A METHOD FOR REDUCING CREDIT SCORES' SENSITIVITY TO ECONOMIC CONDITIONS

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BANCO DE ESPAÑA

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Abstract

The cyclicality of credit risk capital requirements has been a matter of concern for banking regulators, supervisors and the industry for years. The sensitivity to economic conditions of the probability of default (PD) grades to which credit exposures are assigned is often one of the most relevant sources of such cyclicality. Moreover, it is often assumed that a grade assignment method with a high differentiation capacity inherently leads to a high sensitivity to economic conditions. In order to challenge this assumption and foster further research – but with no intention of setting any expectation or recommendation for financial institutions – this article explores a methodology aimed at limiting the sensitivity to economic conditions of a pre-existing score while maintaining its differentiation ability, by adding a module to it. This module subtracts an amount which reflects the estimated effect of economic conditions. This allows the original and the adjusted scores to coexist and be used for different purposes. After testing that the methodology works on a synthetic dataset, its effectiveness is confirmed on a real dataset obtained from Banco de España internal sources. The results indicate a significant reduction in the variability of PD and risk weights when comparing a PD calibration of the original score with a PD calibration of the adjusted score.

Keywords: Scoring methods, grade assignment dynamics, probability of default, risk-weighted assets, cyclicality.

1 Introduction

1.1 Credit risk capital requirements: cyclicality and risk sensitivity

From a solvency perspective, the main aim of the regulatory framework is to ensure that institutions hold an amount of capital which is sufficient to ensure their financial stability over time. To this end, the regulatory approach is to ensure that the capital level of an institution at any time is sufficient to absorb unexpected losses, even in the occurrence of extremely severe adverse conditions and regardless of the current state of the economy.

It is therefore desirable for capital requirements not to fluctuate cyclically with the economy. Otherwise, a deterioration in the economic environment would increase risk-weighted assets (RWAs) at a time when the economy is in great need of continued lending support. Conversely, in good economic times, capital requirements would fall, reducing institutions' resilience to economic downturns. This is clearly undesirable from a prudential point of view.

A second fundamental desired feature is that capital requirements should be risk sensitive, i.e. they should vary over time in a way that reflects changes in the riskiness of the institution's portfolios.

Combining these two features is one of the greatest difficulties in determining capital requirements. Indeed, in order to have capital requirements that are reactive to changes in riskiness but not to cyclical patterns, the effects related to changes in the economy need to be disentangled from unrelated effects. This issue has been a focus of regulatory and supervisory attention since the Basel II[1] accords of 2004.

1.2 The role of grade assignment dynamics (GAD) in internal ratings-based (IRB) models

Under the IRB approach for credit risk, institutions assign each obligor to a rating grade or pool. Obligors with similar default risk should be assigned to the same grade or pool, and obligors with different default risk to different grades or pools. As a result of the PD calibration, each grade or pool is univocally mapped to a PD. Grade or pool assignments must be reviewed as updated and relevant information about the obligor becomes available. However, the PD of the grades or pools remain constant over time until ongoing monitoring identifies a need to recalibrate them. Moreover, according to the regulatory framework, these grade PDs are intended to reflect long-term credit risk, and should therefore be relatively stable.

To obtain a portfolio's IRB capital requirements for credit risk at a specific date, each obligor in the portfolio is given a PD equal to that of the grade or pool to which the obligor is assigned at that date. These PDs are then used as inputs to the regulatory formula that calculates the capital requirement for each exposure. As a result of this framework, the PDs of the obligors in the portfolio, and thus the average PD of the entire portfolio, will vary essentially as a result of changes in the grades or pools to which the obligors are assigned, regardless of the method used to derive the PDs of the grades or pools.

In particular, if the grade assignment process is highly sensitive to economic conditions, changes in the state of the economy will tend to make obligors/facilities migrate in the same direction. In other words, obligors/facilities will tend to migrate to better grades (with lower PD estimates) during upturns and to worse grades (with higher PD estimates) in adverse economic conditions. These cyclical migrations will lead capital requirements to behave cyclically, increasing in bad years and decreasing in good years. Figure 1 below attempts to illustrate this.

