ECONOMIC ADJUSTMENT OF DEFAULT PROBABILITIES

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ABSTRACT

This paper proposes a straightforward and intuitive computational mechanism for the economic adjustment of default probabilities, allowing the extension of the original (usually one-year) probability of default estimates for more than one period ahead. The intensity of economic adjustment can be flexibly modified by setting the appropriate weighting parameter. The proposed mechanism is designed to be useful especially in the context of lifetime expected credit losses calculation within the IFRS 9 requirements.

KEY WORDS

credit risk, probability of default, economic adjustment, economic forecast, IFRS 9

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1 INTRODUCTION

Default probabilities are an essential component of modern credit risk analysis and management in credit institutions, particularly banks. Since accepting deposits and granting loans are the fundamentals of financial intermediation, which is one of the core functions of banks, credit risk is under detailed scrutiny in the banking industry. Credit risk is generally understood as the potential that a borrower or counterparty will fail to meet its contractual obligations (see BCBS, 2000). For banks it is of great importance to evaluate credit risk related to potential clients (loan applicants), as well as to actual clients. This is done within credit scoring, which is a process for prediction of the probability that a loan applicant or a client will default (Hand and Henley, 1997). Hence, credit scoring is commonly divided into application credit scoring (for evaluating loan applicants) and behavioural credit scoring (for evaluating actual clients).

For the past few decades credit scoring has undergone substantial development. Two periods can be distinguished – up to the 1970s (when a qualitative approach dominated, with the credit officer's judgement as the main decision tool) and after the 1970s (when a quantitative approach dominated, with statistical credit scoring models as the main decision tools). For a discussion on history-related topics see Thomas (2000) or Abdou and Pointon (2011). Regarding statistical credit scoring models, logistic regression has built a position above others and has become the standard, especially because of its simple and intuitive character, and also for the relatively good results it provides (Crook et al., 2007). An overview of other models, including more sophisticated ones, is provided for example by Li and Zhong (2012) or Lessmann et al. (2015).

Credit risk evaluation is crucial not only for internal credit decisions, but also for financial regulatory purposes. Since the introduction of the Basel II capital requirements framework in 2004 (see BCBS, 2004) behavioural credit scoring models and modelling of the probability of default has been paid even greater attention in the banking industry. In the context of the Internal Ratings-Based Approach (IRBA) for the calculation of credit risk capital requirements, the Probability of Default (PD) represents one of the four fundamental input parameters. The others are Loss Given Default (LGD), Exposure at Default (EaD) and Maturity (M). Therefore, as a regulatory requirement, banks must hold an adequate level of capital, especially to cover potential unexpected losses (see BCBS, 2004 and CRR, 2013).

Regulatory credit risk requirements will be further deepened from 1/1/2018 when the international financial reporting standard IFRS 9 Financial instruments should come into effect. The widely discussed IFRS 9 standard will also strengthen the link between credit risk and accounting, and substantially affect banks' economic results. Under IFRS 9 banks are required to calculate and recognise loss allowances based on the so-called expected credit losses model. In 2018 IFRS 9 will replace the IAS 39 standard that works with the so-called incurred loss model. Replacing the incurred loss model with the expected credit losses model involves a significant methodological change. According to the expected credit losses model, loss allowances should be estimated based on expectations, meaning before some adverse event (typically the default of a client) has (potentially) occurred. Moreover, either 12-month expected credit losses or lifetime expected credit losses associated with a given asset or a group of assets should be estimated, depending on whether a significant increase in credit risk has occurred since initial recognition. For details see IFRS Foundation (2015).

There are also several methodological differences between the Basel framework and the IFRS 9 requirements. Among the most significant are the following: Within Basel requirements, mostly one-year PDs are estimated. Within IFRS 9, as a part of lifetime expected credit losses calculation, multi-period (lifetime) PDs will have to be estimated. Moreover, Basel requires the estimation of PD and LGD with prudential measures (such as considering an economic downturn), however, IFRS 9 requires the estimation of credit risk parameters having a "neutral" character. Also, under Basel the PDs are commonly estimated more as through-the-cycle (neutralising economic fluctuations) to achieve a lower volatility of credit risk capital requirements. On the other hand, under IFRS 9 the PDs should be more "real-time" estimates, hence point-in-time, including forward-looking information (especially macroeconomic forecasts). For a more thorough description of the differences between the Basel and IFRS 9 frameworks, see Deloitte (2013).

