В связи с наблюдаемым в последнее время небольшим колебанием в объёме предоставляемых кредитов, можно сделать предположение, что сектор потребительского кредитования постепенно оживает.

Из вышесказанного можно сделать выводы:

1. Необходимо изменение в процентном соотношении в секторах экономики. Доля сельскохозяйственного сектора должна увеличиваться.

2. Необходимо увеличение реально располагаемого дохода населения. Поскольку с повышением финансового состояния граждан у них возникнут большие потребности в финансовых услугах, что в свою очередь приведёт к росту банковского сектора.

3. Уровень инфляции и различные экономические индексы должны отображать реальное положение дел, а не подгоняться под желаемый результат.

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УДК 336.774

ВЕРОЯТНОСТЬ ДЕФОЛТА ДЛЯ ОЦЕНКИ ОЖИДАЕМЫХ КРЕДИТНЫХ УБЫТКОВ ПО ФИНАНСОВЫМ АКТИВАМ (СОГЛАСНО МСФО 9)

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Introduction. IFRS 9 «Financial Instruments» (IFRS 9) requires an entity to measure expected credit losses (ECL) of a financial instrument in a way that reflects:

(a) an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes;

(b) the time value of money; and

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(c) reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions.

At the same time IFRS 9 does not prescribe particular measurement methods including the method to determine probability of default in order to calculate expected losses.

The probability of default (PD) is an essential parameter in measuring counterparty credit risk, which in turn has impact on pricing of loans and derivatives. The *default* probability determination model is used to forecast the default probability of each entity and is expressed by a rating class within a rating system. The TTC (*trough the cycle*) approach, on which probabilities of default built for regulatory purposes are based, maximally reduces the influence of the macroeconomic component, whilst PIT (*point in time*) approach, which is to be used in ECL calculation according to IFRS 9 methodology, assumes maximum adjustment to changes resulting from the business cycle. The PIT default probability estimation includes individual and macroeconomic components. A high level of migration of units to lower classes is expected in a period of economic growth, and to higher classes at a time of crisis.

Thus, the probability of default for regulatory purposes cannot be applied directly to expected credit losses impairment calculations under the IFRS 9, because it does not take into account:

- forecasts of the future economic conditions. This forward-looking aspect introduces an extra dimension, which is often captured by relating expected losses to the macroeconomic variables (e.g. Gross Domestic Product (GDP), unemployment rates);

- probability-weighted calculation of ECL, based on appropriate scenarios of macroeconomic variables forecasts;

- any reasonable and supportable information about current conditions at the reporting date (PIT). As mentioned above, the regulatory framework requires stressed TTC probabilities, so as to avoid a procyclical capital charge calculation [4], resulted in the main difference between TTC and PIT is that TTC is not volatile since it incorporates long term averages and is designed in such a way so that the variable increases during good times and decreases during bad times; on the other hand, PIT incorporates only the current state and hence the variable is volatile;

- the time horizon more than future 12 months, while the IFRS 9 requires lifetime probabilities of default for financial assets, the expected life of which can be more than 12 months.

Thus, the purpose of the present paper is to determine one of possible ways of calculation of probabilities of default which is consistent with the principles

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stated in the IFRS 9 and are based on the probabilities of default built for regulatory purposes.

Data and Methodology.

How can TTC probabilities of default be changed to apply for calculation of the expected credit losses and impairment of the financial assets under IFRS 9?

Building of a regression model.

Those macroeconomic variables should be chosen which correlate with entity-specific time series probabilities of default (Table 1). Logit model (Table 2) can be calculated using EViews (Econometric Views) statistical package. Correlation between probabilities of default for certain group of internal credit rating and nominal GDP was revealed based on 9 observations that is confirmed by regression equation (time series are presented on the Table 1). Regression equation here is a logit regression or logit model where the dependent variable (DV) is categorical and binary and where the output can take only two values, «0» and «1», represents 2 outcomes. So, the model built is simplified, based on hypothetical data and used for illustrative purposes only, since 9 observations might seem low, and the model does not take into account additional uncertainty and possible biases of the macroeconomic forecasts.