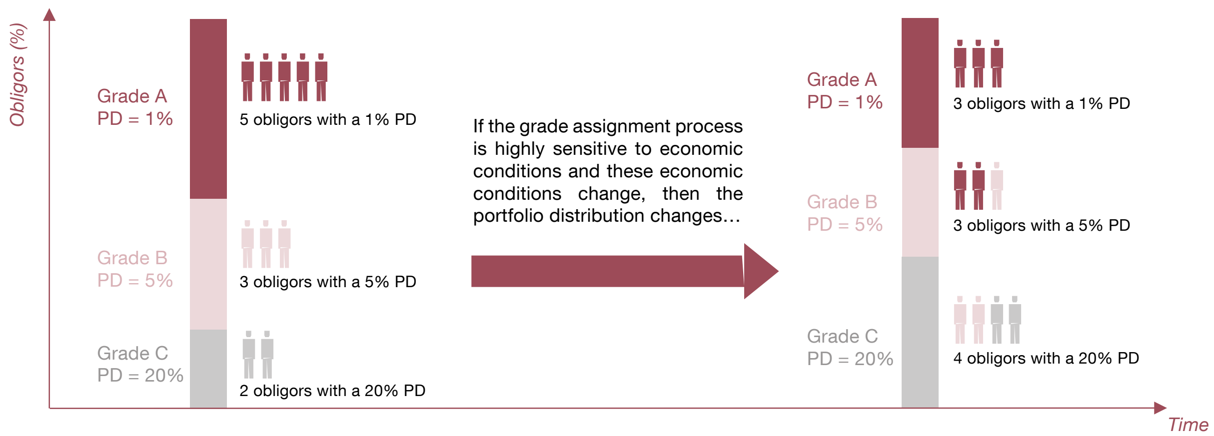
In the example shown in Figure 1 we have a portfolio with 10 obligors and 3 grades (A, B and C). At date 1, when economic conditions are good, 5 obligors are assigned to grade A, 3 obligors to grade B and 2 obligors to grade C. The average portfolio PD is 6% and the portfolio risk weight (RW)[2] is 114.01%. Let us now assume that some time later, at date 2, these economic conditions worsen (and nothing else changes). If the grade assignment process is highly

1 BCBS (2004).

2 RW computed in accordance with Article 153 of Regulation (EU) No 575/2013 by assuming: loss given default (LGD)=45%, maturity (M)=2.5, sales<€5 million, 10 obligors each of them with the same exposure amount.

Figure 1
The role of grade assignment dynamics

EXAMPLE OF A HYPOTHETICAL PORTFOLIO WITH 3 GRADES (A, B AND C) AND 10 OBLIGORS



Date 1
Good economic conditions
Average Portfolio PD = 6 %
Portfolio RW = 114.01%

Date 2
Adverse economic conditions
Average Portfolio PD = 9.8 %
Portfolio RW = 138.61%

$$\overline{PD} = \frac{(1\% * 5 + 5\% * 3 + 20\% * 2)}{5 + 3 + 2} = 6\%$$

$$\overline{PD} = \frac{(1\% * 3 + 5\% * 3 + 20\% * 4)}{3 + 3 + 4} = 9.8\%$$

SOURCE: Banco de España.

sensitive to economic conditions, obligors would migrate to worse grades. The new portfolio distribution would have 3 obligors in grade A, 3 obligors in grade B and 4 obligors in grade C. The average portfolio PD is now 9.8% and the portfolio RW is 138.61%. The average portfolio PD therefore changes from 6% to 9.8% and the portfolio RWs from 114.01%. to 138.61%, simply as a result of a change in macroeconomic conditions and not because of idiosyncratic or structural changes. The observed volatility in macroeconomic conditions impacts the average portfolio PD (+63.3% relative increase), which ultimately impacts the RW (+21.6% relative increase) and hence capital requirements.

The cyclicality of capital requirements is not the only consequence of grade assignment dynamics. As different institutions' grade assignments differ in their level of sensitivity to economic conditions, PDs (and hence RWAs) across institutions will exhibit variability which is not driven by their intrinsic portfolio risk level. This can be an unwarranted source of variability across institutions.

These important consequences of GAD, which are especially relevant for institutions operating in jurisdictions characterised by large economic fluctuations, have been a major source of concern for the different parties involved (regulators, supervisors and industry).

It is worth noting that, at the macro-prudential level, the regulatory framework includes a countercyclical capital buffer aimed at mitigating regulations' system-wide pro-cyclical effects. Its inclusion was motivated by the lessons learnt during the financial crisis. This buffer seeks to address situations in which system-wide risks build up during times of excessive aggregate credit growth. It is set at the level of the country where the exposures are located and is activated in times of excessive credit growth. It should however be noted that situations of excessive credit growth do not necessarily cover all the circumstances where the economy follows a cyclical pattern with an effect on the risk drivers used to assign obligors to grades, as the latest economic developments have shown. This, together with the level at which it operates, makes the countercyclical capital buffer insufficient to prevent capital requirements from varying cyclically at the micro-prudential level as a result of GAD, or to prevent IRB capital requirement differences across institutions from being unduly affected by different levels of grade assignment's sensitivity to cyclical effects.