The main goal of this paper is to present a straightforward and intuitive computational mechanism for the economic adjustment of default probabilities, allowing the extension of the original (usually one-year) PD estimates for more than one period ahead. The proposed mechanism is designed to be useful especially in the context of lifetime expected credit losses calculation within the IFRS 9 requirements.

The relationship between default probabilities, or more generally transition probabilities (considering a case with more rating grades),

and macroeconomic variables (or the business cycle) has been investigated and modelled by researchers within various applications, especially since the beginning of the 21st century – see Nickell et al. (2000), Bangia et al. (2002), Koopman and Lucas (2005), Duffie et al. (2007), Bellotti and Crook (2009), Figlewski et al. (2012), or Gavalas and Syriopoulos (2014). Gavalas and Syriopoulos (2014) note that gross domestic product has proven to be a key macroeconomic variable in the discussed context.

This paper is organised in the following way. Section 2 briefly describes the methodology and data used. Section 3 analyses the relationship between credit risk and selected main macroeconomic variables. As a result, an "economic adjustment coefficient" is estimated that is used in the subsequent section. Section 4, which is the core of the paper, introduces a straightforward and intuitive computational mechanism for the economic adjustment of default probabilities. Section 5 is the conclusion.

2 DATA AND METHODOLOGY

To investigate the relationship between default probabilities and macroeconomic factors, the following variables (in the context of the Czech Republic) will be used:

- share of non-performing loans (NPL) – the share of residents' and non-residents' non-performing loans to gross loans, source: Czech National Bank;
- gross domestic product (GDP) – chain linked volumes, index (2010 = 100), source: Eurostat;
- unemployment (UNE) – percentage of active population, source: Eurostat;
- three-month interest rate (IR3M) – three-month money market interest rate (PRIBOR), source: Eurostat;
- harmonised index of consumer prices (HICP) – annual average index (2015 = 100), source: Eurostat.

The time series are with a yearly frequency and cover the period from 2002 to 2015. In this paper, the variable NPL is treated as a proxy for default probabilities/credit risk.

Also, in the illustrative applications in the next section, the official economic forecasts of the Czech National Bank are utilised, in both the baseline and adverse scenarios – see Financial Stability Report 2015/2016 (CNB, 2016).

In the first place, graphical and correlation analyses will be performed. After that, a simple linear regression model with NPL as a dependent variable and the other variables as covariates will be estimated by the standard ordinary least squares method (with heteroscedasticity and autocorrelation robust standard errors). Based on this regression, the composition of the economic adjustment coefficient will be determined. This coefficient will then be used in a subsequent step to adjust default probabilities to reflect the current and forecast economic conditions.

This procedure allows the separation of economic adjustment of default probabilities from their original estimates. In other words, this logic allows to better distinguish between idiosyncratic and systemic risks. Idiosyncratic risk is understood as risk specific to individual clients or groups of clients. Systemic risk is understood as risk that influences clients as a whole (typically economic development). An analogous logic is followed also for example by Sousa et al. (2013). Due to its transparency, the described procedure is also attractive from a managerial point of view.

Regarding the economic adjustment of default probabilities itself, a straightforward logic will be used. It will be assumed that in the next period, a client can either default or not. Conditionally on this outcome, the probability of default for subsequent time periods is estimated. Based on this reasoning, probabilities of default and non-default have to sum up to 1 in every period. In other words, the probability of default (PD) may be considered as the

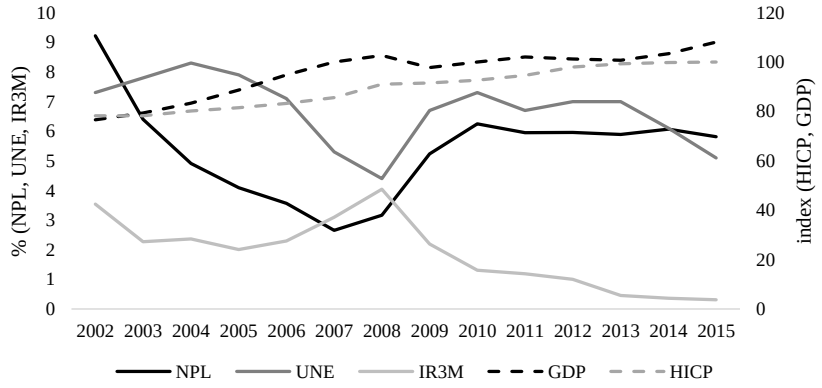

Fig. 1: Development of the considered variables (in levels) in the period 2002–2015

