The impact of macroeconomic factors on collateral value within the framework of expected credit loss calculation

Yurchenko, Yurii

National technical university of Ukraine 'Igor Sikorsky Kyiv Polytechnic Institute'

November 2019

The impact of macroeconomic factors on collateral value within the framework of expected credit loss calculation

Abstract

The study examines the impact of macroeconomic factors on the expected credit losses of a financial instrument related to changes in the value of collateral. The author has developed a method of calculating this impact on the basis of econometric models, as well as simulated the effect on expected credit losses and reserves on a financial instrument. Based on the proposed approach, appropriate models have been constructed based on the data of the US and Ukrainian economies for the maximum period available, taking into account the adequacy of the data. In particular, it has been shown that applying the methodology of adjusting collateral value to macroeconomic factors can lead to a reduction of the reserve according to the requirements of the regulator, i.e. from the financial institution's point of view it is possible to release some of the funds additionally.

***Keywords**: LGD, Collateral value, OLS, Credit risk, valuation, GLM*

I. INTRODUCTION

One of the reasons for 2008-2009 global crisis was divergence in risk perception by professional market participants. For Ukraine, the crisis consequences (as well as the one in 2013-2014) included the sharp fall of Ukrainian currency, particularly as regards foreign currency loans becoming unserviceable, which only highlighted the necessity of studying credit risk and its components.

To avoid similar stresses in the future a number of regulatory guidelines in the sphere of risk evaluation were implemented by global community, including EU Directive 2013/36/EU containing guidelines on the principles and methodology to be used when evaluating credit risk, and, in particular, collateral implications.

Similarly, the National Bank of Ukraine conducted Ukrainian banking system diagnostics in 2015-2016 (the diagnostics included 98% of banking system assets). The diagnostics revealed the inadequacy of loan portfolio risk evaluation.

The majority of relevant studies concerns the probability of default as the most unfavourable realisation of credit risk, whereas the calculation of loss given default (the second key credit risk factor) is limited mostly to the assumption of its constancy. This is explained by the complexity of LGD calculation, mostly due to limited historical data. Therefore, new methods of LGD calculation within the framework of expected credit loss (ECL) calculation are required.

The use of constant LGD is argued primarily on the basis of the differences in collateral characteristics and terms of the loan itself. But if loan tears are stipulated in the loan agreement and tend not to change over time (or changing only given the restructuring case), the collateral value as a factor is constantly changing. Therefore, it can be assumed that overall LGD changes based on collateral change, i.e., its sale value, for which fair value acts as a proxy.

'Fair value' definition itself (in the context of collateral) encompasses the variability nature of this indicator and its dependency on external factors. Particularly, fair value comprises the expectation of benefits to be received by the asset (or losses incurred due to it). Consequently, as macroeconomic environment changes (to be exact, the expectation of further macroeconomic developments changes), the expectations of the benefits/losses also change and are reflected respectively on the fair value of the asset. Nevertheless, to calculate the effect of such impact and make adequate adjustment proves to be cumbersome in practice. The most correct approach from the theoretical perspective is to engage professional evaluator for a detail collateral value analysis at each revaluation. However, it is impracticable due to excess time and money expenses with limited results (in most cases, given no drastic changes in the environment, the change in value is slight). Therefore, the is a necessity to develop a methodology to include the impact of macroeconomics in the value of collateral for the purposes of LGD and ECL calculation.

II. LITERATURE REVIEW

As regards approaches to LGD calculation and evaluation, scientific literature employs widely both accounting [1] [2] and economic approaches [3]. This study

[4] employs both approaches on JP Morgan Chase data for 18 years (1982-1999), which encompassed 3 761 defaulted borrowers. Accounting and economic LGD calculated in [4] averaged 27.0% and 39.8%, respectively. However, it would be incorrect to perceive the difference as a systemic one, as it is described not only by loan portfolio characteristics of the specific bank or macroeconomic conditions, but also by the specifics of their calculations.

It should be noted that the most of literature on LGD evaluation concerns corporate bonds market, which is explained a lot by the availability of public data on the defaulting companies and their financial condition can be evaluated based on that data.

Additional attention is given in literature to the study of the factors impacting LGD. This impact is measured majorly by means of parametric econometric (regression) models. Only least squares (OLS) methodology is generally used to identify parameters of the classical linear regression model; determination coefficient is used for model evaluation. For instance, models in studies of mortgage loans show a wide range of this coefficient – from 0.04-0.06 [5], 0.06-0.17 [6], 0.15 [3], 0.2 [4] до 0.95 [7]. A number of studies marks the bimodality of LGD distribution with most observations concentrated close to probability of zero and one, as well as higher LGD during economic recession [4] [8] [9]. Therefore, parameters estimated received thereby are unreliable and LGD can appear outside zero to one interval. A study by Sigrist and Stahel [10] states that LGD regression parameters estimates are sensitive to the violation of normal distribution or residuals assumption.