In this context, it is very important to have techniques available to perform grade assignments that do not change significantly as a result of fluctuations in economic conditions. This clearly poses a challenge for institutions, since they are required to design risk-sensitive grade assignment processes that take into consideration as much relevant information about the obligors as possible.[3] This leads institutions to consider, among others factors, risk drivers that fluctuate with economic conditions, and these fluctuations are ultimately transmitted to the grade assignments. Here is where the aforementioned difficulty in discerning cyclical vs non-cyclical effects during the grade assignment becomes clear, as it would be desirable for grades to vary in line with changes in the exposure's characteristics that do not result from cyclical effects. The European Central Bank's (ECB) supervisory expectations, as set out in paragraph 105 of the current ECB Guide to internal models[4] (Credit Risk chapter), clearly illustrate this tension, by requiring that *"[…] the rating/grade/pool assignment process should also adequately anticipate and reflect risk over a longer time horizon and take into account plausible changes in economic conditions […]"* while stressing that *"[…] this does not mean that grades remain stable over the longer time horizon in the event of changes in the risks that are specific to the obligor […]".*

However, this tension is not just a result of regulatory requirements. Indeed, institutions often use internal grades for different management purposes. For those that require a longer-term perspective, insensitive grade assignments would be desirable. Conversely, more sensitive assignments would be more adequate for shorter-term management purposes. Having a single grade assignment process would necessarily be suboptimal in at least one of these perspectives. By contrast, having different grade assignment processes for different purposes would increase complexity. In this regard, regulations require that the assignment process used for regulatory purposes be integrated within the institution's risk management and decision-making activities, including credit approval and internal capital allocation, and stipulate that any deviation of regulatory processes from management processes must be duly justified.

3 According to Article 171 of Regulation (EU) No 575/2013, "an institution shall take all relevant information into account in assigning obligors and facilities to grades or pools".

4 ECB (2024).

The approach typically adopted to address these seemingly conflicting requirements is to strike a balance between risk sensitivity and cyclicality, in other words, to seek a minimum sufficient compromise in terms of risk sensitivity so that the grade assignment is not overly sensitive to economic conditions.

1.3 The goal

While there is some research on approaches that attempt to influence PD dynamics during risk quantification (see, for instance, Carlehed and Petrov, 2012, or Rubstov, 2021), the literature on approaches that limit cyclicality in the risk differentiation function is scarce. An exception is found in Rubstov and Petrov, 2016, where a method is proposed to define "floating" grades that removes systemic effects from the scores.

This article falls within the latter type of approaches. Therefore, it does not discuss or address the way in which, given a scoring method, PDs are obtained for its grades. The aim of this article is to explore a possible methodology to limit the sensitivity to economic conditions of the scores assigned using an existing scoring method, while maintaining their risk differentiation ability. The scores would coexist with an adjusted version of them, allowing different assignment dynamics to be considered for different risk management purposes. The adjusted scores can then be used as input to any PD calibration method.

By no means should this article be interpreted as an expectation or recommendation for institutions to follow this particular methodology. Its intention is to foster and promote the development and availability of such techniques, and to test the feasibility of institutions obtaining grade assignments which are sufficiently stable to changes in economic conditions. It is up to the institutions to develop and implement the methodologies that better suit their needs, while complying with the requirements and expectations.

Section 2 below elaborates on the proposal from a theoretical perspective. Sections 3 and 4 use synthetic and real data, respectively, to test the proposal. Some concluding remarks are presented in Section 5.

2 Deriving the idiosyncratic component of a scoring method

It is commonplace within the industry to use scoring methods which synthesise all (or almost all) of the relevant information to rank credit exposures[5] according to their risk of default into a single numerical value, called *score.* Even though macroeconomic indicators are generally not considered explicitly when obtaining this score, economic conditions can still influence the assigned scores. This is due to the interdependence between the state of the economy and many of the risk drivers that are typically considered. For example, a company's turnover

5 Exposure is understood to mean obligor or facility. For the sake of simplicity, it will be referred to as obligor from now on.

or financial ratios (commonly used risk drivers for corporate portfolios) are usually affected by the macroeconomic environment.

The application of a scoring method over time generates a dataset of obligor scores for different dates. Given that obligors enter/exit the portfolio as time goes by, not all obligors are present at all dates. Together with their default flags, this constitutes the basic historical information needed for PD estimation purposes. The score of obligor i at date t within the dataset is denoted as $s_{i,t}$.

Let c_t be a time series for the dates available in the dataset. Natural ways of defining c_t would be centrality measures of the scores of the obligors in the portfolio at date t, such as the mean or the median of the individual scores. Then, $s_{i,t}$ can be expressed as the sum of c_t plus the deviation from it:

$$s_{i,t} = c_t + \left(s_{i,t} - c_t\right)$$

Or, replacing $s_{i,t} - c_t$ with $e_{i,t}$, as:

$$s_{i,t} = c_t + e_{i,t}$$

It may be that c_t is related to some economic indicators $m_1, \ldots, m_M$, allowing a meaningful regression to be obtained for certain coefficients $\beta_0, \ldots, \beta_M$, as:

$$c_t = \beta_0 + \sum_{j=1}^{M} \beta_j m_{j,t} + \varepsilon_t$$

where ε_t denotes the residuals of the regression.