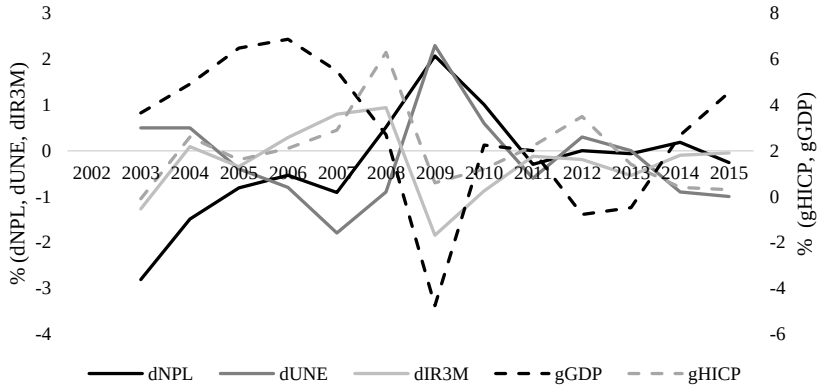

Fig. 2: Development of the considered variables (in changes) in the period 2003–2015

complement of the probability of non-default (PND) to one, i.e. $PD = 1 - PND$. No curing is assumed.

In this place, it should be also noted that this paper does not deal with the original estimates of (usually one-year) default probabilities.

3 CREDIT RISK AND ECONOMIC VARIABLES

3.1 Graphical Analysis

First, a graphical analysis of the share of non-performing loans and macroeconomic variables will be conducted. Fig. 1 depicts NPL and the selected macroeconomic variables in levels (NPL, UNE and IR3M in %, HICP and GDP as indices). Fig. 2 illustrates their changes that are of more interest in this paper (differences in variables originally in %, growth rates of variables originally as indices).

Focusing more on the dynamics of the time series (Fig. 2), it can be seen that there is a visible co-movement (in the opposite direction) of dNPL and gGDP, especially from 2007. Among others, similarly synchronised dynamics on an aggregate level can also be observed even in the case of dUNE and gGDP. However given the nature of these variables this is not surprising. A more detailed view will be provided within a correlation analysis in the next subsection.

3.2 Correlation Analysis

The correlation matrices of the considered variables in levels and changes are presented in Tab. 1 and Tab. 2.

Tab. 1: Correlation matrix of variables in levels

	HICP	IR3M	UNE	GDP	NPL
NPL	0.03	−0.25	0.37	−0.37	1.00
GDP	0.89	−0.50	−0.69	1.00	
UNE	−0.50	−0.10	1.00		
IR3M	−0.72	1.00			
HICP	1.00				

Tab. 2: Correlation matrix of variables in changes

	gHICP	dIR3M	dUNE	gGDP	dNPL
dNPL	0.12	−0.20	0.33	−0.64	1.00
gGDP	0.08	0.59	−0.69	1.00	
dUNE	−0.31	−0.85	1.00		
dIR3M	0.70	1.00			
gHICP	1.00				

The correlation matrix of variables in changes confirms the above-mentioned statements and also shows the strong negative correlation between dIR3M and dUNE and the strong positive correlation between dIR3M and gHICP. However, regarding correlations of macroeconomic variables with dNPL, only gGDP can be considered as relevantly correlated (−0.64). A mild correlation can be also observed between dNPL and dUNE (0.33).

3.3 Economic Adjustment Coefficient

In this subsection, the economic adjustment coefficient (henceforth just "EAC") is calculated using the simple linear regression model estimated by the ordinary least squares method (with heteroscedasticity and autocorrelation robust standard errors). At first, the regression model takes the following form:

$$\begin{aligned} \mathrm{dNPL} \quad = \quad & \beta_0 + \beta_1 \cdot \mathrm{dUNE} + \beta_2 \cdot \mathrm{dIR3M} + \\ & + \beta_3 \cdot \mathrm{gGDP} + \beta_4 \cdot \mathrm{gHICP} + \epsilon. \end{aligned}$$

However, after the backward elimination procedure, only gGDP remained statistically significant, as it can be seen from the summary in Tab. 3.

Therefore the EAC consists only of the impact of the GDP growth. Based on the analyses performed above, this result is not surprising – GDP growth is highly correlated with NPL changes. Even though some correlation between dNPL and dUNE was observed, dUNE was excluded from the model because it is highly correlated with gGDP. Hence, only gGDP remained in the model and was proven to be a significant macroeconomic variable in terms of its relationship with credit risk. This finding corresponds to the findings of the authors mentioned above, e.g. Gavalas and Syriopoulos (2014).

