minimize a cost function (Fuchs, 2019). In general, there are three popular types of gradient descent:

1. Batch gradient descent;
2. Stochastic gradient descent;
3. Mini-batch gradient descent.

Batch Gradient Descent computes the partial derivative of the cost function of an algorithm with regard to its parameters. In other words, the algorithm discovers how the different values of the model parameters impacts on cost function of the algorithm. The disadvantage is that it uses whole training data to compute it at every step. Therefore, the algorithm cannot handle large datasets (Geron, 2019).

Stochastic gradient descent addresses this problem as it picks random instances of training data and computes gradient descent based on that single instance. On the other hand, batch gradient descent will decrease the cost function smoothly, while it bounces up and down until the algorithm stops. The algorithm will not compute optimal parameter values (Geron, 2019).

Mini-batch gradient descent takes a small sample out of training data and computes batch gradient descent algorithm. Therefore, the cost function computation result is less erratic compared to stochastic gradient descent (Geron, 2019).

The method has many hyperparameters which makes it very complex. Important parameters such as loss function and regularization parameters such as penalty and alpha are considered in the tuning process of the model. The method with 'Hinge' loss function performs like linear SVM, while with 'log' function it gives logistic regression (du Boisberranger et al., n.d.).

The algorithm is very sensitive to feature scaling. But it is easy to implement and very efficient, especially for larger datasets (du Boisberranger et al., n.d.). Also, it continues to work without keeping the record in RAM (Fuchs, 2019).

Naïve Bayes classifier

In general, Naïve Bayes (NB) classifier is based on Bayes theorem assuming the independence of every feature:

$$P(y|x_1, \ldots, x_n) = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1, \ldots, x_n)}$$ (du Boisberranger et al., n.d.)

There are several types of NB classifiers. In this research, Gaussian Naïve Bayes (GaussianNB) classifier is used for the estimation of the likelihood of the features based on the formula:

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} e^{-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}}$$ (du Boisberranger et al., n.d.)

where mean and standard deviation are estimated via maximum likelihood.

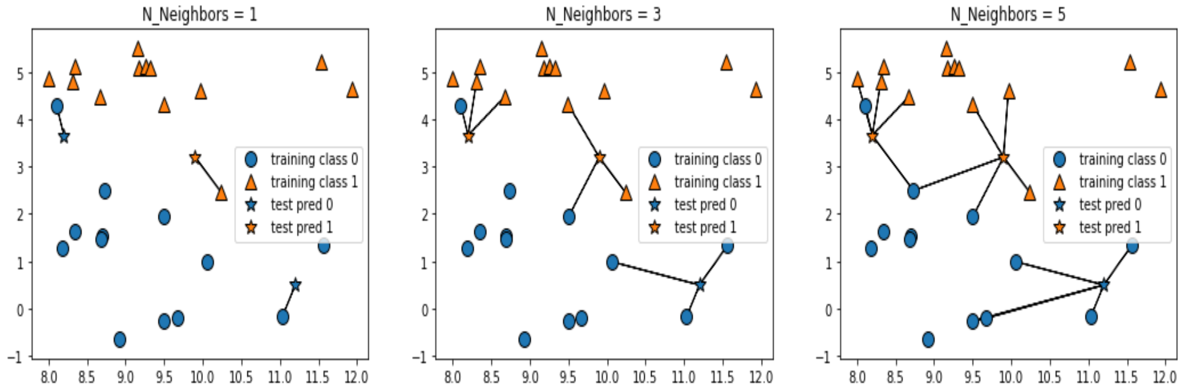
kth Nearest Neighbors

kNN is one of the simplest algorithms of supervised machine learning. The number of nearest neighbors (k) is the main parameter in this algorithm. The result of the new data will be identified based on the majority of the result of the nearest neighbors. The large value of k will overwhelm the effects of noise, but it will have on the boundary of the classification (du Boisberranger et al., n.d.). The distance is measured according to the Euclidean Distance formula:

$$d(x_i, x_j) = \|x_i - x_j\| = \left[(x_i - x_j)^T (x_i - x_j)\right]^{1/2}$$ (Brown & Mues, 2012)

Graph 6

kth Nearest Neighbors classification model



Source: Mglearn library (Mueller & Guido, 2017)

Decision Tree classifier

Decision Tree classifier simple algorithm that predicts target output via applying decision rules based on features data. The strength of the method is the ability to handle numerical, categorical features, and multi-output problems. The simplicity of the model is another advantage. But the model may create over-complex trees which lead to overfitting of the model (du Boisberranger et al., n.d.).

Criterion and a maximum depth of the tree are considered in the tuning process of the model. The first parameter is the function that measures the quality of a split. ‘Gini’ (Gini impurity) and ‘entropy’ (information gain) are two choices for criteria function (du Boisberranger et al., n.d.).

Random Forest Classifier

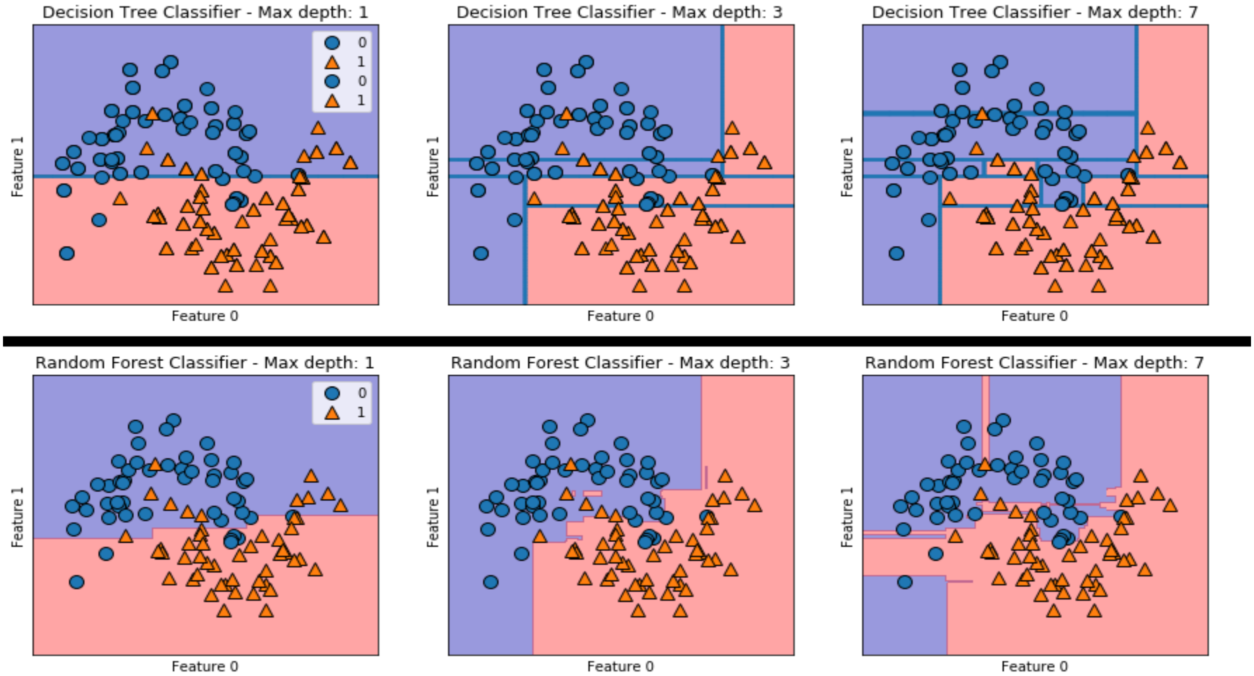
Random Forest Classifier is an ensemble classification method that has all the hyperparameters of the Decision Tree classifier. The difference between the two models is that the former searches for the best feature among a subset of features, while the latter seeks for the best feature when splits a node. Thus, a random forest classifier results in a bigger tree (Geron, 2019).

Decision tree classifier

Decision tree classification shows higher variance which leads to overfitting. Random forest classifier combines diverse trees, thereby achieves the reduction of the variance. Subsequently, it creates a better model than the decision tree classifier (du Boisberranger et al., n.d.).

Graph 7

Decision tree and random forest classifier on scikit-learn dataset



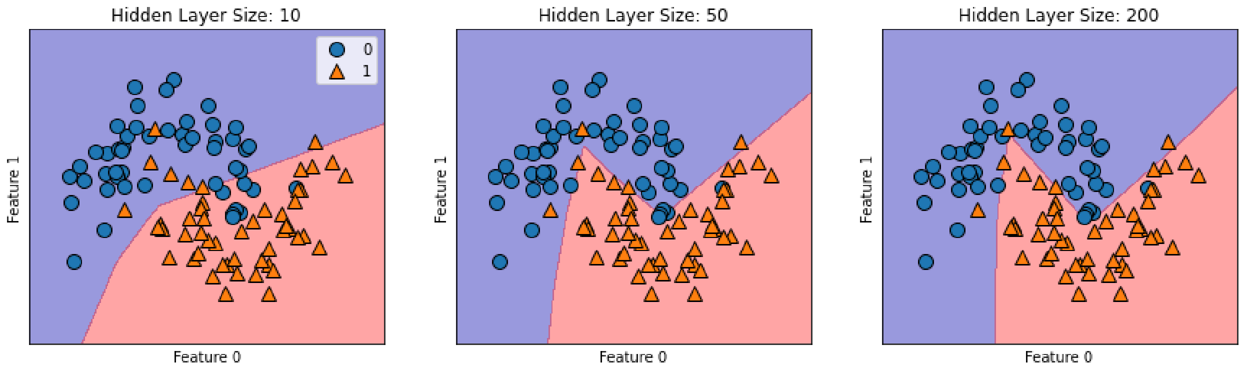
Source: compiled by the authors

Neural Network (Multilayer Perceptron)

A neural network is a model that was inspired by the human brain structure. The main structure of the algorithm consists of input, output and hidden layers. The size of hidden layers is an important hyperparameter of the algorithm. Each layer has nodes that hold a number, and each node receives a signal from each node from the previous layer and sends a signal to the nodes in the next layer. Each signal has weight and it goes along with a bias on which the input has no impact (Hansen, 2019).

Graph 8

Neural network classifier



Source: compiled by the authors

One important feature of the neural network is the gradient descent algorithm. It is used to minimize the deviation between the output and the calculated value of the output. The neural network uses backpropagation to calculate the gradients. Then, it updates all biases and adjusts weights of all nodes starting from the output (Hansen, 2019).

XGBoost

Extreme gradient boosting (XGBoost) is one of the widely used algorithms. It is an implementation of gradient boosted decision trees. The execution speed and model performance are the advantages over other gradient boosting algorithms (Brownlee, 2016).

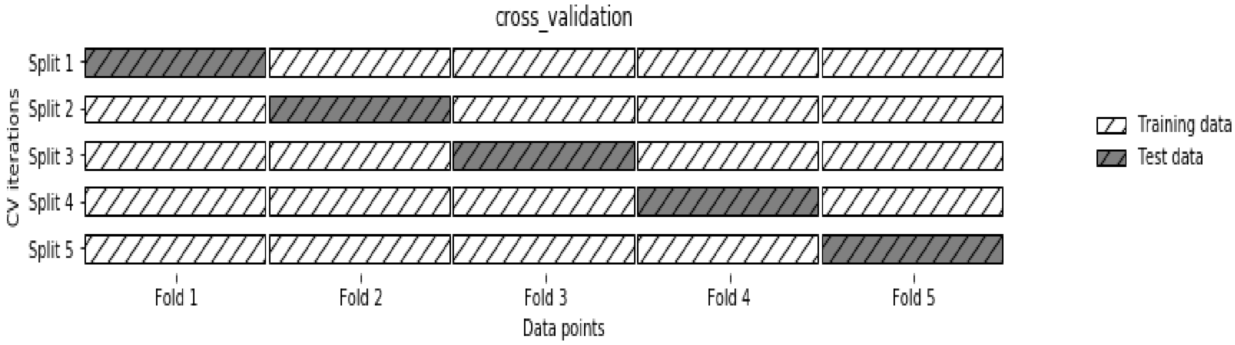
The advantage of the method is scalability. It uses a novel tree learning algorithm for handling sparse data and can handle missing values automatically. Parallel and distributed processing of the data makes it one the fastest algorithms. The algorithm uses out-of-core computation and processes millions of examples on a computer. Therefore, it is one of the best candidates to process large data. Another important feature of the method is called tree pruning. It results in deeper, but optimized trees (Chen & Guestrin, 2016).

Cross-validation

Cross-validation is a statistical method used to measure the performance of the methods based on training and testing dataset. A commonly used version of cross-validation is k-fold cross-validation, where the number of folds is 5 or 10 (Mueller & Guido, 2017). In the research, 5-fold cross-validation was used as it is shown in Graph 9. Consequently, the dataset is divided into five equal folds. If the first fold is used as a test set, the remaining folds as training set. To sum up, the goal is to compute the mean and standard deviation of the accuracies and analyze the impact of datasets on the model accuracy based on metrics.

Graph 9

Five-fold cross-validation



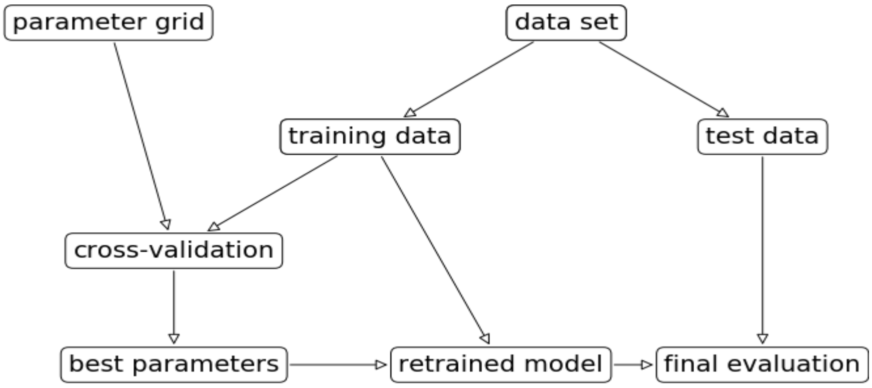
Source: Mglearn library (Mueller & Guido, 2017)

Grid Search

Grid Search is the final step of the model construction. In this step, the selected machine learning model is tuned. The parameter grid is the first step of the tuning process where a set of all possible hyperparameters of the algorithms is listed. Then, the model with a different set of hyperparameters is applied to the training and test data. This step helps to identify the set of parameters by which the model achieves the highest score. The model will be reconstructed with the set of best hyperparameters (Mueller & Guido, 2017).