If this is the case, inserting this expression of c_t into the previous equation gives:

$$s_{i,t} = \beta_0 + \sum_{j=1}^{M} \beta_j m_{j,t} + \varepsilon_t + e_{i,t}$$

From the previous expression, the scores in the dataset can be split into two components:

$$s_{i,t} = s_t^m + s_{i,t}^*$$

The first component,

$$s_t^m \stackrel{def}{=} \beta_0 + \sum_{j=1}^{M} \beta_j m_{j,t}$$

represents the systemic effect on the score centrality measure c_t of the economic conditions reflected by the set of indicators $m_{j,t}$.

The second component,

$$s^*_{i,t} \overset{\text{def}}{=} \varepsilon_t + e_{i,t}$$

is the sum of (i) the part of the score centrality measure c_t that is not explained in terms of economic indicators (residuals of the regression), plus (ii) the deviation of the score of obligor i from the centrality measure c_t. This term, which is the component of the scoring method that is free from the influence of the considered economic indicators, can also be expressed as:

$$s^*_{i,t} = s_{i,t} - \left(\beta_0 + \sum_{j=1}^{M} \beta_j m_{j,t} \right)$$

This expression represents an alternative scoring method (adjusted score) which can be used to obtain scores for any exposure (not only for the ones included in the dataset, but also for exposures outside this dataset, including those observed at any date t not considered when performing the linear regression against macroeconomic indicators). This adjusted score depends on all the inputs and parameters that were already necessary to obtain $s_{i,t}$ with the original scoring method, plus the inputs $m_{j,t}$ (namely, the economic indicators at date t) and parameters β_j. This adjusted scoring method must necessarily be performed in two steps. First, a scoring method, s, is developed. In the second step, the β_j parameters are determined.

This second step includes the identification and selection of the economic indicators to be used ($m_{j,t}$). The selection of economic indicators needs to be done on a case-by-case basis, as it is highly dependent on the specifics of the particular scoring method used, such as the country where the exposures are located, the sector to which they belong and other characteristics of the exposures within the scope of application of the score. This article does not attempt to provide any guidance on how to select the economic indicators or a list of indicators that should be used. Any reference to specific economic indicators made here must be understood as one of a wide range of possible choices.

A practical difficulty in the application of this scoring method is the availability of the values of $m_{j,t}$ at the time of the grade assignment, as these are likely to be economic indicators whose actual values become known with some delay. One way to tackle this is to use lagged indicators when conducting the regression. The use of these lagged indicators is often reasonable, as it usually takes some time for changes in economic conditions to materialise in changes in the inputs to the scoring method. Alternatively, forecasts of the economic indicators could be used.

The advantage of this approach is that the adjusted scores can be expected to be less reactive to changes in the economic conditions represented by the indicators $m_{j,t}$. Hence, calibrations based on them would lead to more stable PD dynamics.

Moreover, an interesting property of this alternative scoring method is that for one particular date t, s^* has the same discriminatory power as the original s. This is because the score of every single obligor within the portfolio at that particular date t is shifted by the same amount, $\beta_0 + \sum_{j=1}^{M} \beta_j m_{j,t}$. Therefore, the rank order of the obligors is not affected by the proposed transformation.

From an operational perspective, the method could be easily implemented in the risk differentiation phase by using an ad hoc GAD-control module during the score generation process. This GAD-control module would complement other modules such as the commonly used quantitative and/or qualitative ones. This has the advantage of producing two scores, $s_{i,t}$ and $s^*_{i,t}$, with the same capacity to rank obligors by their risk of default. The score before the application of this GAD-control module would be more sensitive to changes in macroeconomic conditions, which could be an advantage for short-term management purposes or when quantifying the deterioration of financial instruments under IFRS9 accounting principles. Conversely, the score after the application of the GAD-control module would be less sensitive to changes in macroeconomic conditions, a desired feature for IRB PD models and other long-term management purposes. The straightforward link between these two scores would help IRB institutions to meet the use test supervisory expectations.

It is worth noting that the monitoring of this GAD-control module must be part of the regular monitoring of the overall scoring method. In particular, it must be assessed whether the identified economic indicators and their weights need to be updated in light of newly available information, namely recent unadjusted scores and economic indicators.