Table. 1

Time series: nominal GDP and TTC PD

Date	PD	GDP
01.01.2016	5.0%	96.1%
01.04.2016	4.1%	96.4%
01.07.2016	3.9%	97.3%
01.10.2016	3.5%	97.1%
01.01.2017	3.3%	97.4%
01.04.2017	3.3%	100.3%
01.07.2017	2.8%	101.1%
01.10.2017	1.9%	101.7%
01.01.2018	1.7%	102.4%

Source: authorial computation

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Table. 2

Logit regression

Equation: PD_ALLEXP_OK Workfile: MODEL NEW::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PD
Method: Least Squares
Date: 03/20/18 Time: 15:34
Sample (adjusted): 2016Q1 2018Q1
Included observations: 9 after adjustments
Convergence achieved after 1 iteration
PD=1/(1+EXP(-(C(1)*GDPR+C(5))))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-14.19268	1.934072	-7.338238	0.0002
C(5)	10.57427	1.889029	5.597730	0.0008

R-squared	0.907346	Mean dependent var	0.032063
Adjusted R-squared	0.894109	S.D. dependent var	0.010613
S.E. of regression	0.003453	Akaike info criterion	-8.305771
Sum squared resid	8.35E-05	Schwarz criterion	-8.261943
Log likelihood	39.37597	Hannan-Quinn criter.	-8.400351
Durbin-Watson stat	1.439731		

Source: authorial computation

The model used to relate nominal GDP to the probabilities of default is:

PD=1/ (1+EXP(-(C(1)*GDPR+C(5)))), where C (1) the coefficient is -14,19268 and C (5) is 10,57427.

The equation means that PD represents the estimated default rate, which is the estimated variable. The variable GDPR is the explanatory variable, which is the probability of default in this example. The coefficients C (1) and C(5) are chosen such that the estimated probability of default PD are as close as possible to the observed default rates.

The above mention logit model should be tested by the estimation of:

- the coefficient of determination (R-squared), that is a statistic the main purpose of which is either the prediction of future outcomes or the testing of hypotheses basis of other related information. It provides a measure of how well the observed outcomes are replicated by the model based on the proportion of total variation of outcomes explained by the model. In this example, coefficient of determination is 0.91, that is, exogenous variables explain the endogenous variables by 91% and thus, the model is significant;

- Durbin-Watson statistics. A key assumption in regression is that the error terms are independent of each other. Durbin-Watson statistics should be used to detect the presence of autocorrelation at lag 1 in the residuals (prediction errors) from a regression analysis. The Durbin-Watson test for autocorrelation is a statistic that indicates the likelihood that the deviation (error) values for the regression have

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a first-order autoregression component. The regression models assume that the error deviations are uncorrelated. If e_t is the residual associated with the observation at time t, then the test statistic is:

$$d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}, \tag{1}$$

where T is the number of observations. In the example mentioned above, the number of observations is 9, the number of independent variables is 1, and upper and low critical values for the Durbin-Watson test are 0,824 and 1,320, respectively. For 5% significance level, the meaning of 1,439731 exceed critical value 1,320, and therefore autocorrelation is absent.

If the tested model does not meet the above mentioned criteria, macroeconomic variables can be converted by using moving average or exponential smoothing, that is a rule of thumb technique for smoothing time series data using the exponential window function, whereas in the simple moving average the past observations are weighted equally, exponential functions are used to assign exponentially decreasing weights over time. Also, additional testing such as making heteroscedasticity test and correlogram (autocorrelation plot) can be performed.

Model similar to the above mentioned is to be constructed for probabilities referring to every group of internal credit rating.

Incorporation of the information about forecast of future economic conditions into a regression model.