Graph 10

Grid Search Overview



Source: Mglearn library (Mueller & Guido, 2017)

The big question in this step was to choose the hyperparameters to tune the model. The several models have many hyperparameters and it takes too much time to tune the process. Thereby, the parameter grid was constructed based on the most important parameters. For instance, the only the number of nearest neighbors was the only parameter selected for tuning the kNN model. Kaggle, the website for data scientists, provides a grid search model for some models that were used in the research.

Metrics

In machine learning, regression, clustering and classification algorithms use different performance metrics. Classification algorithms also have different metrics for binary and multiclass classification. There are 6 metrics used in this research:

1. Accuracy score
2. Precision score
3. Recall score
4. F1 score
5. Jaccard score
6. The area under the receiving operating characteristic (ROC) curve
7. Type 2 error percentage

Confusion matrix

The confusion matrix is a matrix table used to evaluate the performance of the classifier. It generally indicates the number of correct and incorrect results of a classification algorithm. It also gives information about the type 1 and type 2 errors which will be explained in this section.

Table 2

Confusion matrix

	Actual class (observation)	
Predicted class (expectation)	TP (true positive) Correct result	FP (false positive) Unexpected result
	FN (false negative) Missing result	TN (true negative) Correct absence of result

Source: Binary classification (du Boisberranger et al., n.d.)

1. *Accuracy score*

Accuracy is the most important metric in the research. It is also used as a scoring metric to tune the model in a grid search. The metric indicates the fraction of the correct results of the model:

$$Accuracy(y_{true}, y_{pred}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(if\ y_{true} = y_{pred}) (du\ Boisberranger\ et\ al., n.d.) = \frac{TP + TN}{TP + FP + FN + TN}\ (Geron, 2019;\ Mueller\ \&\ Guido, 2017)$$

2. *Precision score*

The precision metric is the number of correct positive predictions divided by the number of total positive predictions.

$$Precision = \frac{TP}{TP + FP}\ (Geron, 2019; Mueller\ \&\ Guido, 2017)$$

3. *Recall score*

Recall is the number of correct positive predictions divided by the number of actual positive outcomes.

$$Recall = \frac{TP}{TP + FN}\ (Geron, 2019; Mueller\ \&\ Guido, 2017)$$

4. *F1 score*

Precision and recall are important metrics. However, none of them separately will not give full picture. F1 is another metric used for binary classification, and it is harmonic mean of precision and recall (Geron, 2019; Mueller & Guido; 2017).

$$F_1 = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} = 2 \times \frac{precision \times recall}{precision + recall} = \frac{TP}{TP + \frac{FN + FP}{2}}\ (Geron, 2019)$$

5. *Jaccard similarity coefficient score*

Jaccard similarity score (JSC) is the intersection of actual and predicted output to their union.

$$JSC = \frac{TP}{TP + FP + FN} = \frac{F_1}{2 - F_1}\ (Labatut\ \&\ Cherifi, 2011)$$

6. *Area under ROC curve*

Receiving operating characteristic (ROC) curve is an important tool to analyze the performance of the binary classifiers. It is a line curve that plots the TP rate against the FP rate. The area under this curve is another way to compare the classifiers (Geron, 2019).

The value of these metrics ranges between 0 and 1: the higher the value – the more suitable the model for consumer credit analysis. In addition, these metrics have a very close relationship.

7. *Type 2 percentage*

Machine learning classifiers as statistical models also have type 1 and type 2 errors. Type 1 error is also known as false positive (FP) error (Schmarzo, 2018). For example, one of the second-tier commercial banks implements the models for credit scoring. The model rejects issuing a loan to a consumer as it declares that it will become a non-performing loan in the future. But, in reality, the consumer is capable of fully repaying loans. In this situation, banks reject to issue debt, but it will not have a significant impact on the liquidity and solvency of the bank.

False-negative (FN) is another type of error which is also known as type 2 error (Schmarzo, 2018). Suppose that the bank issues debt to the consumer based on the output of machine learning which claims that the consumer will not fail to repay it. In reality, the loan becomes non-performing and it has negative consequences to the liquidity of the bank. The higher percentage of type 2 error indicates how worse the model is.

4. Discussion of the Results.

As discussed before, the random undersampling and oversampling techniques are not the best resampling technics. The former leads to loss of information, while the latter leads to overfitting problems. In addition, random undersampling was the only adaptable option for regulatory data in this research. In this section, the result of all classifiers will be discussed based on the data on which they were applied.

Undersampling data

According to the outcomes of the exercises, linear classifiers and the Naïve Bayes classifier are not the best options for credit scoring. This shows that linear models and Naïve Bayes cannot be a solution for credit scoring problems. Table 3 indicates that all classifiers had underfitting problems: the algorithms did not model training data well and performed inadequately on testing data.

Table 3

Accuracy of classifiers applied to undersampled data

	Linear Models		Non-Linear Models					
	Logistic Regression	SGD	Naïve Bayes	kNN	Decision Tree	Random Forest	Neural Networks	XGB
Training	58,6%	58,7%	59,0%	68,6%	68,3%	64,9%	70,8%	69,6%
Testing	58,7%	58,9%	59,0%	67,1%	65,9%	64,6%	70,0%	67,2%

Source: compiled by the authors

In spite of weak performance, the stochastic gradient descent (SGD) classifier gave one of the lowest percentages of type 2 error. Neural Networks classifier generated the best result among the models applied to undersampled data based on most of the metrics. But a high percentage of type 2 error does not make it a favorite. Also, the model takes comparatively more time for computation. Thereby, the extreme gradient boosting (XGB) classifier is the best option, because it is fast, accurate, precise, and also had the second highest accuracy score and second-lowest percentage of type 2 error.

Table 4

Models and performance results

		Metrics						
		Accuracy	*Precision*	*Recall*	*F1*	*JSC*	*AUC_ROC*	*Type 2 error*
Linear	Logistic Regression	58,7%	59,0%	58,5%	58,7%	41,6%	58,7%	20,8%
	SGD	58,9%	57,9%	66,5%	61,9%	44,8%	58,9%	16,8%
Non-Linear	Naïve Bayes	59,0%	60,1%	54,3%	57,0%	39,9%	59,0%	23,0%
	kNN	67,1%	68,4%	64,0%	66,1%	49,4%	67,1%	18,6%
	Decision Tree	65,9%	66,9%	63,5%	65,2%	48,3%	65,9%	18,3%
	Random Forest	64,6%	63,5%	69,4%	66,3%	49,6%	64,6%	15,4%

	Neural Networks	70,0%	72,8%	64,1%	68,2%	51,7%	70,0%	18,0%
	XGB	67,2%	67,4%	67,3%	67,4%	50,8%	67,2%	16,4%

Source: compiled by the authors

Oversampled data

The classifiers performed much better on oversampled data. One of the reasons for the success is the SMOTE resampling technique which brought additional information to the data. Linear classifiers and Naïve Bayes classifiers showed the worst performance results. Other classifiers well-fitted training data and performed well on oversampled data.

Table 5

Accuracy of classifiers applied to oversampled data

	Linear Models		Non-Linear Models					
	Logistic Regression	SGD	Naïve Bayes	kNN	Decision Tree	Random Forest	Neural Networks	XGB
Training	64,1%	64,1%	64,9%	99,9%	76,8%	99,6%	73,6%	74,6%
Testing	64,1%	64,1%	64,9%	83,5%	75,3%	84,8%	73,6%	74,4%

Source: compiled by the author

Neural Networks was a promising model, but there is an insignificant difference between the model performance on undersampled and oversampled data.
Despite of an increase in the accuracy on oversampled data in comparison with undersampled data, the Neural Networks could not outperform non-linear models.

According to Table 6, kNN and random forest classifiers outperformed other classifiers based on all indicators. In addition, both models demonstrated the lowest percentage of type 2 error. However, the random forest classifier outperformed the kNN classifier by all metrics except precision.

Table 6

Models and performance results

		Metrics						
		Accuracy	*Precision*	*Recall*	*F1*	*JSC*	*AUC_ROC*	*Type 2 error*
Linear	Logistic Regression	64,1%	63,9%	65,1%	64,5%	47,6%	64,1%	17,5%
	SGD	64,1%	63,9%	65,1%	64,5%	47,6%	64,1%	17,5%
Non-Linear	Naïve Bayes	64,9%	62,6%	74,2%	67,9%	51,4%	64,9%	12,9%
	kNN	83,5%	85,2%	81,0%	83,0%	71,0%	83,5%	9,5%
	Decision Tree	75,3%	74,8%	76,2%	75,5%	60,7%	75,3%	11,9%
	Random Forest	84,8%	84,7%	85,0%	84,8%	73,6%	84,8%	7,5%
	Neural Networks	73,6%	71,2%	79,1%	75,0%	60,0%	73,6%	10,5%
	XGB	74,4%	73,5%	76,2%	74,9%	59,8%	74,4%	11,9%

Source: compiled by the authors

Conclusion

The results of the study showed that the machine learning models work sufficiently well on the basis of regulatory data collected by the central bank. In addition, the analysis of consumer loans with machine learning algorithms demonstrated a unique insight regarding the features of (bad and good) consumer borrowers as well as provided information to check the accuracy of issued consumer loans by second-tired banks.

In this research, we have presented that it is critical to perform data quality checks (during arrangement and cleaning procedures to eliminate unnecessary variables), and it is essential to deal with an imbalanced set of training data to avert bias in favor of most categories.

In terms of forecasting accuracy of models, oversampled data adjusted by the SMOTE method showed more promising results in comparison with randomly undersampled data. In other words, the oversampled data adjusted by SMOTE helped to minimize the loss of information and increase the forecasting power. Models with well-fitted training data performed better on oversampled data compared with randomly undersampled data.

Furthermore, the non-linear models illustrated more accurate predictions compared with the linear models. Specifically, the non-linear models such as the random forest and kNN classifiers on oversampled data outperformed other classification models, on the other hand, the linear models such as logistic regression and SGD classifier showed the weakest results among compared eight models.

To sum up, the models based on regulatory data can be an adequate foundation for the evaluation of credit risk of issued consumer loans by second-tier banks, and also can help the central bank to predict potential systematic risks. So, according to outcomes of the study, an assessment of credit risk through machine learning can be a good supplement for regulation of the second-tier banks that issue consumer loans.

In order to improve the quality of this research several steps should be done:

Additional data: According to Grier (2012), there are some additional data such as incomes, social status, experience, education, and the sector in which a borrower works, which might bring a positive impact on the performance of algorithms.

In terms of models, there are some approaches that are able to improve their accuracy:

a. Application of hybrid machine learning methods
b. Application of modern machine learning algorithms (CatBoost, LightGBM)
c. Including additional parameters in grid search and over/undersampling

List of References

1. Addo, P., Guegan, D., & Hassani, B. (2018). Credit Risk Analysis Using Machine and Deep Learning Models. Risks, 6(2), 38. doi: 10.3390/risks6020038.

2. Alencar, R. (2017). Resampling strategies for imbalanced datasets. Retrieved from https://www.kaggle.com/rafjaa/resampling-strategies-for-imbalanced-datasets.

3. Baesens, B., Van Gestel, T., Viaene, S., Stepanova, M., Suykens, J., & Vanthienen, J. (2003). Benchmarking state-of-the-art classification algorithms for credit scoring. Journal of The Operational Research Society, 54(6), 627-635. doi: 10.1057/palgrave.jors.2601545.

4. Brown, I., & Mues, C. (2012). An experimental comparison of classification algorithms for imbalanced credit scoring data sets. Expert Systems with Applications, 39(3), 3446-3453. doi: 10.1016/j.eswa.2011.09.033.

5. Brownlee, J. (2016). A Gentle Introduction to XGBoost for Applied Machine Learning. Retrieved from https://machinelearningmastery.com/gentle-introduction-xgboost-applied-machine-learning/.

6. Brownlee, J. (2016). Metrics to Evaluate Machine Learning Algorithms in Python. Retrieved from https://machinelearningmastery.com/metrics-evaluate-machine-learning-algorithms-python/.

7. Brownlee, J. (2020). SMOTE for Imbalanced Classification with Python. Retrieved from https://machinelearningmastery.com/smote-oversampling-for-imbalanced-classification/.

8. Chawla, N., Bowyer, K., Hall, L., & Kegelmeyer, W. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research, 16, 321-357. Doi: 10.1613/jair.953.

9. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. Proceedings of The 22Nd ACM SIGKDD International Conference On Knowledge Discovery and Data Mining, 785–794. doi: 10.1145/2939672.2939785.

10. du Boisberranger, J., Van den Bossche, J., Esteve, L., Fan, T., Gramfort, A., & Grisel, O. et al. User guide: contents – scikit-learn 0.23.2 documentation. Retrieved from https://scikit-learn.org/stable/user_guide.html.

11. Fuchs, M. (2019). Introduction to SGD Classifier - Michael Fuchs Python. Retrieved from https://michael-fuchs-python.netlify.app/2019/11/11/introduction-to-sgd-classifier/.

12. Geron, A. (2019). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). Sebastopol, California: O'Reilly Media, Incorporated.

13. Grier, W. (2012). Credit analysis of financial institutions (2nd ed., pp. 294-296). London: Euromoney Institutional Investor PLC.

14. Hansen, C. (2019). Neural Networks: Feedforward and Backpropagation Explained. Retrieved from https://mlfromscratch.com/neural-networks-explained/#overview.

15. Henley, W., & Hand, D. (1996). A k-Nearest-Neighbour Classifier for Assessing Consumer Credit Risk. The Statistician, 45(1), 77. doi: 10.2307/2348414.

16. Labatut, V., & Cherifi, H. (2011). Evaluation of Performance Measures for Classifiers Comparison. Ubiquitous Computing and Communication Journal, 6, 21-34. Retrieved from https://arxiv.org/abs/1112.4133.

17. Lemaitre, G., Nogueira, F., Oliveira, D., & Aridas, C. 2. Over-sampling – imbalanced-learn 0.5.0 documentation. Retrieved from https://imbalanced-learn.readthedocs.io/en/stable/over_sampling.html#smote-adasyn.

18. Lessmann, S., Baesens, B., Seow, H., & Thomas, L. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, 247(1), 124-136. doi: 10.1016/j.ejor.2015.05.030.

19. Mueller, A., & Guido, S. (2017). Introduction to Machine Learning with Python (1st ed.). Sebastopol, California: O'Reilly Media.

20. Munkhdalai, L., Munkhdalai, T., Namsrai, O., Lee, J., & Ryu, K. (2019). An Empirical Comparison of Machine-Learning Methods on Bank Client Credit Assessments. Sustainability, 11(3), 699. doi: 10.3390/su11030699.

21. Schmarzo, B. (2018). Understanding Type 1 and Type 2 Errors [Blog]. Retrieved from https://www.datasciencecentral.com/profiles/blogs/understanding-type-i-and-type-ii-errors

22. Tsai, C., & Chen, M. (2010). Credit rating by hybrid machine learning techniques. Applied Soft Computing, 10(2), 374-380. doi: 10.1016/j.asoc.2009.08.003.