4 COMPUTATIONAL MECHANISM

4.1 Theoretical Framework

In this core section of the paper, a computational mechanism for economic adjustment of default probabilities is proposed. As was stated in the Section 2, a straightforward logic is used. Assuming that a client is assigned a certain probability of default in a given time period, in the next period this client can either default or not. Conditionally on this result, the probability of default for subsequent time periods is estimated. For the sake of clarity it can be repeated that this reasoning also implies that probabilities of default and non-default have to sum up to 1, and therefore the probability of default (PD) may be considered as the complement of the probability of non-default (PND) to one, i.e. PD = 1 − PND. No curing is assumed.

Intuitively, if the one-year PD of a client is 5% in year t, this client will default with a probability of 5% and survive with a probability of 95%. In order to calculate the two-year PD, it has to be assumed that the client will survive

Tab. 3: Results of the final regression model for EAC estimation

Dependent: dNPL	**Coefficient**	**Std. error**	***t*-ratio**	***p*-value**	**Sig.**
Constant	0.38	0.31	1.21	0.25	
gGDP	−0.23	0.06	−4.01	0.00	***
Coef. of determination R^2	0.41	Adjusted R^2			0.36
F-statistic $(1, 11)$	16.07	p-value (F)			0.00
Log-likelihood	−16.66	Akaike inf. criterion			37.32

the first year. Therefore, the probability of non-default (or survival) in the next two years from t is $0.95 \cdot 0.95 = 90.25\%$. Based on the described logic, the PD equals one minus the probability of non-default, i.e. $\text{PD} = 1 - 0.9025 = 9.75\%$.

This mechanism can be written in a general form as

$$\text{PD}\,(t+n) = 1 - \big(1 - \text{PD}\,(t+1)\big)^n,$$

where $\text{PD}\,(t+n)$ is the PD for a desired time horizon (n being a number of time periods ahead) and $\text{PD}\,(t+1)$ is the original one-year PD. For the two-year PD, this formula yields the same result as above. If it is assumed that the three-year PD is desired to be estimated, the formula yields $\text{PD}\,(t+3) = 14.26\%$. However, this formula does not take the economic forecast into account. As was mentioned above, this is the main issue addressed in this paper.

The economic forecast will be incorporated in the following way:

$$\text{PD}\,(t+n) = 1 - \\ - \prod_{k=1}^{n} \Big(1 - \big(\text{PD}\,(t+1) + \Delta_{t+k} \cdot \lambda \cdot w\big)\Big),$$

where Δ_{t+k} denotes a forecast change in the GDP growth in period $t+k$ compared to the base period t, λ denotes the economic adjustment coefficient (from the analysis performed above, it is known that $\lambda = -0.233$), and w represents a weighting that is placed for the economic adjustment effect.

Furthermore, it may be desirable to set a certain threshold for default probabilities. The floor of 0.03% that is set for PD in CRR (2013) in the context of credit risk capital requirements calculation will be considered here as well. Therefore the final formula for the multi-period default probability estimation incorporating economic forecast takes the form

$$\text{PD}\,(t+n) = 1 - \prod_{k=1}^{n} \big(1 - \min\,(X, 1-\tau)\big),$$

where X is $\max\big(\text{PD}\,(t+1) + \Delta_{t+k} \cdot \lambda \cdot w, \tau\big)$ and τ is the floor value – in this case $\tau = 0.0003$.

4.2 Practical Application

For the practical application of the economically adjusted $\text{PD}\,(t+3)$ estimation, the official economic forecasts of the Czech National Bank are used – see Fig. 3 (CNB, 2016).

The forecast growth rates of GDP in baseline and adverse scenarios (as annual averages) together with Δ_{t+k} are summarised in Tab. 4. Since the value in 2016 Q1 is known and the adverse scenario begins in 2016 Q2, the annual average for 2016 is obtained as an average of 2016 Q2–Q4.

Tab. 4: Summary of the forecast GDP growth rates for 2016–2018

	GDP growth rate		**Δ (base = 2015)**		
	baseline	**adverse**	**baseline**	**adverse**	
2015	4.30		–		–
2016	2.28	−4.39	−2.02	−8.69	Δ_{t+1}
2017	3.42	−3.28	−0.88	−7.58	Δ_{t+2}
2018	3.51	−0.74	−0.80	−5.04	Δ_{t+3}

The last parameter that needs to be set is the weighting w for the economic adjustment effect. Regarding the weighting, its setting fully depends on the practitioner and application. Tab. 5 summarises the PD estimates for up to three years ahead, taking the economic forecast in the both scenarios into account, and considering the weightings $w = 0.5$ and $w = 1$.