So far, it has been assumed that all the relevant information to assess the risk of default of an obligor is included in the synthetic score s. However, this is not always the case. In some circumstances, additional information which is deemed relevant is added on top of credit scores when assigning obligors to the final grade or pool scale of the rating system (for example, pools defined as a combination of the sector and score buckets). The proposed methodology is still valid in these cases (i.e. it can still reduce cyclical PD dynamics), as long as the additional risk drivers that are added on top of the resulting adjusted score s^* are (to some extent) insensitive to changes in macroeconomic conditions.

Lastly, an important remark needs to be made about the centrality measure c_t. In situations where the portfolio composition in terms of credit quality has remained stable over the dates from which the data is available, the variability of c_t only reflects the systemic effects on the score. However, where the portfolio composition has changed over time, the systemic effect in c_t will be blurred by these portfolio shifts. In this case, it might be more difficult to identify the effect of the economic environment on c_t. In these situations, techniques can be used to neutralise this effect from the centrality measure c_t. For the sake of simplicity, this discussion is omitted in this article, leaving it as an area for further research in the future.

The following sections describe the results of applying the proposed methodology to both a synthetic dataset and to actual data.

3 Application to synthetic data

In this section, a synthetic reference dataset is created that is used to test the method described in the previous section.

3.1 Data preparation: calibration dataset

A non-retail portfolio composed of 50,000 obligors observed over 24 years is simulated in an economy that follows a perfectly cyclical pattern, with each cycle lasting for 8 years. For the sake of simplicity, it is assumed that obligors either remain in the portfolio or are replaced by equivalent ones. The dataset contains information about the following variables: gross domestic product (GDP) growth in the year prior to each date, score of each obligor at each date, and its default flag.[6]

GDP growth in the year prior to each date is assumed to follow a deterministic and cyclical path, ranging between -0.05 and 0.05 (see Chart 1).

To simulate the scores of the obligors at each date, a target series of their means, c_t, is first simulated, as $c_t = 1 + 5g_t + \varepsilon_t$, where g_t is the GDP growth in the year prior to t and ε_t is simulated from a normal distribution with a zero mean and a standard deviation of 0.05.

The scores of individual obligors in year 1, $s_{i,1}$ are then simulated under a normal distribution with a mean of c_1 and a standard deviation of 0.35.

For the following years the score is obtained in two steps. First, a component representing a change in the score for obligor-idiosyncratic reasons (simulated from a normal distribution with a zero mean and a standard deviation of 0.05) is added to the previous year's score for each obligor i:

$$s_{i,t+1}' = s_{i,t} + \xi_{i,t}$$

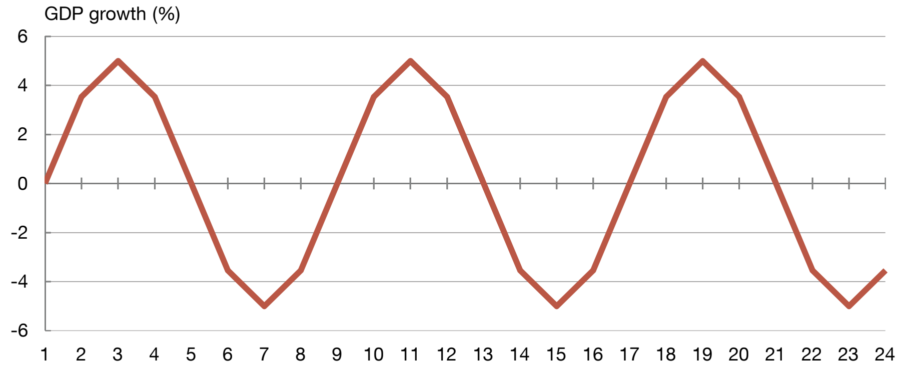
where $\xi_{i,t}$ is simulated from a N(0, 0.05). These scores are then normalised, rescaled and shifted so that their average is c_{t+1} and their standard deviation continues to be 0.35 (hence preventing the distribution from spreading away from its mean due to the idiosyncratic component). The simulated scores are thus expressed as:

$$s_{i,t+1} = c_{t+1} + \frac{s_{i,t+1}' - \mu_{t+1}^{s'}}{\sigma_{t+1}^{s'}} 0.35$$

where $\mu_{t+1}^{s'}$ and $\sigma_{t+1}^{s'}$ denote the sample mean and standard deviation of $s_{i,t+1}'$.