Appendix

```
# Important libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
import os
path = 'E:\...'   #selecting path to document where the file is located
os.chdir(path)
df_ml = pd.read_csv('filename.csv')
X_df = df_ml.iloc[:,:-1].values
y_df = df_ml.iloc[:,-1].values

# Random Undersampling algorithm from imblearn library
from imblearn.under_sampling import RandomUnderSampler as rus
us = rus(random_state=42)
X, y = us.fit_resample(X_df, y_df)

# SMOTE-NC oversampling algorithm from imblearn library
from imblearn.over_sampling import SMOTENC
sm = SMOTENC(random_state=42, categorical_features=[0,1,2,3,4,5])  # there column of the data are categorical variables
X, y = sm.fit(X_df, y_df)

# Encoding categorical data
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder

# the first column of categorical variables contained 18 different variables (three cities and regions (also former name for one region)), thus create 18 rows
ct0 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[0])], remainder='passthrough')
X=np.array(ct0.fit_transform(X))

# the second column of categorical variables contained 4 different variables (four type of currency, in which a loan was issued), thus create 4 rows
ct1 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[18])], remainder='passthrough')
X=np.array(ct1.fit_transform(X))

# the third column of categorical variables contained 2 different variables (credit card or cash), thus create 2 rows
ct2 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[18])], remainder='passthrough')
X=np.array(ct2.fit_transform(X))

# the fourth column of categorical variables contained 2 different variables (for consumer use or autoloan), thus create 2 rows
ct3 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[18])], remainder='passthrough')
X=np.array(ct3.fit_transform(X))
```

```
# the fifth column of categorical variables contained 2 different variables (male or female), thus create 2 rows
ct4 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[18])], remainder='passthrough')
X=np.array(ct4.fit_transform(X))

# the sixth column of categorical variables contained 2 different variables (local or foreigner), thus create 2 rows
ct5 = ColumnTransformer(transformers=[('encoder', OneHotEncoder(),[18])], remainder='passthrough')
X=np.array(ct5.fit_transform(X))

# Label Encoder of y variable
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = le.fit_transform(y)

# splitting data into train and test dataset
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2, random_state=1)

# feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train[:,-3:] = sc.fit_transform(X_train[:,-3:])
X_test[:,-3:] = sc.transform(X_test[:,-3:])

# Principal component analysis (PCA)
from sklearn.decomposition import PCA
pca = PCA(n_components=a)    # a is quantity where cumulative explained variance ratio > 95%
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)

# Logistic Regression
from sklearn.linear_model import LogisticRegression
log = LogisticRegression().fit(X_train,y_train)
y_tr_log_pred = log.predict(X_train)
y_ts_log_pred = log.predict(X_test)

# Stochastic Gradient Descent Classifier
from sklearn.linear_model import SGDClassifier
sgd=SGDClassifier().fit(X_train,y_train)
y_tr_sgd_pred = sgd.predict(X_train)
y_ts_sgd_pred = sgd.predict(X_test)

# Gaussian Naïve Bayes Classifier
from sklearn.naive_bayes import GaussianNB
nbc = GaussianNB().fit(X_train,y_train)
y_tr_nb_pred = nbc.predict(X_train)
y_ts_nb_pred = nbc.predict(X_test)
```

```
# kth nearest neighbors (kNN) Classifier
from sklearn.neighbors import KNeighborsClassifier
knn=KNeighborsClassifier().fit(X_train,y_train)
y_tr_knn_pred = knn.predict(X_train)
y_ts_knn_pred = knn.predict(X_test)

# Decision Tree Classifier
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier(max_depth=14, criterion='entropy').fit(X_train,y_train)
y_tr_dt_pred = dtc.predict(X_train)
y_ts_dt_pred = dtc.predict(X_test)

# Random Forest Classifier
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier().fit(X_train,y_train)
y_tr_rf_pred = rfc.predict(X_train)
y_ts_rf_pred = rfc.predict(X_test)

# Multi-layer perceptron Classifier (Neural network)
from sklearn.neural_network import MLPClassifier
nnc = MLPClassifier().fit(X_train,y_train)
y_tr_nnc_pred = nnc.predict(X_train)
y_ts_nnc_pred = nnc.predict(X_test)

# Extreme gradient boosting (XGB) Classifier
from xgboost import XGBClassifier
xgb = XGBClassifier().fit(X_train,y_train)
y_tr_xgb_pred = xgb.predict(X_train)
y_ts_xgb_pred = xgb.predict(X_test)

# Cross-validation
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = xgb, X = X_train, y = y_train, cv = 5)
print('Accuracy: {:.2f} %'.format(accuracies.mean()*100))
print('Standard deviation: {:.2f} %'.format(accuracies.std()*100))

### Note: we can put other models instead of XGB to analyze cross-validation result

# Grid Search for Logistic Regression
from sklearn.model_selection import GridSearchCV
parameters = [{'penalty': ['none'], 'solver':['newton-cg', 'sag', 'saga', 'lbfgs']},
              {'penalty': ['elasticnet'], 'C': [0.01, 0.1, 0.25, 0.5, 0.75, 1, 5, 10], 'solver':['saga']},
              {'penalty': ['l2'], 'C': [0.01, 0.1, 0.25, 0.5, 0.75, 1, 5, 10], 'solver':['newton-cg', 'sag',
'saga', 'lbfgs']}]
grid_search = GridSearchCV(estimator = log,
                           param_grid = parameters,
                           scoring = 'accuracy',
                           cv = 5,
                           n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
```

```
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for SGD Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{"loss" : ["hinge", "log", "squared_hinge", "modified_huber"],
            "alpha" : [0.0001, 0.001, 0.01, 0.1], "penalty" : ["l2", "l1", "none"]}]
grid_search = GridSearchCV(estimator = sgd,
                    param_grid = parameters,
                    scoring = 'accuracy',
                    cv = 5,
                    n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for Gaussian Naïve Bayes Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'var_smoothing': [1e-12,1e-10,1e-7,1e-4,1e-3,1e-2,1e-1,1,10]}]
grid_search = GridSearchCV(estimator = nbc,
                    param_grid = parameters,
                    scoring = 'accuracy',
                    cv = 5,
                    n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for kNN Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'n_neighbors': list(range(1, 81))}]
grid_search = GridSearchCV(estimator = knn,
                    param_grid = parameters,
                    scoring = 'accuracy',
                    cv = 5,
                    n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for Decision Tree Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'criterion':['gini', 'entropy'],'max_depth': list(range(1,21))}]
grid_search = GridSearchCV(estimator = dtc,
                    param_grid = parameters,
                    scoring = 'accuracy',
```

```
                         cv = 5,
                         n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for Random Forest Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'n_estimators': list(range(1,21)), 'max_features': ['auto', 'sqrt', 'log2'],
              'max_depth' : ['None',8], 'criterion' :['gini', 'entropy']}]
grid_search = GridSearchCV(estimator = rfc,
                         param_grid = parameters,
                         scoring = 'accuracy',
                         cv = 5,
                         n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for MLP Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'hidden_layer_sizes':[100,200,300,[200,50],[100,100],[200,100]],
              'activation':['identity','logistic','tanh','relu'],
              'solver': ['adam'],
              'learning_rate':['constant','invscaling','adaptive'],
              'max_iter': [1000,1500,2000 ]}]
grid_search = GridSearchCV(estimator = nnc,
                         param_grid = parameters,
                         scoring = 'accuracy',
                         cv = 5,
                         n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

# Grid Search for XGB Classifier
from sklearn.model_selection import GridSearchCV
parameters = [{'n_estimators': [1000], #number of trees, change it to 1000 for better results
              'max_depth': [6,7,8],
              'learning_rate': [0.05], #so called `eta` value
              'objective':['binary:logistic'],
              'tree_method':['exact'],
              'min_child_weight': [11],
              'subsample': [0.8],
              'colsample_bytree': [0.7]}]
grid_search = GridSearchCV(estimator = xgb,
```

```
                  param_grid = parameters,
                  scoring = 'accuracy',
                  cv = 5,
                  n_jobs = -1)
grid_search.fit(X_train, y_train)
best_accuracy = grid_search.best_score_
best_parameters = grid_search.best_params_
print('Best accuracy: {:.2f} %'.format(best_accuracy*100))
print('Best parameters: ',best_parameters)

### After grid search, all best parameters should be implemented to be sure that the model with the best accuracy give higher accuracy and after that other metrics should be analyzed

# Example where all metrics that were used
from sklearn.metrics import confusion_matrix, accuracy_score
knn_cm_tr = confusion_matrix(y_train,y_tr_knn_pred)
print(knn_cm_tr)
accuracy_score(y_train, y_tr_knn_pred)

knn_cm_ts = confusion_matrix(y_test,y_ts_knn_pred)
print(knn_cm_ts)
accuracy_score(y_test, y_ts_knn_pred)

from sklearn.metrics import roc_auc_score, jaccard_score, f1_score, precision_score, recall_score
print(roc_auc_score(y_test,y_ts_knn_pred))
print(jaccard_score(y_test,y_ts_knn_pred))
print(f1_score(y_test,y_ts_knn_pred))
print(precision_score(y_test,y_ts_knn_pred))
print(recall_score(y_test,y_ts_knn_pred))

### Here, the metrics were used to analyze the performance of kNN Classifier, the variables should be changed to achieve the result of the other models
```

LIQUIDITY OF THE GOVERNMENT SECURITIES MARKET: PROBLEMS AND PROSPECTS FOR SOLUTIONS

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This Paper discusses the factors behind the low liquidity and depth of the government securities market in Kazakhstan. The potential of market development, options for improving its structure and functioning are considered. We focus on the microstructural characteristics of the government securities market, which affect the level of its liquidity. We discuss factors such as the structure of debt instruments, competition and concentration, nomenclature management, and the level of information transparency. In particular, we propose to discuss and try to understand how certain changes in some of these factors over time can affect the evolution of liquidity, the depth and structure of the market.

Key Words: government securities, liquidity, government debt, securities market.
JEL-Classification: H63, G11, G14, G15.

1. Introduction

In many countries, the government debt market is the most important link in the efficient functioning of the entire financial system. Since the government securities market performs several key functions, the central banks practicing inflation targeting policies show particular interest in it. This is where they often conduct their domestic monetary operations and retrieve information about the expectations about future changes in interest rates. The governments raise funds in this market and it becomes the main space for implementing their policies for the central banks, which are entrusted with the function of placing agent. Due to their virtually risk-free nature, government securities serve as a pricing benchmark and hedging instrument for other fixed income securities. They serve as collateral or as part of regulatory requirements for various financial intermediaries, allowing them to finance their operations. Finally, since other fixed income markets share many of the structural and institutional characteristics of the government securities market, an insight into how the government securities market functions allows central banks to better understand other fixed income markets. It is obvious that liquidity is an important aspect of all financial markets, and the task of increasing and maintaining the liquidity of the government securities market should become of the most important one for both the central bank and the government [10].

Because of its multidimensional nature, the concept of market liquidity defies simple definition or easy measurement. Although most market participants to some extent determine whether a particular market is liquid, few of them will be able to pinpoint all the factors that affect the liquidity of that market. Nevertheless, there is a certain consensus: a liquid market is a market in which large transactions are concluded quickly, with little or no impact on prices [2].

In the literature, market liquidity is often defined in terms of four dimensions: responsiveness, depth, width, and sustainability. Efficiency means the speed at which a deal of a given amount is closed; below the depth means the maximum amount of transaction for a given spread; the width means the cost of providing liquidity (a narrow spread implies more liquidity); and the sustainability means the speed of return of prices to their equilibrium level after a large transaction or how quickly the imbalance disappears in flow transactions [1]. However, various aspects of liquidity can correlate strongly.

Liquidity of the government securities market affects the core activities of the central bank in three ways. First, liquidity of the market affects the monetary policy formation and implementation, the efficiency of operations in the open market. Since the regulator, based on the data retrieved from prices, receives information about current and expected monetary conditions, liquidity determines how objectively the pricing process itself is taken into account.

Thus, the degree of market liquidity affects the confidence of the central bank in its expectations and how efficiently the market is able to aggregate information about certain categories of investors into prices. Low market liquidity prevents the pass-through of monetary policy measures onto fixed income instruments with a longer maturity.

Second, in some cases, market illiquidity is often one of the symptoms, if not the cause, of systemic financial failures. With low market liquidity, stress shocks to financial markets are exacerbated by associated problems of trust, circulating liquidity and solvency of key financial players. These problems can lead to disruptions in payment systems and reduce the efficiency of capital allocation. Whereas a liquid market, on the contrary, helps to weaken shocks, mitigating a chain of panic reaction of some participants, since it carries more information on expectations in monetary conditions. On the other hand, fluctuations in the market liquidity can have a direct impact on the activities of supervisors, both as a lender of last resort and as a financial stability monitor. In addition, when calculating market risks, liquidity and liquidation risks are often ignored, defined as the risk of inability to liquidate a position in a timely manner at a reasonable price. In particular, the VaR (Value-at-Risk) methodology assumes that prices change continuously and ignores the possibility that price movements may be intermittent in the environment of high liquidation risks [9]. These factors can cause and exacerbate failures in financial stability.

Third, the central bank shares the government's desire to minimize debt service costs. High liquidity in the secondary market tends to facilitates the issuance by the government of large amounts of debt at relatively low rates. This is due to the fact that the active demand of investors in the primary market directly depends on the ability to predictably trade in the secondary market. Thus, the government, in its role of debt placing agent, should work with the central bank to improve the integrity and efficiency of the government securities market.

Market structure affects liquidity. Usually, prices in the government securities markets are set by quotations of many participants. Consequently, the study of factors affecting the incentives of market participants is one of the ways to assess the level of market liquidity. The overall liquidity of the market also depends on the liquidity of specific securities. The liquidity of a paper, in turn, depends on several factors, including its volume and effective supply. Other factors affecting the level of liquidity in the government securities market include transparency, transaction costs, interest rate volatility and activity in adjacent markets.

This survey is divided into three parts. We focus on the microstructural characteristics of the government securities market, which affect its liquidity level. We discuss factors such as the structure of debt instruments, competition and concentration, nomenclature management, and the level of information transparency. In particular, we propose to discuss and try to understand how certain changes in some of these factors over time can affect the evolution of liquidity, the depth and structure of the market.