As mentioned above, ECL should be calculated taking into account reasonable and supportable information about forecast of future economic conditions. In addition, ECL should be measured as a probability-weighted amount that is determined by evaluating a range of possible outcomes.

Therefore, the next stage is forecasting of macroeconomic variables and ECL calculation using appropriate scenarios. If there is a non-linear relationship between ECL and forward-looking information, multiply scenarios are relevant 8]. In this example, the dependence between estimated variable and explanatory variable is non-linear as the increase in GDP resulted in the decrease in PD. Thus, base, pessimistic and optimistic scenarios of macroeconomic variable (GDP as mentioned above) forecast one year in advance should be considered, estimating likelihood of each scenario.

State authorities and /or International Monetary Fund (IMF) publishes forecasts of macroeconomic data such as GDP, unemployment rate etc, which can

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be used in PD calculation as a base forecast scenario for macroeconomic variable. Based on available historical data it can be estimated which scenario be used and its likelihood.

Table. 3

Example: probability-weighted expected credit losses and probabilities of default

Scenario	**Macroeconomic variable used in PD model – GDP (forecast one year in advance)**	**Scenario probability**	**PD**	**Exposure at default (EAD)**	**Loss given default (LGD)**	**Associated expected credit losses (ECL)= PD*EAD*LGD**
Base case forecast of GDP	2,5%	90%	5,2%	1000	45%	23,5
Pessimistic case forecast of GDP	-1%	5%	7,8%	1000	45%	35,2
Optimistic case forecast of GDP	3%	5%	3,6%	1000	45%	16,1

Source: authorial computation

Probability-weighted ECL= 23,5*90%+35,2*5%+16,1*5%=23,7.
The same result based on PD:

if probability-weighted PD=
((5,2%*90%+7,8%*5%+3,6%*5%))/100%=5,27%,
then ECL=5,22%*1000*45%=23,7

Therefore, first probability-weighted PD can be calculated and further used for calculation probability- weighted expected credit losses.

Converting the TTC PD to a PIT PD.

In business cycle theory and finance, any economic quantity that is positively correlated with the overall state of the economy is said to be procyclical. That is, any quantity that tends to increase in expansion and tend to decrease in recession is classified as procyclical. GDP is an example of a procyclical economic indicator. Conversely, any economic quantity that is negatively correlated with the overall state of the economy is said to be countercyclical.

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A rating model will have no distinction in TTC PD and PIT PD if there is no cyclicality factor. Thus, cyclicality factor should be calculated and added to TTC PD to get PIT PD.

In the mentioned above logit regression has correlation between GDP growth and probabilities of default which is confirmed by appropriate regression equation and illustrates statistically that probability of default is inversely proportional to the change in GDP growth, meaning if change in GDP growth is positive, then probabilities of default falls and vice versa. The time series of nominal GDP has a trend component and a cyclicality component (or in simple terms volatility). A cyclicality component can be extracted by applying Hodrick–Prescott filter, a mathematical tool used in macroeconomics to remove the cyclical component of a time series from raw data, which filters short term fluctuations from a time series. To get a much smoother result it is possible to use the GDP natural logarithm as a time series and then apply Hodrick–Prescott filter to get the cyclicality component. Time series should include historical information and forecast one year in advance. Cyclicality component (fig. 1) is 0.95 and has been calculated using EViews statistical package.

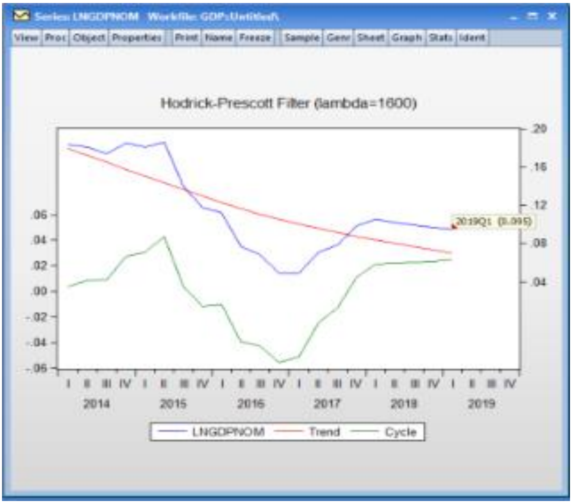

Fig.1. Cyclicality component.