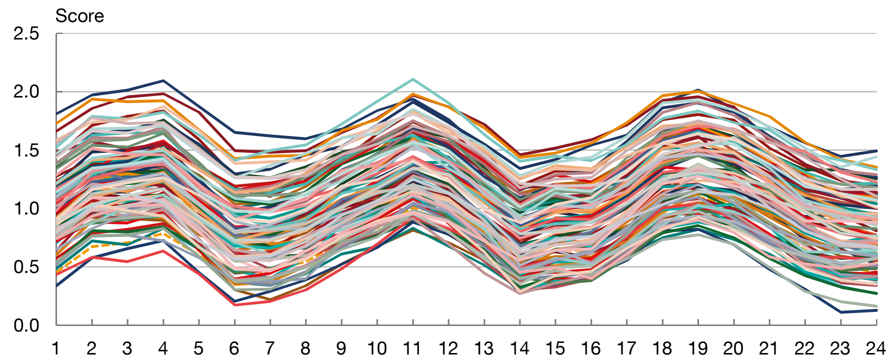
6 12-month forward-looking default flag. For the sake of simplicity, the term default flag is used.

Chart 1
GDP growth per year (synthetic data)



SOURCE: Banco de España.

Chart 2
Score of the first 100 obligors (synthetic data)



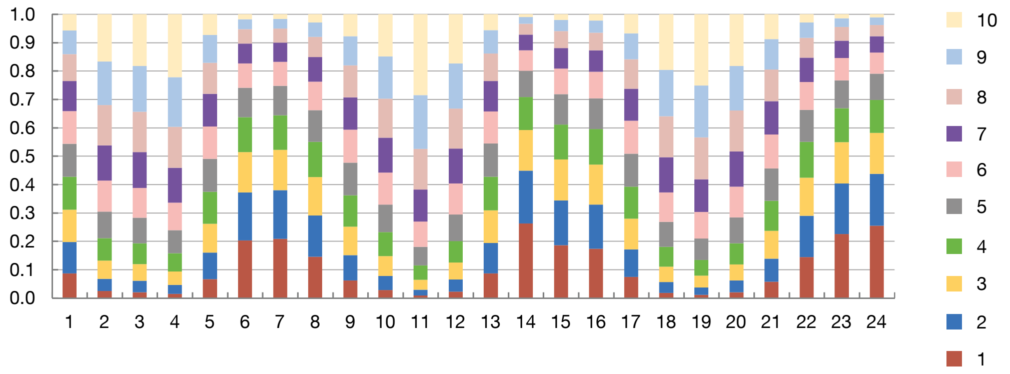
SOURCE: Banco de España.

Charts 2 and 3 provide further details on the simulated scores. Chart 2 shows that the scores behave cyclically while simultaneously being affected by idiosyncratic changes. In Chart 3, score buckets are defined as deciles for the total dataset, including all years. The chart shows the proportion of observations in these score buckets per year, and how they shift significantly in line with GDP growth.

To simulate the default flags, a default probability is simulated for each obligor and date by assuming a logit shape dependent on the score:

$$p_{i,t} = \frac{1}{1+e^{-(\alpha_0 - s_{i,t})}}$$

Chart 3
Proportion of observations by decile and year (synthetic data)



SOURCE: Banco de España.

where α_0 is chosen so that the probability of default of an obligor with a score equal to the mean is 0.05.[7] Default flags are then simulated for each record in the database based on the previous probability of default. Charts 4 and 5 show the simulated one-year default rates (DR). As expected, default rates vary according to both economic conditions and the score.

3.2 Adjusted score

In addition to the aforementioned score, an adjusted score is obtained by following the indications in Section 2. In particular, this score would be calculated as:

$$s^*_{i,t} = s_{i,t} - \left(\beta_0 + \beta_1 \times GDP_t\right)$$

where β_o and β_1 are the coefficients of a linear regression of the series of original score centrality measures[8] c_t against the GDP of the year to which the observation corresponds, denoted GDP_t.[9]

3.3 IRB PD estimation

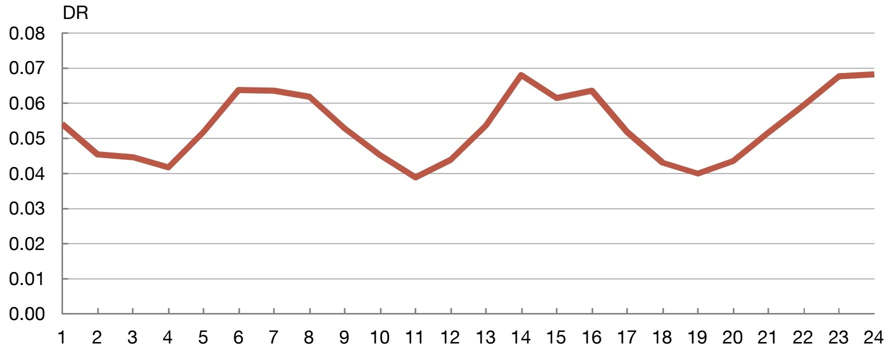
Firstly, grades are defined as the deciles of the (cumulative) distribution of obligors across scores. This process generates one set of *original grades* (grades based on the original score) and one set of *adjusted grades* (grades based on the adjusted score).