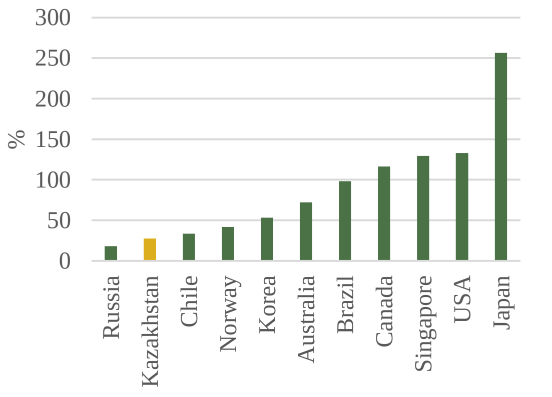
2. Kazakhstan's Debt Market

The government debt market in Kazakhstan emerged in the 1990s and grew with the uprising of the pension system [31]. Now, the government debt market has a fairly significant volume, although it is much lower than the government debt in relation to GDP in more developed countries. Despite its long history, the government securities market, like the entire stock market in Kazakhstan as a whole, remains undeveloped, illiquid and ineffective. Confidence in the stock market in Kazakhstan remains low, and banks are the main financial intermediaries. Unlike countries with a developed stock market, the business in Kazakhstan is mostly financed through the banking system, and households prefer to keep funds in banks rather than invest them on the stock exchange. These factors reduce both the number of issuers and the number of investors in the stock market. The main portion of securities listed on the Kazakhstan Stock Exchange falls on government securities, and securities of companies in the quasi-government and financial sectors.

The institutional investor market in Kazakhstan, which is already limited enough, has narrowed even further since the merger of pension funds in 2014. This has practically destroyed the liquidity of the market. At the same time, it was not a priority task for the Ministry of Finance of the Republic of Kazakhstan (MoF RK) to increase liquidity of the government securities market, since, on the one hand, a significant part of the budget deficit was financed with transfers from the National Fund of the Republic of Kazakhstan, and, on the other hand, the presence of captive investors supported the demand for public debt.

Figure 1

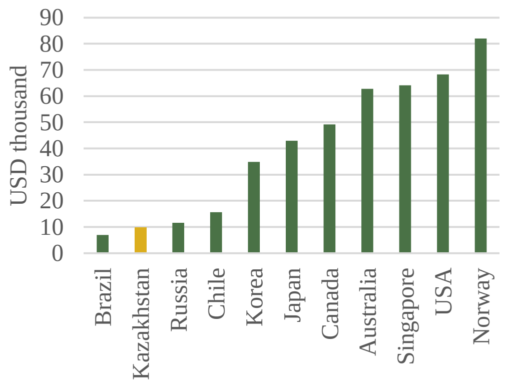
Government debt to GDP



Source: IMF, as at 01.04.2021

Figure 2

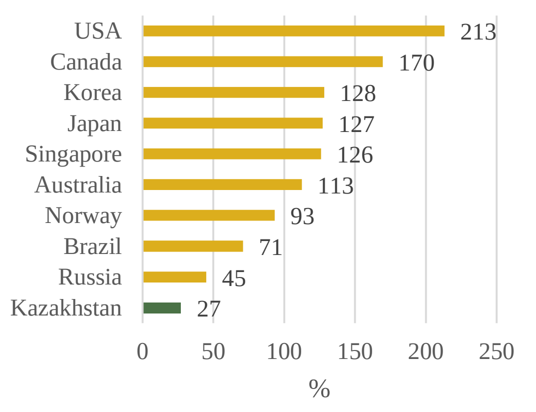
GDP per capita



Source: IMF, as at 01.04.2021

Figure 3

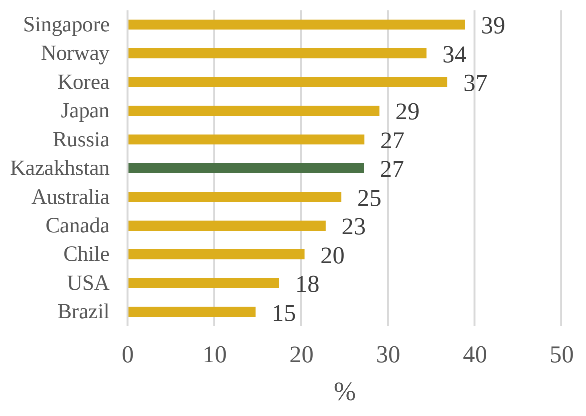
Stock market capitalization to GDP



Source: Bloomberg, KASE.
Note: data on Kazakhstan is presented based on performance in 2020; data on other countries is presented as at 03.06.2021.

Figure 4

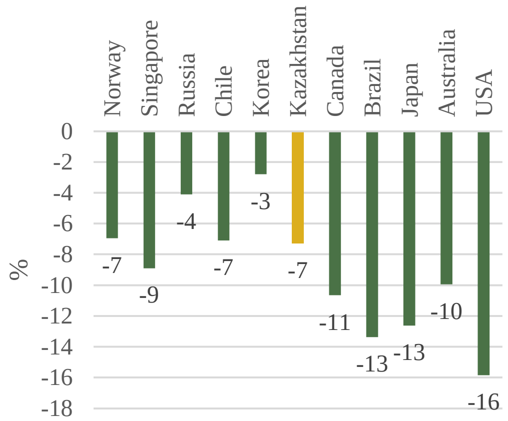
Gross national savings (% of GDP)



Source: IMF

Figure 5

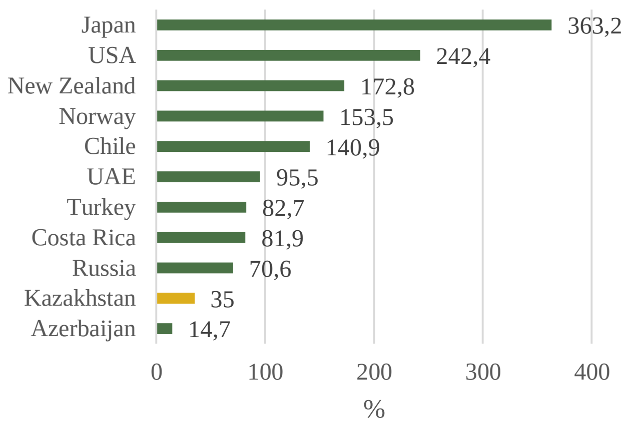
Net government lending/borrowing (% of GDP)



Source: IMF

Figure 6

Domestic credit provided by the financial sector (% of GDP)



Source: World Bank

3. Liquidity and Structure of the Government Securities Market

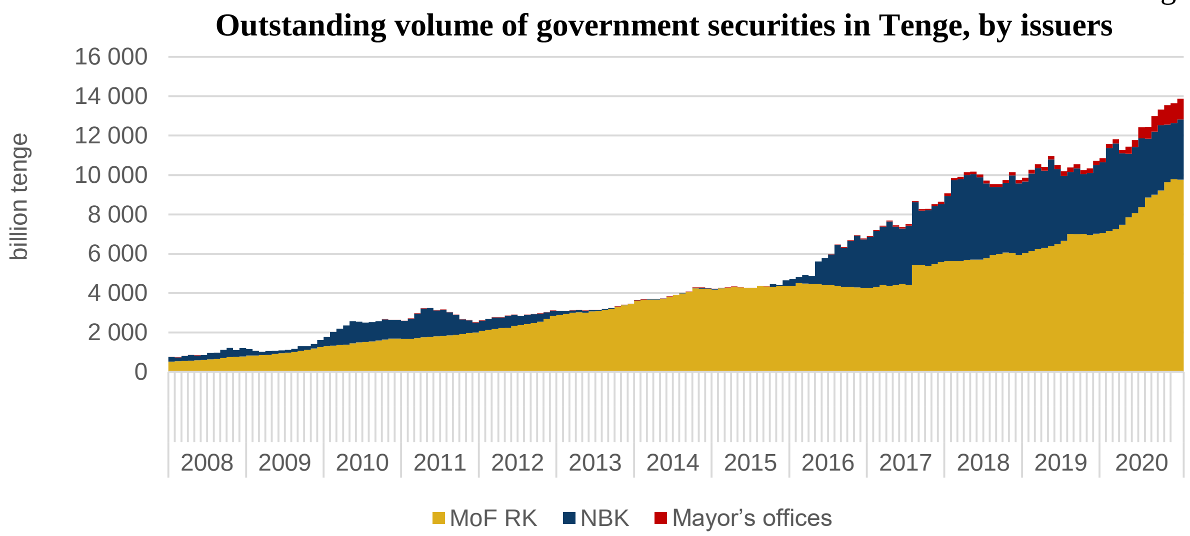
At the end of 2020, the total outstanding volume of government securities of the Republic of Kazakhstan issued in Tenge amounted to 14.3 trillion tenge (Figure 7). Treasury bonds issued by the Ministry of Finance of Kazakhstan (hereinafter referred to as the MoF's bonds) account for the largest share of outstanding government securities. Thus, in 2013-2015, the main issuer of government securities was the Ministry of Finance. However, in 2016, the National Bank of Kazakhstan activated the placement of notes within the framework of the interest rate management policy, which led to a reduction in the share of government securities of the Ministry of Finance of Kazakhstan to an average of 60-65% (Figure 7).

The main issuer of government debt is the Ministry of Finance of Kazakhstan, which issues bonds in Tenge, as well as Eurobonds in foreign currency, government securities with a fixed coupon and government securities with an indexed coupon. In order to construct a risk-free yield curve in the medium and long-term horizon, the key role is played by government securities with a fixed coupon, issued in Tenge. At the same time, recently the Ministry of Finance of Kazakhstan has resumed the issuance of discount bonds with a maturity of up to one year and government securities with a fixed coupon with a maturity of up to three years. Thus, the profitability of government securities issued by the MoF RK also began to influence the formation of the yield curve at the short-term end.

The government securities market of local executive bodies in Kazakhstan has low activity and an insignificant volume of placement in the total volume of government securities (7% at the end of 2020); it does not have a significant impact on the government securities market and on the formation of the yield curve of government securities.

Therefore, the key role in the construction of a risk-free yield curve with a maturity of up to one year is played by the notes issued by the National Bank of Kazakhstan, and with a maturity of more than one year – by bonds of the Ministry of Finance of Kazakhstan issued in Tenge. However, low liquidity of these markets remains the main obstacle for building an adequate curve. Further, we will take a closer look at these markets and the reasons limiting their liquidity.

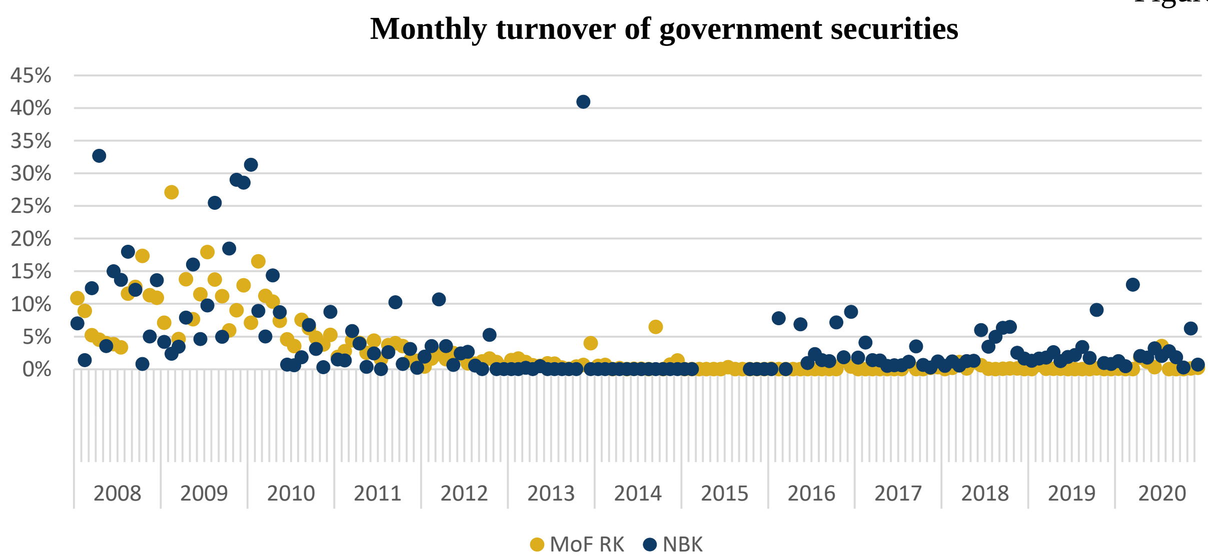
Figure 7



Source: Central Securities Depository

The government securities market of the Republic of Kazakhstan has low liquidity. Despite a significant volume of the primary market, transactions in the secondary market are extremely rare. So, the maximum value of the monthly turnover of bonds of the Ministry of Finance in 2020 was 3.6%, while during 5 months out of 12 months this indicator was close to zero (Figure 8). Liquidity in the government securities market began to decline in 2012 and further decreased in 2013. In 2012, the demand for government securities decreased due to the growing devaluation expectations and easing of regulatory requirements regarding investment of resources of pension funds [25]. In 2013, the consolidation of pension funds was announced and severe restrictions were imposed on the investment activities of pension funds, the sale of government securities from pension portfolios was prohibited [19], which explains the decreased liquidity of government securities in 2013.

Figure 8

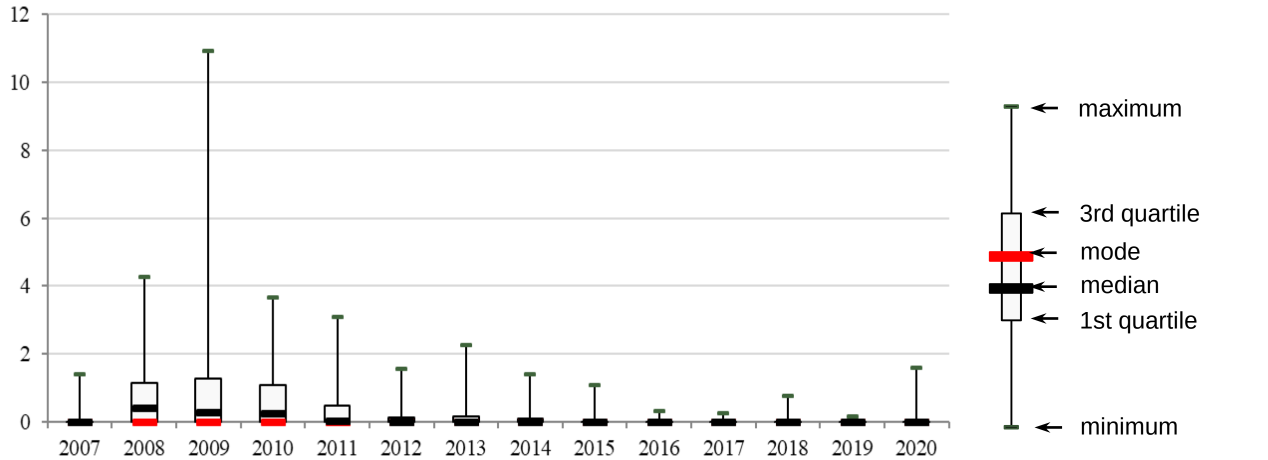


Source: Central Securities Depository

Note: the indicator is calculated as the ratio of operations in the secondary market over the month and the placed volume as at the beginning of the month.