Non-parametric models are rarely used for the purposes of LGD modelling. Non-parametric and non-linear regression trees are used in [11] for banks' LGD modelling for SME segment. Another study [12], when modelling mortgage LGDs for one of the European banks, employs quantile regression to forecast collateral sale discount, or haircut.

A number of empirical studies are dedicated to the comparable analysis of LGD models forecasting power. Forecasting power of different classes of LGD models are tested in [13], including classical regression model, tobit-model, regression trees, beta-regression and logit-regression. The analysis was based on 55 000 credit cards data from UK, for which arrears were monitored throughout 1999-2005. The study results showed that the classical regression model employing OLS methodology and including macroeconomic factors possesses the highest forecasting power.

Similar conclusions were deduced by the authors of [14]. The study was based on debt instruments from S&P LossStat database. Three time periods were covered in the analysis – 1990-1991, 2001-2002, 2008-2009 – the periods of high default levels and the largest LGD. The models tested comprised classical regression model, tobit-model and three level tobit-model (distinguishing three states – LGD =0, <0LGD<1, LGD=1), linear beta-regression and its modification – inflated beta-regression model [15]. According to the empirical evidence, classical regression model along with beta-regression proved to be the best predictors of LGD. Nevertheless, the authors stress that LGD model forecasting power depends primarily on the quality of input data and only secondly on the modelling technique.

It is also important to highlight the impact of macroeconomic factors on LGD, which is consistently high for housing market during economic decline as compared to stable economy [3]. Within the framework of the approach, the IRB approach supposes that banks can rely on their own credit risk estimates. This, in turn, allows such institutions to adjust their estimates to reflect the economic cycle stage. In case probability of default increases, LGD normally tends to increase as well, leading to higher regulatory capital requirements as per Basel II. Further, these increases are procyclical in nature [16]. The procyclical nature can negatively affect the overall economy since if banks' capital is limited during downturn, they will be forced to squeeze their activities and reduce lending volume exactly at the time it is much needed.

Ukrainian banks' lending practice lacks proper grounding for collateral evaluation methodology, it is not uniform in terms of dependency of maximum loan on collateral value and. It should be noted that the issues above are debatable not only in practice, but they are also not studied thoroughly in scientific terms. Nevertheless, studies of market value of property for the purposes of sale are conducted by many researchers and this topic is studied quite thoroughly. Such researchers include Halasiuk, Drapikovsky, Lebed, Ivanova, Markus, Mendul, Maksymov and Yievnukh.

III. DATA DESCRIPTION

Macroeconomics data of two countries were used for the purposes of the models – USA and Ukraine. The use of Ukrainian data is obvious – the models are designed to reflect Ukraine. However, Ukrainian data sample is quite limited with regard to both time covered and data categories available. Given this, the models also encompassed US data, which are characterized as the most complete and covering the longest time frame.

As concerns the periodicity of the data, quarterly data were used – a trade-off between the availability if data and their economic sense (monthly data normally are more volatile and are characterizes as autocorrelating with the previous 1-2 months).

Sources of data used were the respective agencies and statistics services of the countries included (Ukraine State Statistics Service, Fed statistics division, US Bureau of Labour Statistics) as well as international profile organizations (IMF World Economic Outlook Database).

Given that the majority of economic data incorporate trend (i.e., have a tendency to grow over time), further analysis employed the first differences of these indicators as percentage changes. Thus, the trend was excluded from the modelling process.

The next step was to check the data stationarity as a prerequisite of its ability to be used in forecasting. In particular, Augmented Dickey-Fuller test was used to check time series for stationarity. The results showed that the dynamics of a number of US time series changed following 1980-1982 crisis. Therefore, it was decided to use only data starting from 1983 in the analysis. Thus, the time series are characterized as stationary.

Another factor to consider is data seasonality (with special regard to price data). Normally, economic data season period is one year. Therefore, the data were transformed so as to reflect no changes q-q, but y-o-y, i.e., the change of indicator compared to the same quarter of the previous year, or four quarters ago. This helps mitigate seasonality impact; besides, this approach also allows determine actual improvement of deterioration of macroeconomics more accurately.

IV. RESEARCH METHODOLOGY

In order to determine the impact of macroeconomic factors on collateral value regression models were developed and employed, as, in accordance with the research conducted, OLS models manage to get the best forecasting power. It is important to mention that as the components to arrive at net collateral value (i.e., the amount of money the lender would receive after all the deductions and dues) are assumed to be stable, for the purposes of the modelling collateral value and net collateral value shall be used interchangeably.