7 This entails that the previous equation for such an obligor would be $0.05 = \frac{1}{1+e^{-(\alpha_0 - \overline{s_{i,t}})}}$, which can be solved for α_0 to obtain that $\alpha_0 = -\ln\left(\frac{1}{0.05} - 1\right) + \overline{s_{i,t}}$, where $\overline{s_{i,t}}$ denotes the average of all the scores at all dates.

8 In this case, the centrality measure used is the mean.

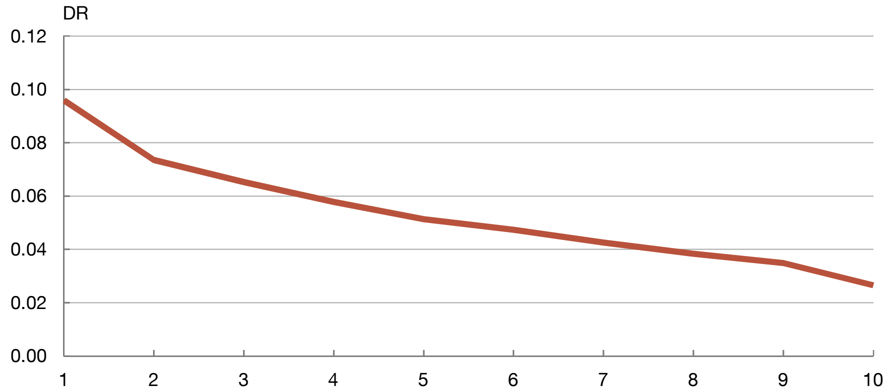
9 For simplicity, no lagged indicators are used in the synthetic example.

Chart 4
Average one-year default rate by year (synthetic data)



SOURCE: Banco de España.

Chart 5
Average one-year default rate by score decile (synthetic data)

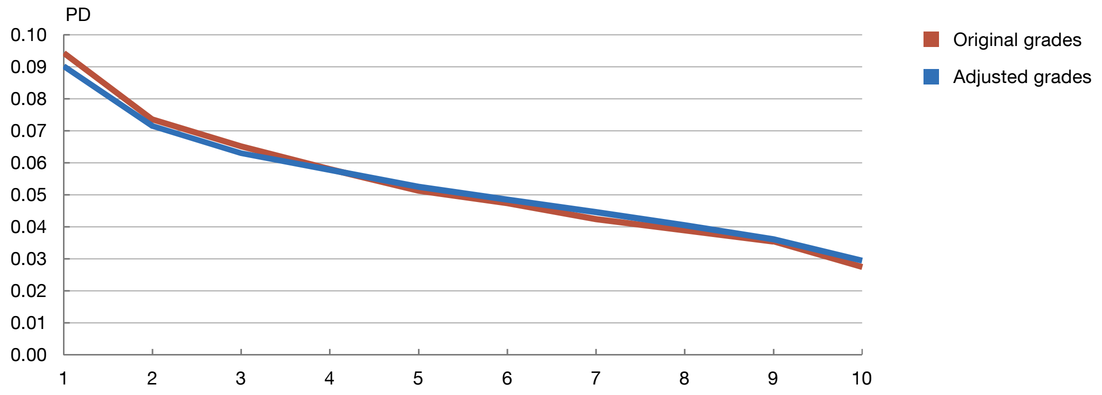


SOURCE: Banco de España.

Secondly, two different calibrations are obtained at grade level (where the PD for each grade is calculated as the observed average default rate by grade),[10] one using the original grades and a second one using the adjusted grades. Chart 6 shows the results of the aforementioned calibration processes. It can be observed that the resulting estimates by grade are quite similar.