Figure 9

Annual turnover of the MoF's bonds, by issues

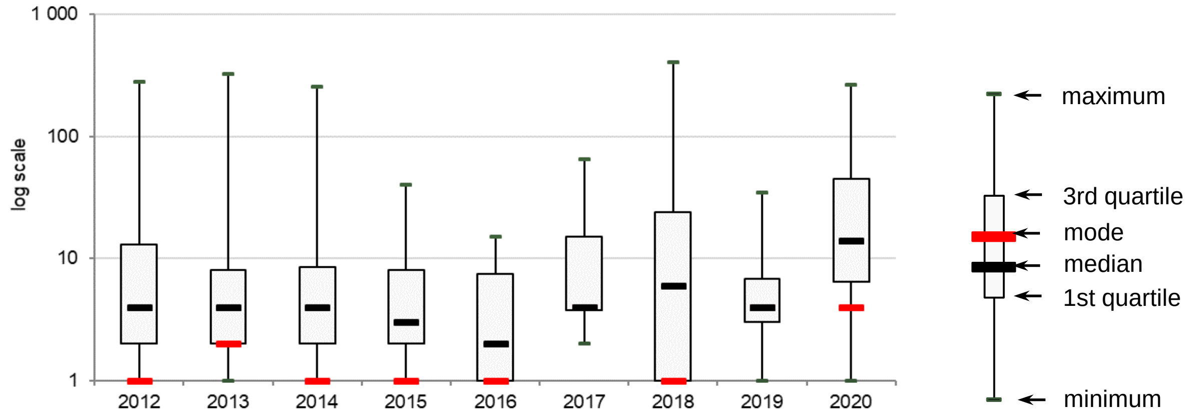


Source: Central Securities Depository

At the same time, the analysis of the number of transactions in the context of individual securities issues demonstrates positive dynamics over the past few years. The number of transactions on individual issues increased, which is explained by the efforts of the Ministry of Finance to enlarge the volume and increase liquidity of individual issues in order to include MoF's bonds in the international global bond indices. Nevertheless, liquidity of most issues remains low, and the number of transactions on a significant part of issues does not exceed 1-4 transactions per year. In addition, for the majority of outstanding issues, transactions on the secondary market are not conducted at all. So, out of 143 issues in circulation in 2019, transactions in the secondary market were conducted on 18 issues only, and in 2020 – in 46 out of 111 outstanding issues.

Figure 10

Annual number of transactions in the secondary market of MoF's bonds, by issues



Source: Central Securities Depository

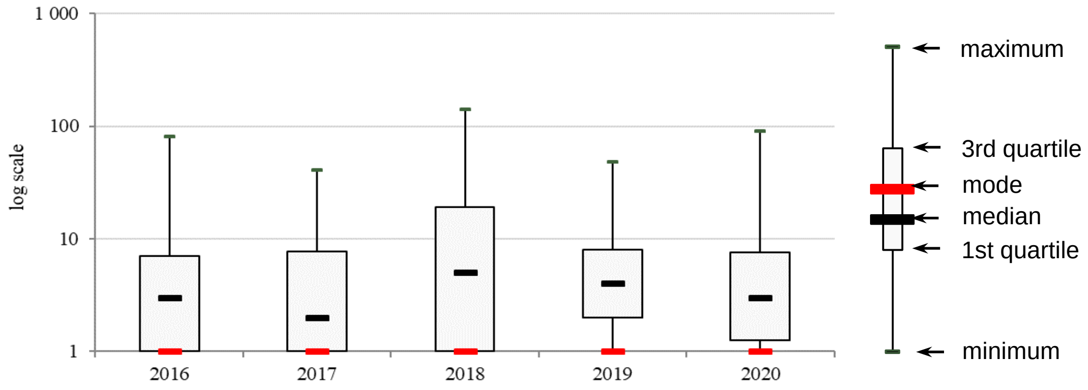
Note: only those issues that were transacted in the secondary market were taken into account in designing the graph.

The Market of the NBK's Notes

The market of the NBK's notes has a relatively large turnover (Figure 8); nonetheless, it is also low liquid. There is not more than one transaction a year among a significant part of note issues (Figure 11).

Figure 11

Annual number of transactions in the secondary market of NBK's notes, by issues



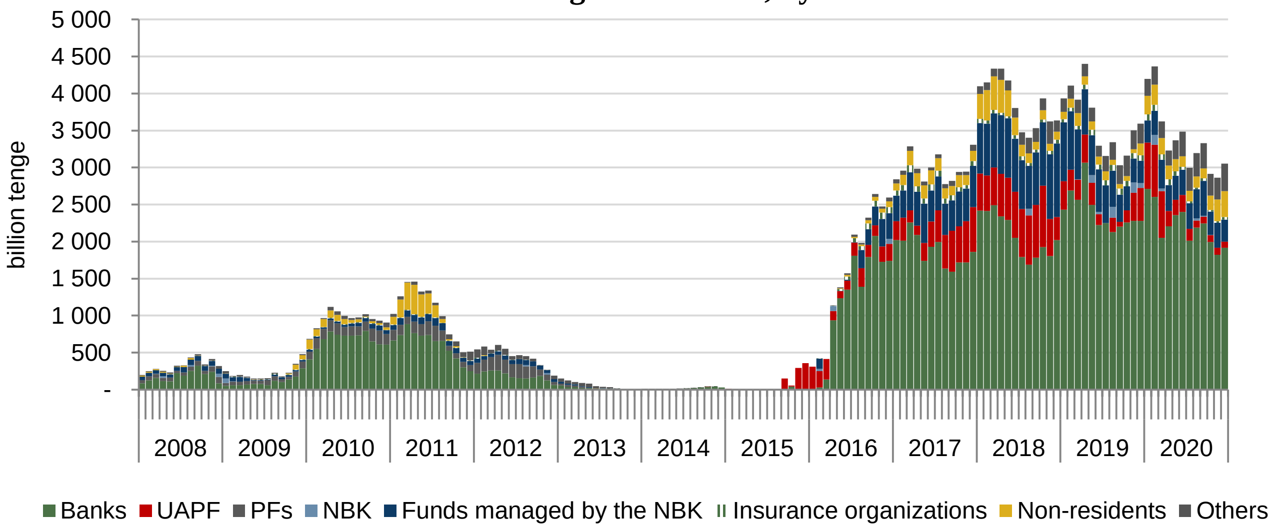
Source: Central Securities Depository

Note: only those issues that were transacted in the secondary market were taken into account in designing the graph.

In 2013-2015, the volumes of notes issued by the NBK were insignificant and their major portion was held by pension funds in 2013 and by the UAPF in 2015 (Figure 12). In 2016-2017, the banking sector experienced a liquidity surplus due to the budget deficit, bank rehabilitation programs and de-dollarization of their liabilities. In 2015, the NBK switched to inflation targeting and in 2016, within the framework of the interest rate management program, began to withdraw excess liquidity using notes.

Figure 12

Outstanding NBK's notes, by holders



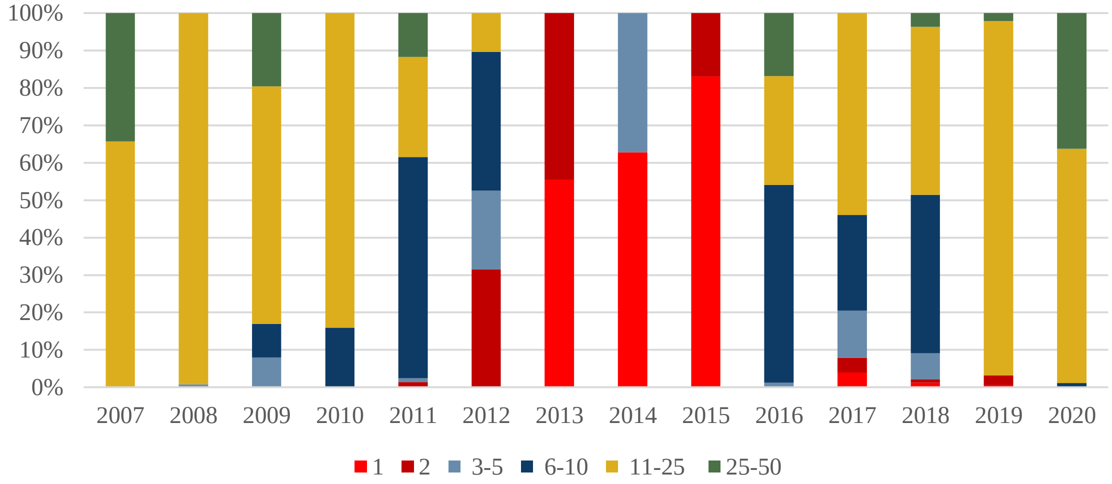
Source: Central Securities Depository

The yields on the notes reflected expectations of voluntary market participants regarding the cost of the tenge liquidity, and the maturity of notes reflected the banks' short investment horizon. Therefore, since 2016, the main demand for notes has been formed at the expense of the second-tier banks. Non-residents and insurance organizations also participate in the notes market as voluntary investors, but their share is insignificant. Due to the interest from market participants, the NBK's notes are distributed more evenly, most of note issues have a larger number of holders than government securities of the MoF RK, while government securities of the MoF RK have a significant concentration in the context of holders.

Figure 13

NBK's note issues are distributed more evenly among holders

Distribution of the NBK's note issues depending on the number of holders



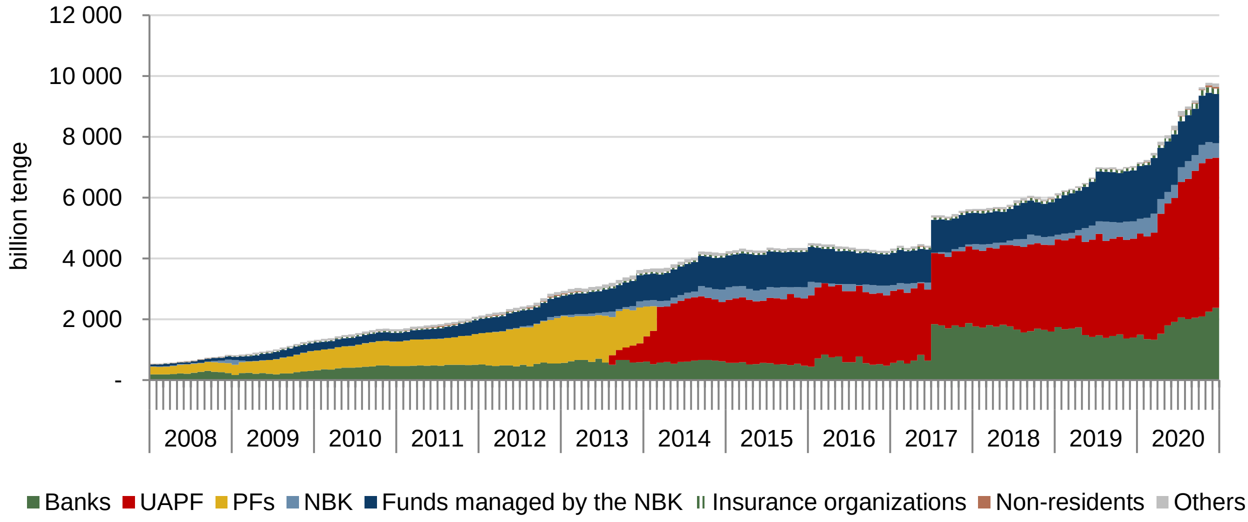
Source: IRIS Finance

Reasons for Low Liquidity. The main reason for the decreased liquidity in the government securities market of the MoF RK after 2014 was the merger of pension funds into the Unified Accumulative Pension Fund (UAPF). Historically, pension funds have been the main investors in the government securities market. This happened due to prudential capital adequacy requirements, whereunder all assets of pension funds were weighted based on their risk according to the regulator, and depending on this number the level of capital adequacy was determined. Government securities of the Republic of Kazakhstan are considered risk-free, and therefore their weight is zero and, accordingly, do not require additional capitalization, which was the reason for the demand for government securities on the part of pension funds [31].

After the merger of pension funds, the UAPF continued to be the main investor in the market of the MoF's bonds. In addition, a significant share of the MoF's bonds was bought up by other funds managed by the National Bank of Kazakhstan. With the transition of the National Bank of Kazakhstan to the inflation targeting regime, the real yield on government securities became positive, which allowed the UAPF to build the yield on the pension portfolio above inflation. Despite the increase in the real yield on government securities, its level did not always meet the requirements of market participants; therefore, their participation in the market of the MoF's bonds was limited. In addition, the attractiveness of government securities for market participants reduced the risk of devaluation of Tenge. Under the pressure on the Tenge exchange rate, the yield on government securities ceased to reflect the risk premium on the tenge instruments; a spread usually appeared between the yield on government securities and NDF rates [31]. With the emergence of the NBK's note market, the demand on the part of banks shifted from the government securities market to the notes market, since the maturity of notes was more consistent with the investment horizon of banks and as a result of short maturity, their requirements for liquidity premium were decreasing.

Figure 14

Outstanding MoF's bonds, by holders



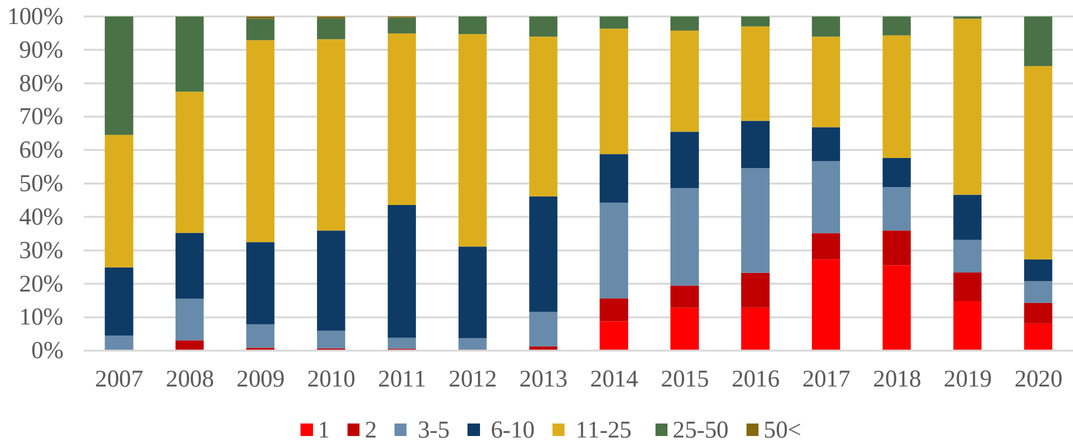
Source: Central Securities Depository

In addition, one of the factors reducing liquidity of the government securities market was the policy of the Ministry of Finance of Kazakhstan to launch many issues with small volumes [27]. Given such size of issuance, one issue could end up in the hands of one or more holders. After the merger of pension funds, a significant share of such issues ended up in the hands of the UAPF, which explains the absence of transactions on them (Figures 15, 16).