Models were designed based on the following itinerary – firstly, one-factor regression models are built (utilizing OLS methodology) with macroeconomic as exogenous (independent) factor reflecting the overall change in the macroeconomic environment, and a specified indicator reflecting the change in value of collateral as endogenous (dependent) factor. For instance, price per square meter was used for real estate value, producers' price index of equipment and machinery producers for equipment value (based on the assumption that such producers shift the increase in prices to equipment consumers, thus retaining a stable margin). Price index of secondary market cars and trucks is a good proxy for transport vehicle value forecasting. Overall producer's price index was used as a proxy for the remaining categories of collateral.

As regards macroeconomic variables, the choice depends on the essence of the independent variable. Thus, if the connection being analysed concerns indicator in real terms, the real GDP growth is used as a respective independent variable. Alternatively, if the dependent variable is nominal, inflation indicator (Consumer's price index change as a proxy) is used.

Further, the sample was separated into two subsamples in the proportion 80%:20%. The first subsample was used to train the model (i.e., get regression coefficients estimates), whereas the second one was used to test the model to see its prediction power.

The models were built and trained on two data sets – for US market and for Ukrainian one. Later, depending on the model results the applicability of the model, along with necessary adjustments, if any, were decided for each of collateral categories.

V. EMPIRICAL EVIDENCE

Modelling results should be considered separately for each category of collateral.

Residential real estate property

In order to forecast change of value of residential real estate property a model using real GDP change was constructed.

The modelling results are shown in table 1. As seen from the table, t-statistics for the intercept coefficient (coef) precludes from declaring it as a significant one. Given the abovementioned, the intercept was excluded from the model and the model was recalculated based on proportional dependency of the variables. The result of the second iteration are shown in the table 2 below.

Table 1

Real residential property prices vs real GDP change model (with intercept)

Dep. Variable	res_prop_r
Model	OLS
No. Observations:	150

Model results	
R-squared:	0.157
Adj. R-squared:	0.151
F-statistic:	27.57
Prob (F-statistic):	5.18e-07
Log-Likelihood:	-427.19
AIC:	858.4
BIC:	864.4
Estimation Accuracy	
MAE	4.084
MAPE	215.7%
Symmetric MAPE	123.8%
MSE	24.3
RMSE	4.9

Coefficient estimates						
	coef	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
const	-0.2293	0.588	-0.390	0.697	-1.391	0.933
rGDP	0.8535	0.163	5.250	0.000	0.532	1.175

Table 2

Real residential property prices vs real GDP change model (no intercept)

Dep. Variable	res_prop_r

Model	OLS
No. Observations:	150

Model results	
R-squared:	0.325
Adj. R-squared:	0.321
F-statistic:	71.87
Prob (F-statistic):	2.08e-14
Log-Likelihood:	-427.27
AIC:	856.5
BIC:	859.5
Estimation Accuracy	
MAE	4.087
MAPE	216.8%
Symmetric MAPE	122.8%
MSE	24.5
RMSE	4.9

Coefficient estimates						
	coef	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
rGDP	0.8020	0.095	8.478	0.000	0.615	0.989

When comparing two models results, it can be concluded that the regression coefficient estimate did not change significantly, whereas the determination coefficient had a two-fold increase (given the models built are characterized by single independent variable, the determination coefficient should suffice to make conclusion on the model significance). Within the context of forecasting power, the exclusion of intercept did not affect significantly forecast accuracy compared to the previous model.

Since the model reflects the real changes in indicators, the inflation component should also be considered (as the general formula for LGD and PD requires discounting at the nominal rate, which also includes inflation component).

Machinery and Equipment

A model of the dependency of producer's price index for equipment manufacturers on the consumer's price index was used for the purposes of machinery and equipment value change forecast.

The modelling results are presented in table 3. Overall, the conclusions regarding the model and its parameters are similar to those for the residential property. Given the same insignificance (based in t-statistics) of intercept, it was further excluded and the model was recalculated given additional assumption. The updated results are as follows (table 2).