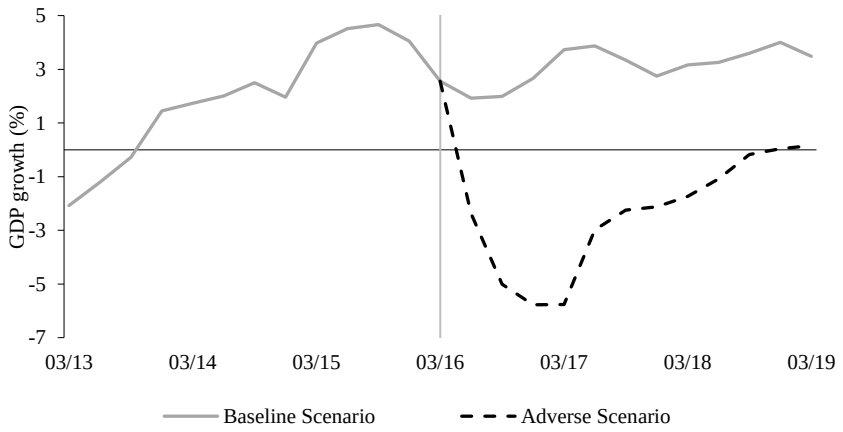

Fig. 3: The quarterly GDP growth forecast of the Czech National Bank (year-on-year changes in %)

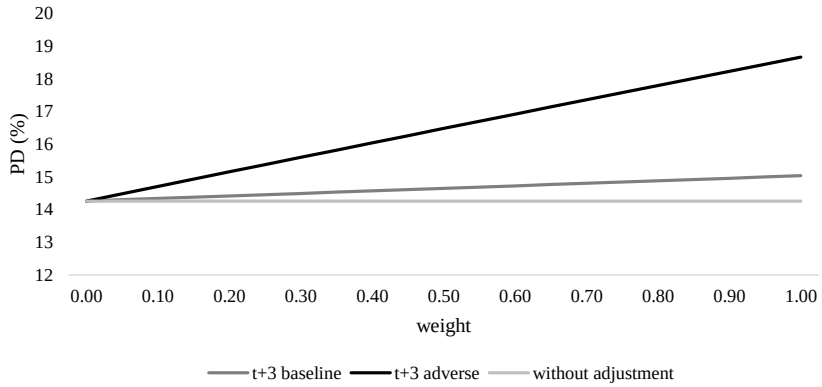

Fig. 4: Three-year PD using different weightings for economic adjustment

Tab. 5: Summary of PD estimates (in %) under different assumptions

Time period	**PD with no adjustment**	**PD** ($w = 0.5$) **baseline**	**adverse**	**PD** ($w = 1$) **baseline**	**adverse**
$t+1$	5.00	5.24	6.01	5.47	7.02
$t+2$	9.75	10.07	11.54	10.39	13.32
$t+3$	14.26	14.65	16.48	15.04	18.67
Difference	–	0.39	2.22	0.78	4.41

The economic adjustment mechanism works as expected and desired. It can be seen that the GDP growth in 2015 is relatively very high. In years 2016–2018, there is still positive GDP growth (in the baseline scenario), but not as high as in 2015. Therefore, the original one-year PD of 5% was estimated in an optimistic economic environment. The proposed mechanism takes this fact into account and with the mildly slower forecast GDP growth in subsequent years it slightly increases the estimated PD. Naturally, in the adverse scenario this increase is significantly stronger. It can also be observed that the intensity of the economic adjustment can be adapted in a flexible way by setting the weighting w – the higher the weighting, the more intense the economic adjustment is. For this application this fact is also illustrated in Fig. 4.

5 CONCLUSION

This paper has proposed a straightforward and intuitive computational mechanism for economic adjustment of default probabilities, allowing to extend the original (usually one-year) PD estimates for more than one period ahead. The proposed mechanism is designed to be useful especially in the context of lifetime expected credit losses calculation within the IFRS 9 requirements. Economic adjustment is based on the official economic forecasts of the Czech National Bank and the estimated economic adjustment coefficient reflecting the relationship between credit risk and economic variables. The intensity of economic adjustment can be adapted in a flexible way by setting the corresponding weighting parameter.

At the end it can be noted that the proposed computational mechanism assumes "only" a non-default or default state of the client or financial instrument (depending on the definition of default). However, especially within IRBA, banks use rating systems with multiple rating grades. In the case of these rating systems, not only default probabilities would have to be adjusted, but also all other transition probabilities between individual grades. Therefore, an extension and generalisation of the proposed computational mechanism using the theory of Markov chains is the subject of further research.

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