Figure 15

The number of one-holder issues increased after the pension funds merger

Distribution of the NBK's notes issues depending on the number of holders

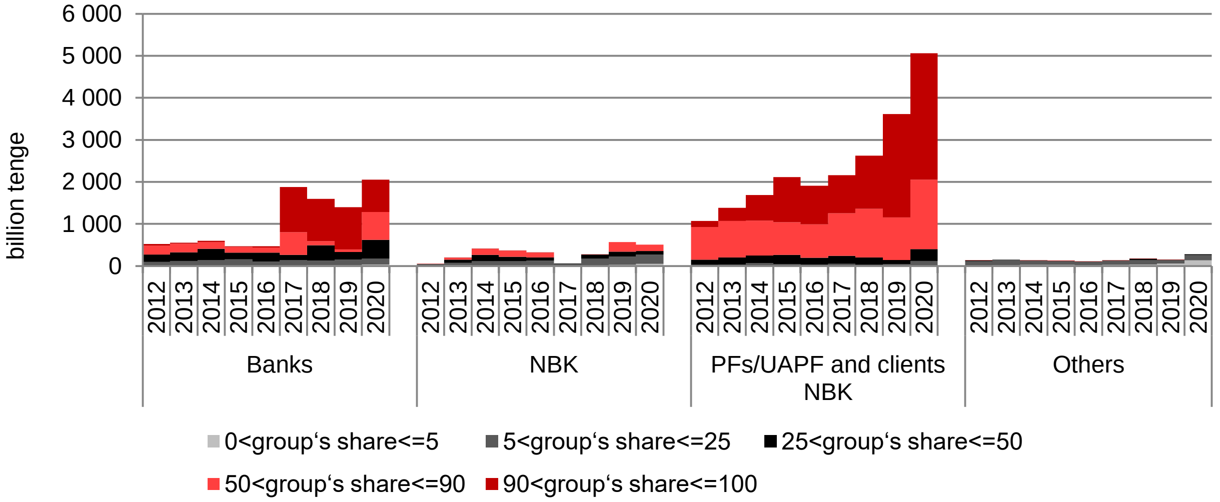


Source: IRIS Finance

Figure 16

Growing concentration of the MoF's bonds held by captive investors

The distribution of the MoF's bonds other than MEUZHKAM, by the percentage of types of holders in the volume of each issue



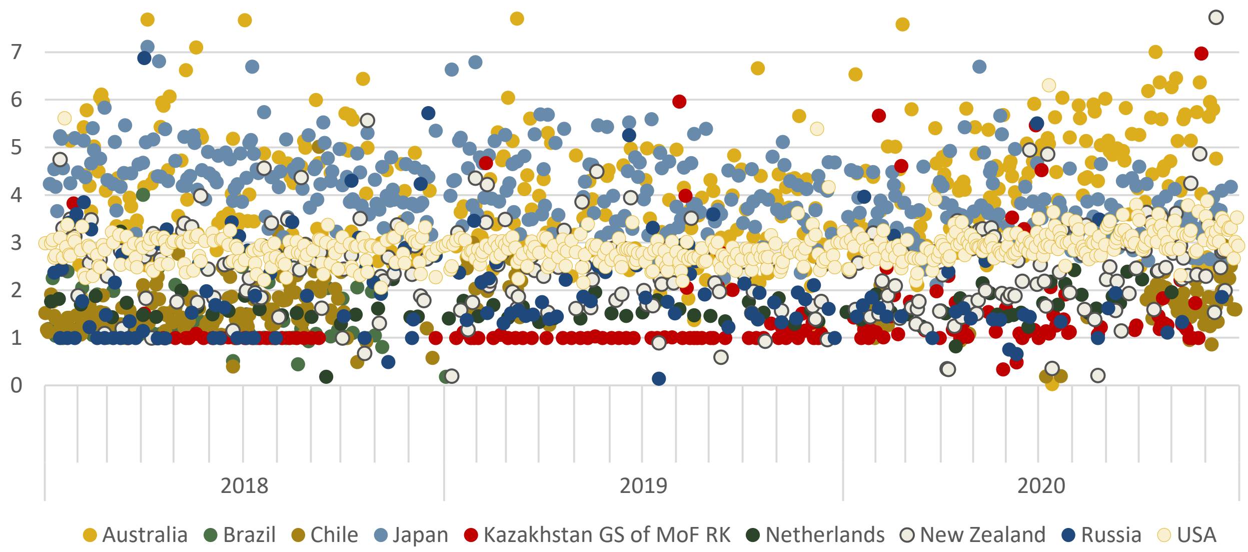
Source: Central Securities Depository, NBK's computations

Note: government securities purchased by a systemically important bank in July 2017 as part of its turnaround were excluded from the sample

The demand for government securities in the countries with better developed markets significantly exceeds the demand for government securities in Kazakhstan (Figure 17). At the same time, in most cases the bid-to-cover[1] on auctions in Kazakhstan varies from 1 to 2, that is the demand either fully covers the volumes of auctions of Kazakhstan's government securities or exceeds them, sometimes nearly twice as much.

Figure 17

Bid/Cover ratio of the government securities auctions



Source: Refinitiv Eikon

Note: on the graph, the Bid/Cover ratio is weighted by the volume of auctions a day.

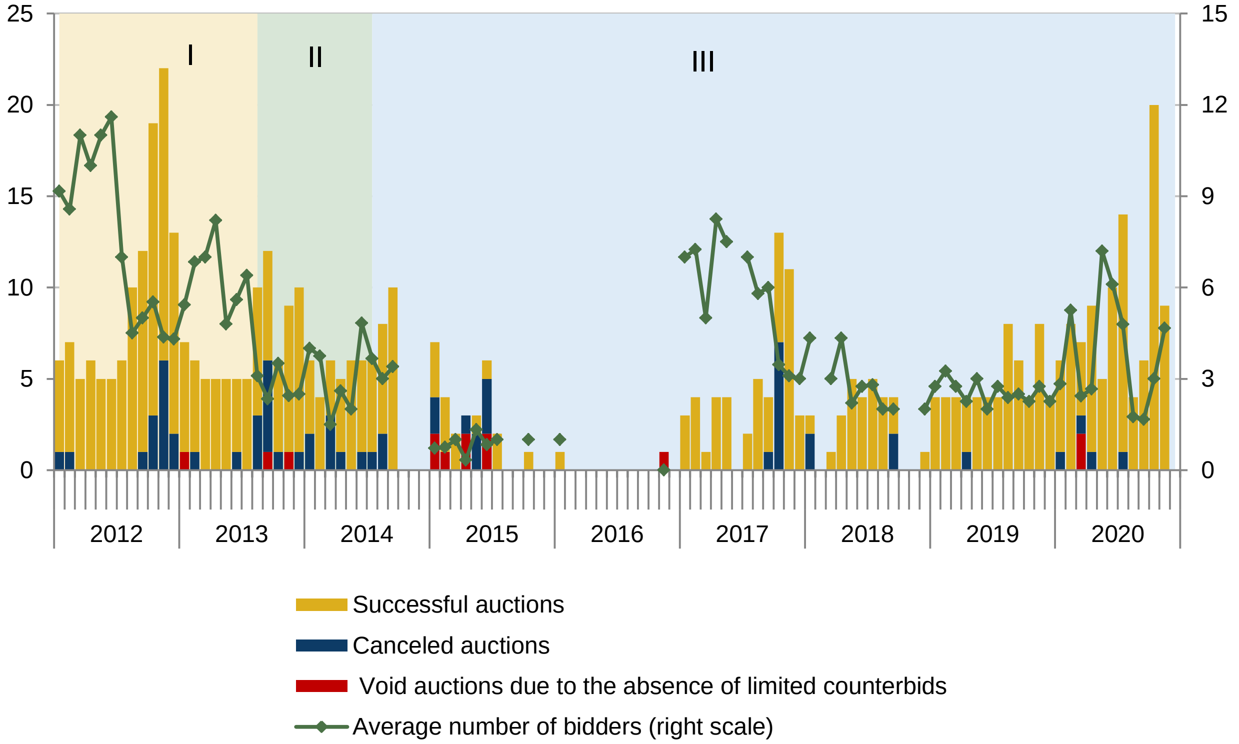
[1] In this case, bid-to-cover reflects the volume of active bids in relation to satisfied bids.

Despite a significant demand in the analysis of the volume of bids, the analysis of the number of auction participants shows that the demand for the MoF's bonds is limited. In 2019, on average, about three buyers participated in the auctions of government securities of the MoF RK. The limited demand for the government debt under normal conditions should have led to an increase in the yield on government securities; however, the presence of captive investors allowed the Ministry of Finance to place debt below the cost required by market investors. So, the major demand in 2019 was built by captive investors. In addition to the non-competitive price, the demand from market participants decreased due to the increased maturity of the placed government securities because of the uneven structure of repayment of obligations of the Ministry of Finance (Figure 21) and their concentration on the near-term maturities in 2018-2019. The MoF began to place government securities with maturities over 10 years in order to distribute the structure of debt repayment for longer periods. Market participants, in particular, banks, during this period mainly participated in the NBK's notes market, where the investment horizon is shorter and more corresponds to their needs. Thus, taking into account that transactions are extremely rare in the secondary market, and the Ministry of Finance issued only long-term bonds, in 2018-2019 the yield curve on maturities from one to 10 years was formed on the basis of transactions that became irrelevant long time ago. Accordingly, the information value of the yield curve of government securities was extremely low; the market did not have a benchmark for the cost of risk-free funds at the mid-term end of the yield curve, which hindered the development of the capital market as a whole.

To maintain the relevance of the yield curve of the MoF's government securities, it is necessary to constantly ensure that there are events at all maturities of the yield curve.

Figure 18

Bid/Cover ratio of the MoF's auctions



Source: KASE

Note: 1) government securities purchased by a systemically important bank in July 2017 as part of its turnaround were excluded from the sample; 2) I – the period of private accumulative pension funds; II – the period of merger; III – the UAPF period.

We would like to remind that one of the factors reducing liquidity was the high fragmentation of government securities issues. So, for example, in 2017 there were 147 issues of government securities of the MoF RK in circulation in Kazakhstan, while in Australia the number of active issues was 32, in Russia – 43, and in New Zealand – 13. Moreover, the number of participants in these markets is much more than in Kazakhstan, and, accordingly, the depth of these markets significantly exceeds that of the government securities market in Kazakhstan. In our opinion, a decrease in the level of fragmentation of government securities should increase their liquidity. Theoretically, with an increase in the volume and a decrease in their number, one government securities issue will have more holders. To reduce the fragmentation of securities issues, in accordance with the international practice it is necessary to carry out additional placements of "new" (on-the-run[2]) government securities issues with a view to increase their volume and to redeem "old" (off-the-run[3]) securities issues at key points of the yield curve. Therefore, market liquidity will be concentrated in a small number of securities, which should increase their liquidity. In addition, holding auctions on active government securities will provide up-to-date information about value, which will increase the information value of the yield curve and will serve as a benchmark for the cost of tenge funds for adjacent capital markets.

In 2019, the Agreement on the Coordination of Macroeconomic Policy Measures (hereinafter referred to as the Agreement) was concluded between the Government of the Republic of Kazakhstan and the National Bank of the Republic of Kazakhstan, which is aimed at enhancing the confidence of market participants in the debt management policy and increasing liquidity of the government securities market. By agreement with the Ministry of Finance, it undertook the obligation to publish the schedules of government securities issues for the coming year, as well as to hold repeated auctions for the placement of government securities, to enlarge the government securities issues and reduce their number to 30-40 issues in circulation in the medium and long term.

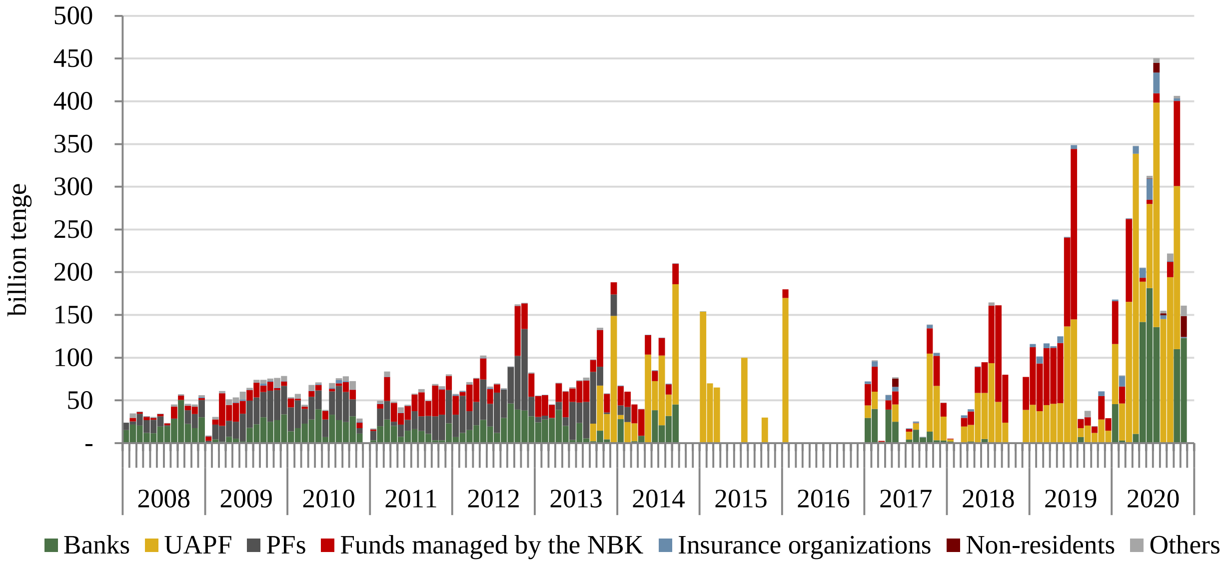
In addition, in the middle of 2019, the Ministry of Finance of Kazakhstan changed the schedule for issuing government securities in such a way that, starting from August 2019, the Ministry of Finance began to place government securities with different maturities of up to 10 years [27]. As a result, the Ministry of Finance began to make additional placements of government securities with maturity of less than 3 years, and in 2020 resumed the issuance of MEKKAM – discount government securities with maturity of up to 1 year.