Table 3

PPI (Equipment) change vs CPI change model (with intercept)

Dep. Variable	ppi_equip
Model	OLS

No. Observations:	116								
Model results			Coefficient estimates						
				coef	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
R-squared:		0.153	**const**	0.0104	0.239	0.044	0.965	-0.462	0.483
Adj. R-squared:		0.145	**cpi**	0.3713	0.082	4.530	0.000	0.209	0.534
F-statistic:		20.52							
Prob (F-statistic):		1.46e-05							
Log-Likelihood:		-177.91							
AIC:		359.8							
BIC:		365.3							
Estimation Accuracy									
MAE		0.809							
MAPE		163.9%							
Symmetric MAPE		85.5%							
MSE		0.98							
RMSE		0.99							

Table 4

PPI (Equipment) change vs CPI change model (no intercept)

Dep. Variable	ppi_equip								
Model	OLS								
No. Observations:	116								
Model results			Coefficient estimates						
				coef	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
R-squared:		0.486	**cpi**	0.3745	0.036	10.428	0.000	0.303	0.446
Adj. R-squared:		0.482							
F-statistic:		108.7							
Prob (F-statistic):		2.53e-18							
Log-Likelihood:		-177.92							
AIC:		357.8							
BIC:		360.6							
Estimation Accuracy									
MAE		0.810							
MAPE		164.1%							
Symmetric MAPE		85.9%							
MSE		0.98							
RMSE		0.99							

The next step was to construct similar model based on Ukrainian data with intercept coefficient also excluded. Coefficient of determination reached 0,90 for the model, whereas p-value of F-statistics accounted to 3.74e-19. Figure 1 represents the two models received. It is obvious that the one based on Ukrainian data closer describes Ukrainian data sample. However, given the comparatively small number of observations (data sample for test training comprised 36 observations), the fact that regression parameters estimates received reflect the true parameters can be challenged.

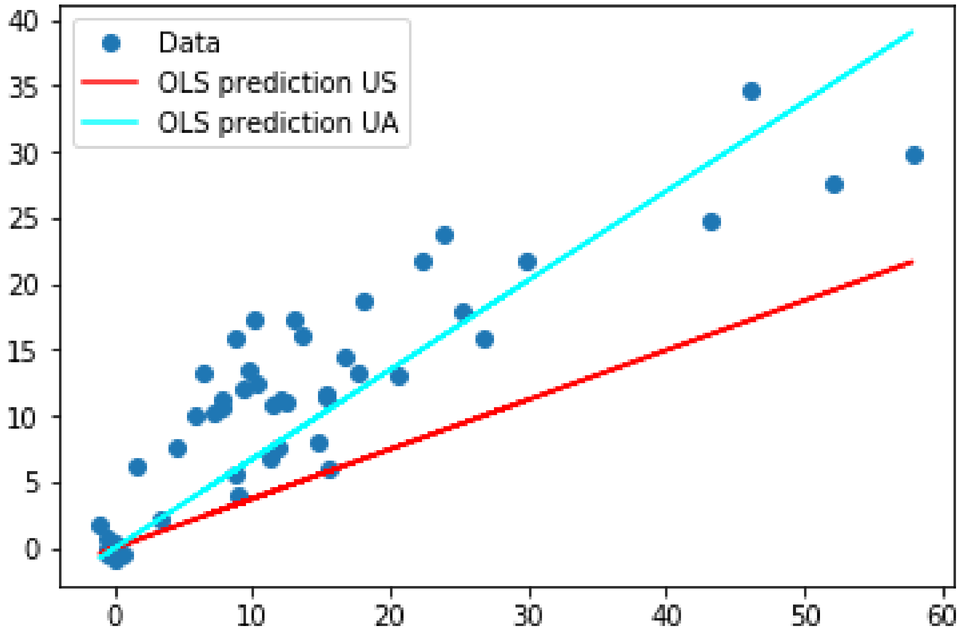

Figure 1. Comparison of US data-based and UA data-based models on Ukrainian data

In order to approach this issue, Bayesian estimation for the General linear model was applied. Parameters estimates were transformed from point estimates to random variables with a certain known distribution. The prior data are the parameters received when modelling US data dependencies (an assumption of variables having normal distribution have been added to the model). Afterwards, the likelihood function was constructed and two Markov chains run. These actions allowed to adjust the coefficients.

As seen from Figure 2, the use of general liner regression model effectively adjusted Ukrainian data-based model for the analogous model of US data.