Source: authorial computation

Realized default rates can be derived by constructing transition matrices. Credit migration matrices are used to describe and predict the movement that an obligor takes through different credit rating classes. Transition matrix is a

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matrix which shows the migration frequency in percent of the number of obligors from one rating to another rating during a specific period, usually 1 year. The last column of a transition matrix are the observed default rates over a period.

In Table 4 the fragment of TTC transition matrix (4.1) shows migration frequency in percent of the number of obligors with the internal credit rating 1 (the best rating) to lower credit ratings and default (3%, 3% and 1%, respectively). Credit rating of 93% obligors remain unchanged over a period.

Then cumulative matrix (4.2) should be calculated based on the transition matrix. NORMSINV Excel function can be used to calculate cumulative inverse norm of transition matrix (3.3). NORMSINV function returns the inverse of the standard normal cumulative distribution with appropriate probability. The distribution has a mean of zero and a standard deviation of one. For example, inverse of the standard normal cumulative distribution, with a probability of 93% is 1,475791; for default rate it is always 1 (4.3).

Then cyclicality component 0,95 (Figure 1) should be added to cumulative inverse norm of transition matrix (4.4) and NORMSDIST Excel function should be used to return the normal distribution for the specified mean and standard deviation (4.5).

Finally, the cumulative component should be removed to get the cyclicality adjusted transition matrix with (PIT) (4.6).

Table. 4

Transition matrix and converting the TTC PD to a PIT PD

4.1 Transition matrix (TTC)				
%	**1**	**2**	**3**	**Default**
1	93.0%	3.0%	3.0%	1.0%
4.2 Cumulative matrix				
%	**1**	**2**	**3**	**Default**
A	93.0%	96.0%	99.0%	100.0%
4.3 Bins Corresponding to Cumulative Transition Rates				
%	**1**	**2**	**3**	**Default**
1	1.475791	1.750686	2.326348	1.0
Cyclicality component = 0,95 (Figure 1)				
4.4 Bins Corresponding to Cumulative Transition Rates after cyclicality component incorporation				

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%	1	2	3	Default
1	2.425791	2.700686	3.276348	1.0
4.5 Cumulative matrix after cycle index incorporation				
%	1	2	3	Default
1	0.992362	0.996540	0.999474	1.0
4.6 Transition matrix (PIT)				
%	1	2	3	Default
1	99.24%	0.42%	0.29%	0.05%

Probabilities of default for financial assets the expected life of which more than 12 months.

For financial assets with significant increase in credit risk and credit-impaired financial assets lifetime probability of default is required for calculation lifetime expected credit losses, including financial assets, the expected life of which is more than 12 months, whilst TTC PD usually used for 12 months in advance. To determine lifetime PDs, it is possible to build from the 12-month PD model assuming that the default rate does not change during the lifetime of the loan [14] or other financial assets. General formula for calculation of PD for the period of time in month is: 1-[(1-PD)^(1/n)], where PD is cumulative PD and n is the number of months.

For example, for cumulative PD 5,27%:

PD for 1 month is 1-(1-5,27%)^((1/12))=0,45%;

PD for 17 months is 1-(1-0,45%)^17=7,38%.

Conclusion.

To sum up, the following steps can be done in order to calculate probabilities of default under IFRS 9 based on regulatory probabilities of default:

-to build regression model with macroeconomic variable and test it;

-to forecast macroeconomic variable and calculate a probability-weighted probability of default that is determined by evaluating a range of possible outcomes;

-to extract a cyclicality component from macroeconomic variable and get the cyclicality adjusted PIT transition matrix based on TTC transition matrix;

-to determine lifetime PDs.

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