The measures taken increased liquidity of the government securities market in 2020, market participants again began to participate in the government securities market of the MoF RK, and the number of auction participants went up. The greater interest of market participants in the MoF's bonds market was also driven by the fact that in the middle of 2020 the National Bank of Kazakhstan stopped issuing one-year notes. Thus, the demand for one-year notes of the National Bank of Kazakhstan that existed in the market was shifted to the market of the MoF's bonds.

[2] On-the-run – issues placed most recently among issues with a certain maturity.
[3] Off-the-run – issues, which are placed earlier, before the most recent ("new") issue and are still in circulation.

Figure 19

Volume of MoF's primary market by participants



Source: Central Securities Depository

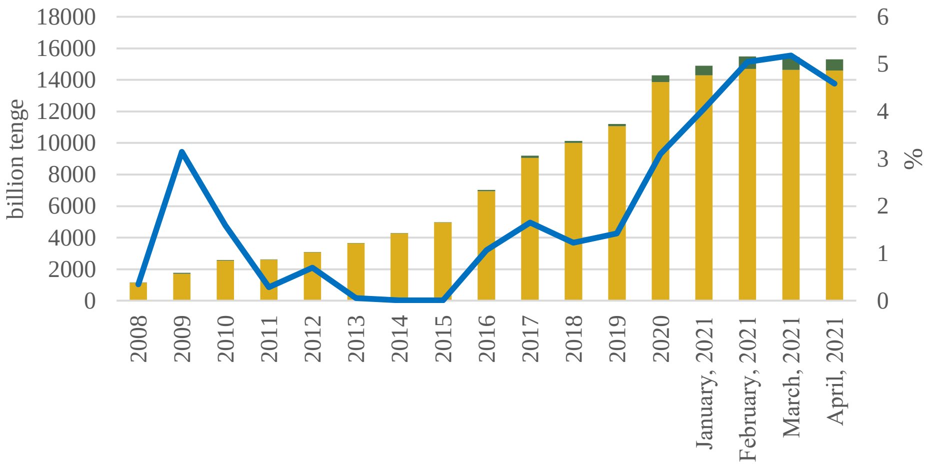
Note: government securities purchased by a systemically important bank in July 2017 as part of its turnaround were excluded from the sample.

It is worth mentioning that the demand for Kazakhstani government securities issued in Tenge is formed mainly owing to the domestic market, while in more developed markets a significant part of the demand is generated by foreign investors. A larger number of participants in developed markets of government securities creates a more competitive environment and enables to increase the efficiency of pricing.

In 2018, the National Bank of the Kazakhstan and the Ministry of Finance of Kazakhstan initiated a joint effort to increase attractiveness of the government securities market for foreign investors: 1) the work was started to include Kazakhstani government securities in the JP Morgan Government Bond Index-Emerging Markets (GBI-EM; 2) in August 2020, the international payment line was upgraded to the Delivery versus Payment type on the National Bank's notes and the MoF's bonds. The share of non-residents in the structure of holders of government securities of the Republic of Kazakhstan remains low; however, as a result of the measures taken, it began to increase. The largest growth was observed in 2020-2021: as at June 1, 2021, the share of non-residents among holders of government securities of the Republic of Kazakhstan reached 5.7%.

Figure 20

Share of non-resident holders of the government securities of Kazakhstan (excluding eurobonds)



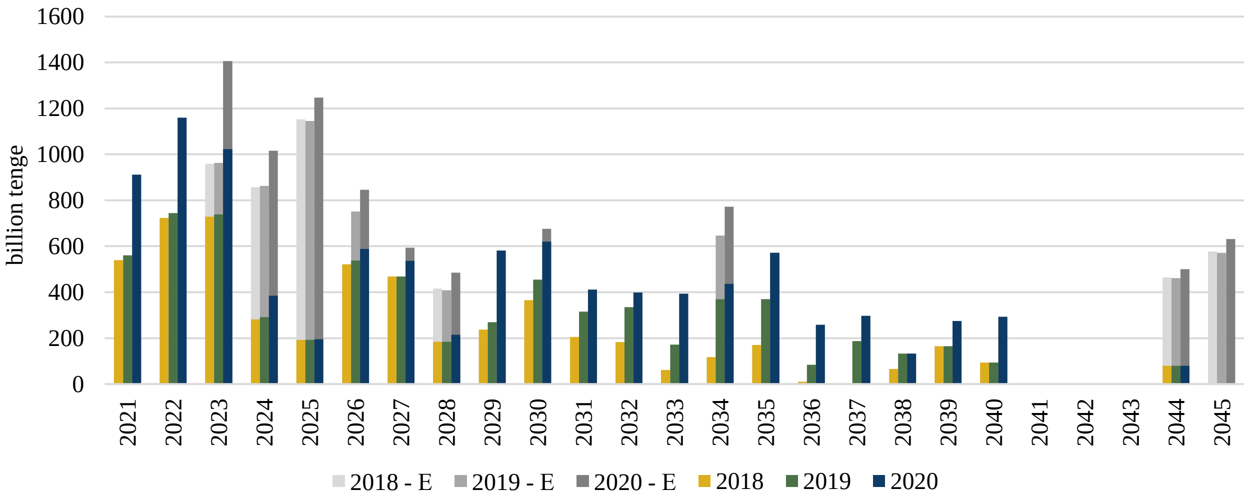
Source: Central Securities Depository, NBK's computations

Thus, in the past years, government debt management policy of Kazakhstan was largely focused on the current problems of the budget financing, and the problems of liquidity of the government securities market were not a priority. When issuing debt, the Ministry of Finance of Kazakhstan was guided by the present value, not taking into account liquidity risks associated with the concentration of liabilities on crtain maturities and currency risks when liabilities in foreign currency were issued.

The lack of a clear policy for managing the state debt is clearly illustrated by the time structure of redemption of bonds issued by the Ministry of Finance. The pursuit of low foreign exchange rates in the mid-2010s, followed by depreciation of the tenge, led to a serious imbalance in the principal repayment schedule. This information is obviously already included in the rates of borrowing.

Figure 21

Principal debt repayment schedule on government securities of the MoF (including eurobonds) as at period-end



Source: Central Securities Depository, NBK's computations

Note: 1) E – MOF's liabilities on redemption of Eurobonds; 2) the amount of principal debt repayment on Eurobonds has been converted into the tenge at the official exchange rates at period-end.

So, in 2019, the principal debt repayment amounted to 3.37% of non-oil revenues to the budget, and in 2020 it increased to 4.23%. Also, according to the projected numbers of receipts from the draft national budget for 2021-2023, by 2021 the debt burden on the non-oil budget will reach 9.78%, and by 2022 it will be 11.05%. Despite a relatively low level of public debt in relation to GDP, the ratio of debt service to the debt issued by Kazakhstan (present value of debt) exceeds this indicator in many countries. The high cost of debt service is determined by higher interest rates in Kazakhstan compared to other countries, as well as by revaluation of liabilities in foreign currency, which occurred along with the depreciation of the tenge.

Investor confidence is of great importance for optimizing government borrowing. At the same time, for the lender, the pattern of the repayment schedule is often an indicator of the borrower's pragmatism.

As a result of the joint effort of the National Bank of Kazakhstan and the Ministry of Finance of Kazakhstan, there are positive changes in the borrowing policy aimed at increasing liquidity of the government securities market and building a risk-free yield curve. Among those listed earlier: the efforts of the Ministry of Finance to enlarge and reduce the number of issues in circulation, work on including the issues in global international indices, realization of the opportunity of settlements in Clearstream, as well as the issuance of government securities at the short- and medium-term end of the yield curve. In addition, it is worth mentioning the joint effort of the National Bank of Kazakhstan and the KASE to create the institution of market makers for the government securities market, which may also have a positive effect on liquidity of government securities. The presence of market makers enables to exit from a position on an instrument, which is an important factor for investors with a shorter investment horizon. Besides, one of the necessary conditions for building up liquidity of the government securities market and increasing the marketability of decisions, in our opinion, is the development of the institutional investor market. One of the solutions is to transfer pension savings for investment management to private management companies, thus creating a more competitive environment in the securities market.

4. Government Debt Management Policy

A relatively low ratio of the government debt to GDP in Kazakhstan does not mean that the tasks of transition to a policy of active government debt management become less relevant. The development dynamics of the government securities market in small open economies in general and in Kazakhstan in particular consist primarily of the key macroeconomic conditions and prerequisites for the domestic economy. In Kazakhstan, where a high and growing in recent years transfer from the National Fund of the Republic of Kazakhstan is still the channel for covering the budget deficit, the dependence of financing the fiscal balance on oil revenues is increasing accordingly. This enhances the pro-cyclical nature of the fiscal policy (increased government spending during the periods of high oil prices), thereby narrowing the potential of the fiscal space as a buffer during crisis periods. Also, the prevalence of this trend indirectly affects the long-term decline in the investment rating, which negatively affects the ability to attract foreign capital into domestic debt [30]. In turn, the presence of non-residents as holders of government debt can improve the diversification of the investor base, thereby contributing to an increase in the liquidity of government securities – the central task of a well-coordinated macroeconomic policy.

Therefore, an effective development of the government securities market is a priority task for both the fiscal arm of the government and its monetary component. Effective transmission of the monetary policy interest rates relies on the correct functioning of a competitive sovereign yield curve, which is also necessary for the pricing of risky assets. In addition to this, further evolution of the government securities market should be aimed at its development as a primary link in the monetary policy transmission mechanism: to increase the efficiency of transmission of monetary policy rates to government securities rates and to directly influence the funding environment in the economy [16]. In addition, the research on debt management in developing countries shows that an increasing debt issuance in the local currency contributes to a greater market response to changes in the monetary policy.

The systematic and comprehensive development of the public debt market, in addition to its primary macroeconomic task, should also include the tasks of the structure of the expenditure side of the budget and the purposes for which the government debt is issued. One of the strategic pathways in the development of active government debt management can be the assessment of the investment focus of loans – an industry-based analysis of funds that are financed through the issuance of government securities [3]. Thus, the implementation of programs that provide a bias towards a knowledge-intensive and capital-intensive production contributes to a better and higher rate of economic growth through an increase in labor productivity, which, in turn, increases the demand for further volumes of government borrowing and their effective functioning.

In our opinion, the scope of objectives of the fiscal agency lies in the priority of short-term goals over goals of real purpose: long-term stable improvement of the country's welfare, and reduction of borrowing from the National Fund – the fund of reserves for future generations. Thus, from the government's point of view, the goal of effective public debt management should not be the current cost of borrowing but a logical long-term debt structure and, in fact, reduction of the burden on future generations. In this context, it is necessary to level down the existing conflict of interests: for the government, the market should be a reliable, transparent and stable financing channel, and for the financial regulator it should be an effective platform for implementation of the monetary policy.

The existing temporary structure of government securities redemption, which is currently exposed to significant liquidity and foreign exchange risks, can be optimized by using one of the main repurchase methods:

1. Buy-back. The auction is held in the same way as an ordinary auction except that auction participants submit the selling bids similar to the primary market mechanism.

2. Outright purchase. This method of debt redemption may be accomplished in two ways. First is to repurchase government securities in the secondary stock exchange market. The second is a purchase on the over-the-counter market.

3. Replacement or refinancing, when one security is provided as payment for the purchase of another security. During each buyback transaction, it is important to take into account the profitability of cutting off the bought-back government security. Assessment of the yield curve in the secondary market will give an idea of the fair market value of the security. In this context, the theoretical model of the yield curve should be the best metric in determining the real cut-off prices.

Consolidation of government securities issues as well as maintenance of large issues increases market liquidity. Ineffective securities in terms of competitive pricing increase distrust on the part of market participants, which generally hinders the development of the market to its potential and prevents capitalization of other capital exchange platforms from growing. On the contrary, maintaining large "effective" securities will support and increase liquidity of the government securities market. This increases efficiency of the funding system, both in terms of long-term goals for the government and less long-term goals of the monetary authorities, which is possible only if they are closely coordinated in respect of active government debt management.

5. Conclusion

In general, liquidity in the securities market has been gradually improving over the past two years. During this period, an important factor was the change in the practice of issuing debt. This included a commitment to create large benchmark issues that helped boost liquidity. The government securities market was also supported by changes in the structure of market participants, which intensifies dealer competition. The move to a new yield curve model that improves transparency also offers potential for increased liquidity in the future. The degree of market liquidity continues to significantly depend on the local conjuncture: during the periods of instable interest rates, liquidity drops rapidly.

In terms of the development potential, the Kazakhstani market seems to stand out of the sample of compared countries. However, in terms of the structural factors that create the environment, the degree of debt fragmentation, the pattern of maturity schedule and a relative underdevelopment of the stock market may impede a further liquidity growth.

The need for a rational policy of government debt management determines the relevance of research on international practices and the development of models in this area. The transition to a new model of government debt management policy will ensure its sustainability and continuity. This paper provides a brief overview of the structure of the government securities market liquidity, helping to understand and organize this multifaceted solution.

List of Used References

1. Broto C., Lamas M., “Measuring market liquidity in US fixed income markets: A new synthetic indicator” // Working Paper No. 1608, Bank of Spain, 2016.
2. Elliot D., “Market liquidity: A primer. The Brookings Institution” // Working paper, The Brookings Institution 2015.
3. Fiscal policy, government debt and monetary policy in emerging market economies, BIS Papers, №67, 2012. https://www.bis.org/publ/bppdf/bispap67.pdf.
4. Gehde-Trapp M., Schuster Ph., Uhrig-Homburg M., “The Term Structure of Bond Liquidity” // Journal of Financial and Quantitative Analysis, vol. 53, No. 5, p. 2161-2197, 2018.
5. Global Financial Stability Report: Markets in the Time of COVID-19. International Monetary Fund. Washington, DC., April 2020. https://www.imf.org/en/Publications/GFSR/Issues/2020/04/14/global-financial-stability-report-april-2020.
6. Grobety M., «Government debt and growth: The role of liquidity» // Journal of International Money and Finance, vol. 83, p 1-22, May, 2018.
7. Gulliver J., «Money Market Funds and the 2020 COVID Crisis» // Committee on Capital Markets Regulation, May 2021. https://www.capmktsreg.org/wp-content/uploads/2021/05/CCMR-Prime-MMFs-and-COVID-05.24.2021-.pdf.
8. Kazakhstan: Reversing Productivity Stagnation - Country Economic Memorandum // World Bank Document.
9. Le Saout, E., «Intégration du risque de liquidité dans les modèles de valeur en risque» // Banque et Marchés №61, p. 15-25, novembre 2002.
10. Muranaga J., T. Shimizu, «Market Microstructure and Market Liquidity» // Working paper of Institute for Monetary Economic Studies, Bank of Japan, 1997.
11. Nazlioglu S., Gupta R., Bouri E. «Movements in International Bond Markets: The Role of Oil Prices» // Working paper № 2019:35, International Review of Economics & Finance. – 2020.
12. Phillip R.D. Anderson, A. Velandia-Rubiano, A.C. Silva, «Government debt Management in Emerging Market Economies: Has this Time Been Different?» // World Bank Policy Research Working Paper, No. 5399, April, 2016. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1658774.
13. V. Premathiratne, «The Emerging Asia Pacific Capital Markets Sri Lanka» // 2021 CFA Institute Research Foundation, May, 2021.
14. Semernina Y., Yakunina A., Yakunin S., «Some trends of the Russian sub-federal bond market development in the presence of the global challenges» // Advances in Economics, Business and Management Research (AEBMR), vol. 39, p. 162–165, 2018.
15. Yakunina A.V., Semernina Y.V., Yakunin S.V., Ermakova E., «Impact of foreign economic sanctions on the Russian market of bonds denominated in foreign currencies» // SHS Web Conf. Innovative Economic Symposium Milestones and Trends of World Economy (IES 2018), vol. 61, 2019.