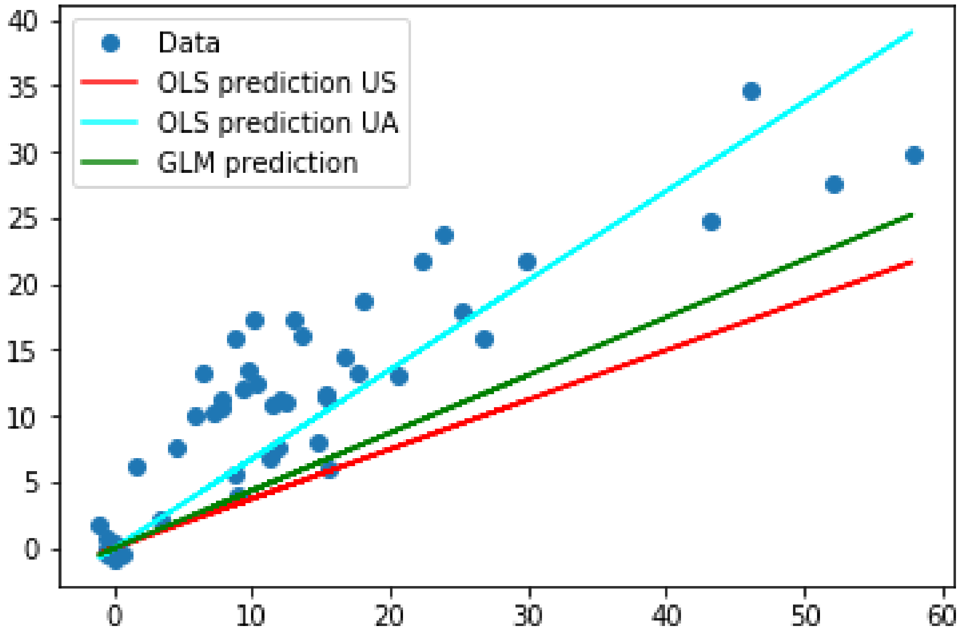

Figure 2. Generalized linear model (ppi_equip ~ cpi)

Commercial real estate property

The forecasting methodology for commercial real estate property resembles the one for residential property. Against the backdrop of economic sense, the assumption of the absence of intercept coefficient was added to the model.

The modelling results are presented in table 6.

Table 6

Real commercial property prices vs real GDP change model (with intercept)

Dep. Variable	com_prop_r
Model	OLS
No. Observations:	180

Model results	
R-squared:	0.452
Adj. R-squared:	0.449
F-statistic:	147.9
Prob (F-statistic):	3.46e-25
Log-Likelihood:	-581.04
AIC:	1164
BIC:	1167
Estimation Accuracy	
MAE	4.406
MAPE	104.1%
Symmetric MAPE	92.4%
MSE	33.2
RMSE	5.7

Coefficient estimates	*coef*	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
cpi	1.2594	0.104	12.160	0.000	1.055	1.464

Other collateral categories

The model for other collateral categories is based on the dependency of producers' price index on consumers' price index.

The modelling results are presented in table 7. Overall, the model can be said to have a moderate accuracy, given the level of determination coefficient and estimation error.

Table 7

PPI change vs CPI change model (with intercept)

Dep. Variable	ppi
Model	OLS
No. Observations:	115

Model results	
R-squared:	0.262
Adj. R-squared:	0.255
F-statistic:	40.08
Prob (F-statistic):	5.09e-09
Log-Likelihood:	-307.41
AIC:	618.8
BIC:	624.3
Estimation Accuracy	
MAE	2.499
MAPE	80.2%
Symmetric MAPE	88.9%
MSE	10.13
RMSE	3.18

Coefficient estimates						
	coef	*std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
const	-2.4377	0.808	-3.018	0.003	-4.038	-0.837
cpi	1.7186	0.271	6.331	0.000	1.181	2.256

In the similar way the model based on Ukrainian data was constructed with no intercept coefficient. The model is characterized with determination coefficient of 0.49 and p-value for F-statistic of 5.33e-6. Given the small size of data sample, the fact that regression parameters estimates received reflect the true parameters can be also be challenged.

Bayes estimation was used for this issue, as well as for the equipment and machinery model. As seen from Figure 3, the use of general liner regression model effectively adjusted Ukrainian data-based model for the analogous model of US data.

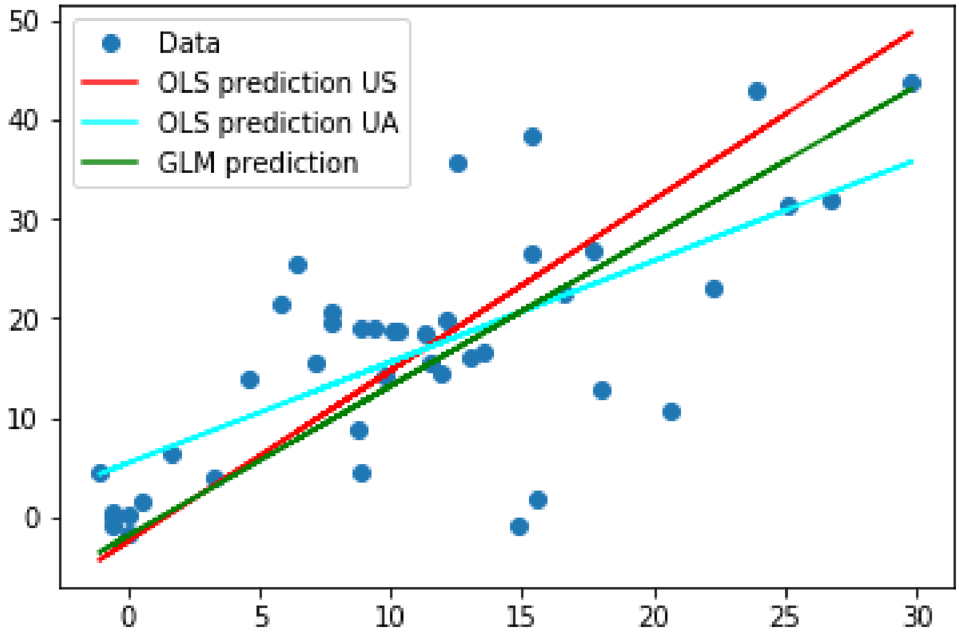

Figure 3. Generalized linear model (ppi ~ cpi)

VI. CONCLUSIONS

The simulation results allow to more accurately estimate the amount of money a lender should expect to receive in the event of a borrower's default. This is reflected in the change in the net mortgage value (the sale value of the mortgage, taking into account all related costs and losses). Applying the regressions obtained, one can predict the value of the collateral at the reporting dates and, accordingly, how this will affect the expected cash flows of the instrument.

To illustrate the point, a hypothetical financial instrument is used (uniform repayment loan with a tenor of 5 years).

Figure 3 shows the expected losses at each of the reporting periods. The cumulative amount will be the amount of the reserve. In this case, it is 5.72% of the total loan amount (that is, the issuing institution is required to reserve 5.72% of the loan amount).

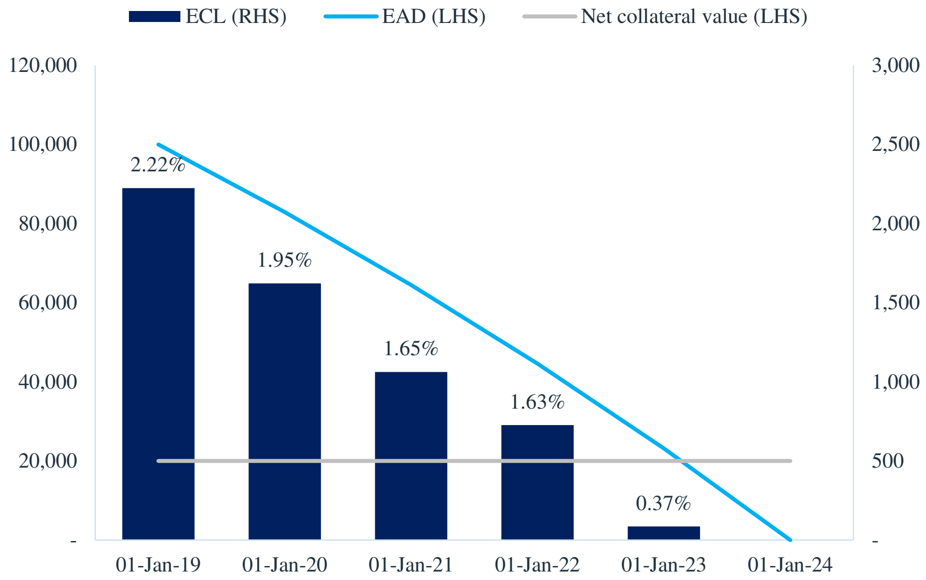

Figure 4. Sample ECL calculation with constant collateral value

In this calculation, LGD remains constant, since the value of the collateral does not change. However, given that the economic recovery is expected (reflected in the forecast of real GDP and inflation index), so should the asset price, or value, rise. Figure 5 illustrates the following example.

It has been provisionally assumed that the value of collateral will increase by 5% p.a. (including real price growth and inflation).