16. Alexeyeva I.A., Petrova I.A., "Federal Loan Bonds Market: Evolution and Prospects" // Bulletin of the Baikal State University, V. 28, No. 4, 2018. https://cyberleninka.ru/article/n/evolyutsiya-i-perspektivy-razvitiya-rynka-obligatsiy-federalnyh-zaymov.

17. Alekhin B.I., "Placement of Government Bonds through the Lens of the Market Microstructure" // Financial Journal, No. 6, p. 95–108, 2018.

18. Belokopytov A.V., Mironkina A.Yu., " Federal Loan Bonds for the Population" // Economic Journal, pp. 54–62, 2017. https://cyberleninka.ru/article/n/obligatsii-federalnogo-zayma-dlya-naseleniya.

19. Mustafin Ye.T., "Debt Market in the Period of APF Reform" // Halyk Finance, January, 2013. http://history.halykfinance.kz/ru/site/index/research/report:81987.

20. Mustafin Ye.T., "The Yield Curve in Kazakhstan: Declining Demand for the Government Debt Pending Prudential Easements" // Halyk Finance, September, 2012. http://history.halykfinance.kz/ru/site/index/research/report:81322.

21. Mustafin Ye.T., Khakimzhanov S.T., "Liquidity Risk, Exchange Rate and the Cost of Funding in the Tenge" // Halyk Finance, January, 2014. http://history.halykfinance.kz/ru/site/index/research/report:87302.

22. Ogurtsova Ye.V., Komkov I.V., "Development of the Domestic Market of Government Debt in Russia: Drivers, Prospects, and Changes" // Bulletin of the Saratov University", the "Economics. Management. Law" Series, V. 19, Issue 3, 2019. https://doi.org/10.18500/1994-2540-2019-19-3-246-256.

23. Orazalin R., "The Monetary Policy Transmission Mechanism in the Republic of Kazakhstan" // Economic Study No.2018-3, Research and Statistics Department, National Bank of the Republic of Kazakhstan, 2018.

24. Strategic Objectives of the Financial Market in the Russian Federation for 2019–2021 // Bank of Russia. https://cbr.ru/content/document/file/71220/main_directions.pdf.

25. Financial Stability Report of Kazakhstan, 2012. National Bank of the Republic of Kazakhstan. Almaty, December, 2012. https://nationalbank.kz/file/download/26119.

26. Financial Stability Report of Kazakhstan, 2015 – 2017. National Bank of the Republic of Kazakhstan. Almaty, 2018. https://www.nationalbank.kz/ru/news/otchet-o-finansovoy-stabilnosti/rubrics/235.

27. Financial Stability Report of Kazakhstan, 2018 – 1H of 2019. National Bank of the Republic of Kazakhstan. Almaty, 2020. https://nationalbank.kz/ru/news/otchet-o-finansovoy-stabilnosti/rubrics/236.

28. Pokrovskaya N.N., Kurilenko M.V., 'The Government Securities Market in Russia: Problems and Development prospects" // "Science Studies" Internet Magazine, V. 8, No. 4, 2016. http://naukovedenie.ru/PDF/34EVN416.pdf.

29. Ryzhanovskaya L.Yu., Chistova V.Ye., "Liquidity Problems of the Government Securities Market" // "Financial Journal", No.3, pp. 19–32, 2011.

30. Stakhovich L.V., Shakhnazaryan G.E., "Liquidity Problems of the Modern Government Securities Market" // "Financial Analytics: Problems and Solutions", No. 1 (1), pp. 34–43, 2008.

31. Khakimzhanov S., Mustafin Ye., Kubenbayev O., Atabeck D., "Constructing the Yield Curve in a Low Liquidity Market" // "Money and Credit" Magazine, No.4, December, 2019.

PROSPECTS AND DEVELOPMENT OF NON-BANK FINANCIAL ORGANIZATIONS

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The Paper is devoted to the role and significance of functioning of non-bank organizations in the Republic of Kazakhstan, microfinance organizations in particular, and describes the possible lines of their development and business outlook

Key Words: non-bank organizations, microfinance organizations, business of microfinance organizations in the Republic of Kazakhstan.

JEL-Classification: G21, G23.

1. Characteristics of the Credit Market in Kazakhstan

Issues related to the formation and development of the financial system, including the credit system, have always been of great importance and relevance. Non-bank organizations, as participants in the financial market, play an essential role in the financial system development. The introduction of new mechanisms for optimizing operations of non-bank organizations contributes to better efficiency of the credit services market and to creation of financial market entities that comply with modern international standards and are able to maximally meet the needs of the market in providing financial services.

In this regard, the study of the current situation and the adoption of informed decisions in the future development of the country's financial system are necessary conditions for ensuring effective and efficient operation of financial institutions, including credit institutions.

Thus, consideration of the features and development prospects of non-bank organizations in the Republic of Kazakhstan is a fairly relevant topic of research.

In general, today the banking sector in the Republic of Kazakhstan plays a dominant role in the financial system in terms of services provided, including the disbursement of loans.

Every year, the dynamics of the volume of loans is growing; in 2020 alone, banks provided loans worth 1 trillion tenge.

The growth of bank loans in 2020 was driven, in particular, by the anti-crisis measures of the government taken as part of lending to the economy and subsidizing loans. The main borrowers of banks in the credit services market are individuals. As at January 1, 2021, their share accounted for 45.1% of all loans; since the beginning of the year, this figure has grown by 796 billion tenge. At the same time, loans to corporate entities decreased by 267 billion tenge, or by 24.3%. This indicates that recently the focus has shifted to retail lending to individuals, whose solvency is growing.

Big banks with a large client base, a network of branches and cash offices throughout the country are mainly engaged in consumer lending to the population.

In the growth prospects of competition in the financial services market to ensure affordable lending not only in large cities but also in the regions of the country, the priority objective is the development of such non-bank credit organizations as microfinance organizations for providing service to a wide variety of consumers with a large range of loan products offered.

Thus, the main difference between non-bank organizations and commercial banks lies in:

- the range of banking services provided;
- regulation of their operations;
- the possibility to open branches and subsidiaries, etc.

2. Microfinance Organizations in Kazakhstan

According to statistics, 67% of borrowers of microfinance organizations live in rural areas and are not interested in banks due to the geographical geographic location, lack of liquid collateral, low financial and digital literacy.

The development of the market of microfinance organizations contributes to the development of agro-industry, including such spheres as cattle breeding, bee farming, etc., which are unattractive for the second-tier banks. The main target audiences for microcredit are rural areas and small businesses. For more than 20 years, microfinance organizations have been working with this category of the population and know their needs, have their own microcredit methodology based on the best world practices, material and technical base and software, trained and qualified personnel, a wide network of branches and offices in the regions. Microfinance organizations support newbie entrepreneurs and their start-up projects by providing start-up capital to those who do not have access to bank loans. This is how microfinance organizations expand opportunities and create an enabling environment for them.

Thus, the formation of a network of microfinance organizations in the country’s regions is the main prerequisite for expanding access to financial resources for the unemployed, self-employed population, small and medium-sized businesses.

As at April 1, 2021, the microfinance sector of the Republic of Kazakhstan is represented by 179 organizations engaged in microfinance business (licensed). The assets of microfinance organizations amounted to 574.3 billion tenge, with the positive dynamics of 57 billion tenge, the total loan portfolio of microfinance organizations equaled 463.8 billion tenge, having increased by 48.2 billion tenge since the beginning of the year.

Historically, microfinance organizations have evolved from a non-regulated sector to the licensed activities.

In order to build a transparent market of microfinance organizations and increase confidence, improve the quality and accessibility of the services they provide, a regulatory framework has been formed in Kazakhstan and is being adequately improved.

In order to protect the rights of financial services consumers, the Law of the Republic of Kazakhstan dated July 3, 2020 "On Amendments to Some Legislative Acts of the Republic of Kazakhstan Related to Mortgage Loans in Foreign Currency and Improvements in the Regulation of Entities", the licensing of microfinance business was introduced in the Republic of Kazakhstan from January 1, 2021.

Licensing of the microfinance business enabled to regard the entities engaged in the microfinance business as financial organizations and created opportunities for a unified legislative definition of financial services and the financial market, established higher requirements to their activities and their financial soundness, in order to maintain fair competition in the financial market, created equal conditions for their activities that helps to protect the rights and interests of financial services consumers.

At the same time, in order to protect the rights of financial services consumers, it is necessary that the financial affordability of services and financial literacy of citizens develop in parallel.

The objectives for development of the business of microfinance organizations are to provide affordable borrowed resources to the population, medium-sized and small businesses, and individual entrepreneurship as well as to increase the level of competitiveness and financial soundness of these organizations.

The growing level of competition, high requirements to the quality of services provided determine the constant striving of credit institutions to achieve high quality standards, attain a leading position in the financial sector, and gain competitive advantages.

Thus, microfinance institutions should help filling gaps in the financial services market that had been possibly created by the second-tier banks.

At the same time, one of the key problems in microlending is high interest rates. Today, the average annual effective interest rate on microcredits in the market of microfinance organizations is about 38%.

High interest rates are primarily driven by the 17% funding rate. According to the information of the ALE "Association of Microfinance Organizations of Kazakhstan", microfinance organizations are experiencing the problem of attracting resources within Kazakhstan that are used for their main operations. Domestic banks require from microfinance organizations to provide liquid collateral, which they do not have or lack in sufficient quantity. In this regard, microfinance organizations are forced to turn to foreign lenders, which mostly provide unsecured loans. About 70% of all microcredits provided in Kazakhstan are issued with the help of foreign funding. Second, it is necessary to take into account the operating costs associated with the issuance and servicing of microcredits – which is about 14%. The main advantage of microfinance organizations is to operate in remote regions of Kazakhstan, where banks are poorly represented. This implies direct contact with borrowers, assessment of the client's solvency by visiting the place of his/her business, systematic monitoring of microcredit. As mentioned above, according to statistics, 67% of borrowers of microfinance organizations are residents of rural areas. It is quite expensive to maintain an extensive network of branches and a large number of trained personnel. Therefore, in operating expenses, the main share is occupied by personnel costs (payroll, payroll taxes), depreciation of fixed assets and intangible assets. Additionally, provisions for credit risks are created that account for 18% of all expenses. Other expenses (rent and security guarding of premises, repair and maintenance of offices, utility bills, communication and the Internet, personnel training, marketing expenses, maintenance of transport vehicles, etc.) account for 27%.

Thus, all of the above components in total make up the rate of 34%. If the average interest rate is 38%, then it is obvious that the profit generated is 4%.

3. Proposals Regarding the Microfinance Market Development

Compensation for operating expenses of microfinance organizations could fully meet the financing needs of the population in rural areas with low interest rates. In this regard, it is proposed to provide incentives for operating microfinance organizations to reduce costs in microlending, which will reduce rates for end consumers. One of the possible incentives may be tax incentives for private organizations that provide microcredits to start-up entrepreneurs, agricultural producers and other small and medium-sized businesses in the regions of Kazakhstan.

It is possible to reduce the operating costs by introducing innovative technologies into the operation of these organizations, expanding remote customer service channels, and automating credit processes. At the same time, such changes require resources, time and enabling regulatory environment.

The implementation of these measures would allow reducing the costs of microfinance organizations and also meeting the population's need for financing with low interest rates.

Currently, there is a low interest among banks in financing micro- and small businesses as part of the program of loan interest subsidy. In this regard, it is also proposed to involve microfinance organizations in the programs of interest rate subsidies.

In accordance with the National Development Plan of the Republic of Kazakhstan until 2025, in order to develop financial inclusion and the affordability of basic financial services for the population and micro- and small businesses, it is necessary to activate the sector of non-bank lending and microfinance.

In order to increase the affordability of financial services for the population, counteract illegal financial and fraudulent transactions and further reduce the shadow economy, it is also necessary to improve the system of regulation and supervision of the sector of non-bank microfinance organizations.

To make the implementation of government support measures more efficient and to maximize their coverage of the larger portion of micro- and small businesses, it is proposed to involve the non-banking sector in the implementation of anti-crisis programs for supporting priority sectors of the economy, primarily the agro-industrial complex.

As you know, due to implementation of anti-crisis measures in the economy, banks have accumulated excess cash liquidity. At the same time, there are niches to which these funds do not flow. The second-tier banks are not interested in investing in small projects in the regions of Kazakhstan.

In accordance with the Message of the Head of State K. Tokayev dated September 1, 2021, “The Unity of the People and Systemic Reforms are a Solid Foundation for the Country's Prosperity”, it is necessary to use the potential of microfinance organizations that operate in the local communities and know their clients, their business and opportunities.

With this in mind, it is worth mentioning that the infrastructure of credit relations plays an important role in the functioning of financial markets, since in the process of its operations it solves macroeconomic financial problems and represents a segment of the national financial system.

List of Used Reference

1. The Law of the Republic of Kazakhstan dated July 3, 2020 “On Amendments to Some Legislative Acts of the Republic of Kazakhstan Related to Mortgage Loans in Foreign Currency and Improvements in the Regulation of Entities”.
2. Statistical data from the web-site of the National Bank of the Republic of Kazakhstan and the Agency of the Republic of Kazakhstan for Regulation and Development of Financial Market.
3. The Message of the Head of State K. Tokayev dated September 1, 2021, “The Unity of the People and Systemic Reforms are a Solid Foundation for the Country's Prosperity”.