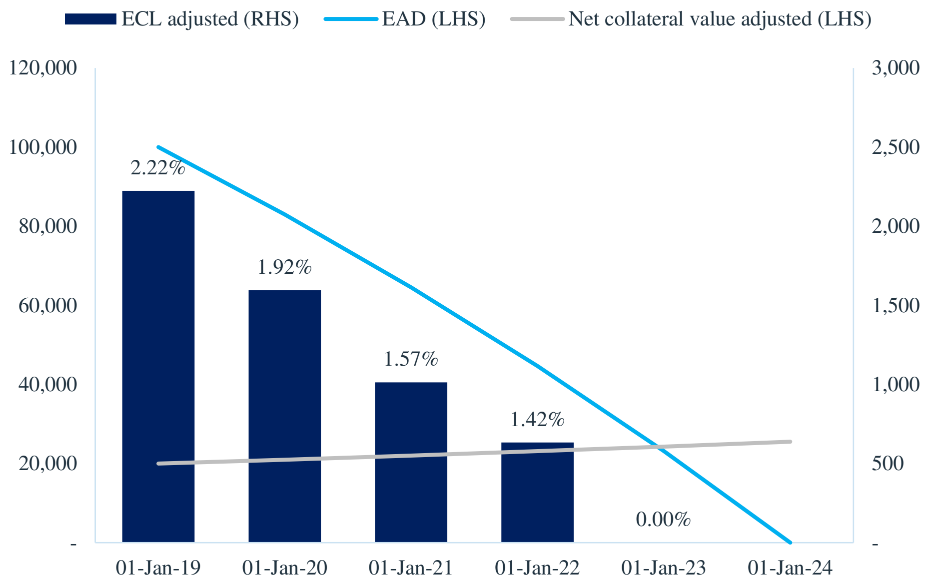

Figure 5. Sample ECL calculation with collateral adjusted for macroeconomics

Apparently, the magnitude of the expected credit loss decreases for each subsequent reporting date, as the value of the collateral increases and therefore the LGD decreases. The cumulative expected credit loss on the instrument will amount to 5.47%, which 0.25 pct. below the ECL with a fixed collateral value. In absolute terms, applying the methodology of adjusting collateral value for macroeconomic factors resulted in a 4.4% reduction in the reserve, i.e. 4.4% of the reserve was released and can be put into circulation from the financial institution's point of view.

As regards further research, for more accurate forecasting, it makes sense to adjust the resulting models for collateral categories according to their typology (eg, the allocation of different commercial real estate groups), or to consider other temporal factors (eg, impairment of transport vehicles over time). However, all of these adjustments depend on the availability of the data required ti make such adjustments and volume thereof.

It is worth noting that the methodology and the corresponding impact on the reserves largely depends on both the forecasting models selected and the macroeconomic forecasts to which these models are applied. Arguably, these projections should be consistent with those employed in the development of macroeconomic scenarios for the purposes of PD calculations.

REFERENCES

[1] M. Leow and C. Mues, "Predicting Loss Given Default (LGD) for Residential Mortgage Loans: ATwo-stage Model and Empirical Evidence for UK Bank Data," *International Journal of Forecasting,* vol. 28, no. 1, pp. 183-195, 2012.

[2] B. Zhang, "Fair Lending Analysis of Mortgage Pricing: Does Underwriting Matter?," *The Journal of Real Estate Finance and Economics,* vol. 46, no. 1, pp. 131-151, 2013.

[3] M. Qi and X. Yang, "Loss Given Default of High Loan-to-value Residential Mortgages.," *Journal of Banking and FInance,* vol. 5, no. 33, pp. 788-799, 2009.

[4] M. Araten, M. Jacobs and P. Varshney, "Measuring LGD on Commercial Loans: An 18-year Internal Study," *RMA Journal,* vol. 8, no. 86, pp. 96-103, 2004.

[5] M. LaCour-Little and Y. Zhang, "Default Probability and Loss Given Default for Home Equity Loans," *Working paper,* pp. 1-21, 2014.

[6] V. Lekkas, J. Quigley and R. Order, "Loan Loss Severity and Optimal Mortgage Default," *American Real Estate and Urban Economics Association Journal,* vol. 4, no. 21, pp. 353-371, 1993.

[7] A. Pennington-Cross, "Subprime and Prime Mortgages: Loss Distributions.," *Working paper,* 2003.

[8] J. Dermine and C. Carvalho, "Bank Loan Losses-given-default: A Case Study," *Journal of Banking and Finance,* vol. 4, no. 30, pp. 1219-1243, 2006.

[9] T. Schuermann, "What do We Know about Loss Given Default?," *Working paper no 04-01,* 2004.

[10] F. Sigrist and W. Stahel, "Using the Censored Gamma Distribution for Modeling Fractional Response Variables with an Application to Loss Given Default," *ASTIN Bulletin,* vol. 2, no. 41, pp. 673-710, 2011.

[11] J. Bastos, "Forecsting Bank Loans Loss-give-default," *Journal of Banking & Finance,* vol. 10, no. 34, pp. 2510-2517, 2010.

[12] M. Somers and J. Whittaker, "Quantile Regression for Modelling Distributions of Profit and Loss," *European Journal of Operational Research,* vol. 3, no. 183, pp. 1477-1487, 2007.

[13] T. Bellotti and J. Crook, "Loss Given Default Models Incorporating Macroeconomic Variables for Credit Cards," *International Journal of Forecasting,* vol. 1, no. 28, pp. 171-182, 2012.

[14] O. Yashkir and Y. Yashkir, "Loss Given Default Modeling: Comparative Analysis.," *Journal of Risk,* vol. 7, no. 1, pp. 25-59, 2013.

[15] T. Pereira and F. Cribara-Neto, "A Test for Correct Model Specification in Inflated Beta Regressions," *Working Paper, Institute de Matematica, Estatistica e Computaceo Cientifica Universidade Estadual,* 2010.

[16] E. Altman, B. Brady, A. Resti and A. Sironi, "The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implication," *Journal of Business-Chicago,* vol. 6, no. 78, pp. 2203-2228, 2005.

[17] O. N. Arvydas Paškevičius, *The Impact of Macroeconomic Indices Upon the Liquidity of the Baltic Capital Markets,* Вільнюс: International Business School, 2011.

[18] T. Bellini, IFRS 9 and CECL Credit Risk Modelling and Validation: A Practical Guide with Examples worked in R and SAS, Лондон: Academic Press, 2019.

[19] OICV_IOSCO, *Factors Influencing Liquidity in Emerging Markets,* 2007.

[20] J. W. Gathuru, *The Effect of Macroeconomic Variables on the Value of Real Estates Suppliend in Kenya,* Найробі, 2014.

[21] Deloitte, *The post-IFRS 9 era for the lending industry,* София, 2018.

[22] D. R. Cox, *Regression Models and Life Tables,* vol. 34, 1972, pp. 187-220.

[23] T. Shumway, "Forecasting Bankruptcy More Accurately: A SImple Hazard Model," *Journal of Business 74 (1),* pp. 101-124, 2001.

[24] O. M. Magnus Laurin, The Influence of Macroeconomic Factors on the Probability of Default, Lund University School of Economics and Management, 2009.

[25] E. Ozbay, The Relationship between Stock Returns and Macroeconomic Factors^ Evidence from Turkey, University of Exeter, 2009.

[26] "Credit Risk Modeling: Current Practices and Applications".

[27] J. A. Chan-Lau, "Fundamentals-Based Estimation of Default Probabilities - A Survey,," *IMF Working Papers 06/149,* 2006.

[28] T. Schuermann, What do We Know About Loss Given Default?, Federal Reserve Bank of New York, 2003.

[29] B. Yang and M. Tkachenko, "Modeling Exposure at Default and Loss Given Default: Empirical," *Journal of Credit Risk,* vol. 2, no. 8, pp. 81-102, 2012.

[30] *EU Directive 2013/36/EU of June 26, 2013,* 2013.

[31] *Law of Ukraine 'On Collateral' of October 2, 1992,* Visnuk Verhovnoi Rady Ukrainy , 1992.

[32] "IRFS 13 Fair value measurement," 2018. [Online]. Available: https://mof.gov.ua/storage/files/IFRS-13_ukr_2016.pdf.

[33] "IFRS 9 FInancial instruments," 2018. [Online]. Available: https://mof.gov.ua/storage/files/IFRS_9_Ukrainian-compressed.pdf.

[34] *Regulation on determining the size of credit risk by active banking transactions of banks of Ukraine of June 30, 2016,* 2016.

[35] *NBU Resolution No. 351 of June 30, 2016 "On Approval of the Regulation on the Determination of Credit Risk by Banks of Ukraine for Active Banking Transactions,* Kyiv, 2016.

[37] K. M. Totmyanina, "An overview of probability of default models," *Financial Risk Management,* vol. 1, no. 25, pp. 12-24, 2011.

[39] A. Karminsky, A. Lozinskaya and E. Ozhegov, "Methods of estimating the losses of a lender in housing lending," *HSE Economic Journal,* vol. 20, no. 1, pp. 9-51, 2016.

[40] D. Nekhaychuk and D. Kurtbedinov, "Valuation ofcollateral in the banking lending," *Problems of Material Culture - Economic Sciences,* pp. 70-74.

[41] S. Figlewski, H. Frydman and W. Liang, *Modeling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions,* Нью-Йорк, 2012.

[42] K. Carling, T. Jacobson, J. Linde and K. Roszbach, *Corporate Credit Risk Modeling and the Macroeconomy,* Journal of Banking and Finance 31, 2007.

[43] Y. A. Xie, J. Shi and C. Wu, "Do Macroeconomic Variables Matter for Pricing Default Risk?," *International Review of Economics and Finance 17,* pp. 279-291.