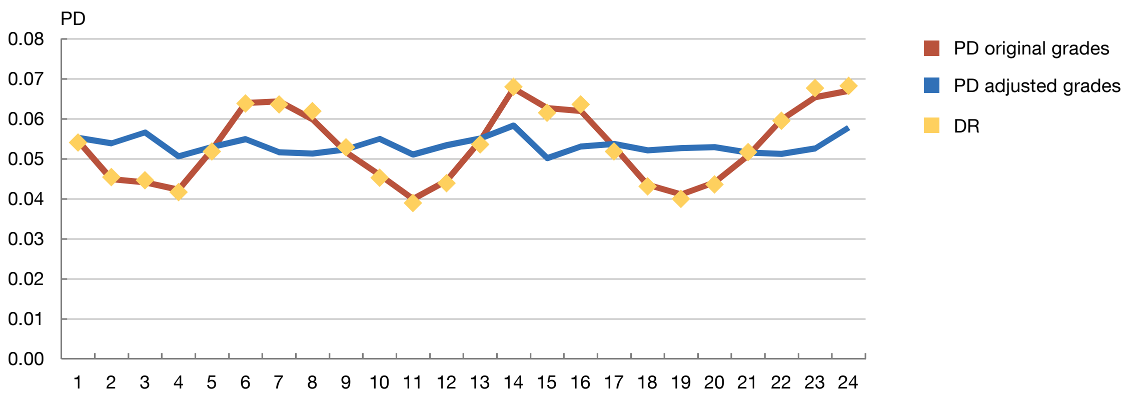
10 By performing a calibration at grade level, in accordance with paragraph 92(a) of EBA/GL/2017/16, the grades' PDs are calibrated to the observed average default rate (OAvDR) within the period representative of the likely range of variability of the one-year default rates (LRVDR). It is assumed that the observed historical period is representative of the LRVDR and also that there are not any representativeness issues within the dataset. For each grade, the OAvDR is the simple average of the one-year default rate by grade and date.

Chart 6
PDs by grade (synthetic data)



SOURCE: Banco de España.

Chart 7
Average PD (synthetic data)

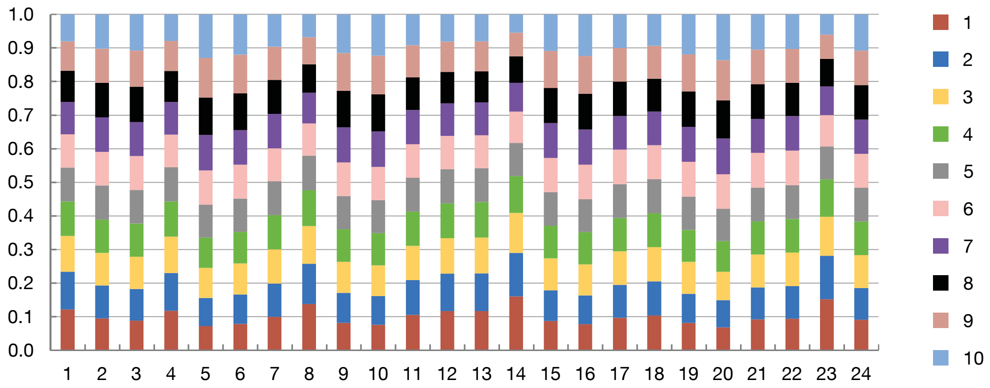


SOURCE: Banco de España.

3.4 IRB PD dynamics

Despite the similarities in the PDs by grade, when these estimates are applied to the available years (see Chart 7), the proposed calibrations show different patterns. First, the (number-weighted) average PD at aggregate (portfolio) level based on the adjusted score calibration is less volatile over time and its correlation with GDP is lower (indeed, the volatility in the series is driven by the idiosyncratic and noise terms used to generate the synthetic data). Second, the average PD based on the original score calibration shows a much higher volatility. In particular, the average PD at portfolio level closely follows the average one-year default rate of the portfolio, indicating a clear excessive sensitivity to macroeconomic conditions in the assignment of exposures to grades.

Chart 8
Proportion of observations by adjusted decile and year (synthetic data)



SOURCE: Banco de España.

This is the result of the adjusted scores' more stable grade distribution, as shown in Chart 8 below, when compared with the grade distribution based on the original scores (shown in Chart 4).

It can therefore be concluded that the proposed adjustment to the scores worked as expected with the synthetic dataset specifically designed to test it, given that PD cyclicality was indeed reduced.

In the next section, this method is applied to actual data.

4 Application to actual data

4.1 Data preparation: calibration dataset

In this section, actual data is used to test the proposed methodology. In particular, historical credit information on small and medium-sized enterprises (SMEs) is obtained from the Banco de España Central Credit Register (CCR).[11] This information is further enhanced with the in-house credit assessment system of the Banco de España (ICAS BE), an internal credit assessment system of public and private Spanish non-financial corporations that allows the loans extended to these corporations to be used as collateral in monetary policy operations. It has two different rating systems: the Full-ICAS BE for large companies, which is based on a quantitative approach plus a human expert assessment, and the Statistical-ICAS BE for SMEs, based purely on statistical models without the intervention of an analyst.[12] By combining the CCR and ICAS BE, a database with the following information is obtained:

11 For more details about the CCR database, see Banco de España (2022).

12 A full description of the Banco de España in-house credit assessment system can be found in Gavilá et al. (2020).

— Obligor identifier.

— Date, spanning from August[13] 2011 to August 2021 (yearly frequency).

— A default flag that indicates if the obligor had a 90 days past due default event in the 12 months following the ICAS assessment.

— Score assigned by the ICAS BE. For the purposes of this exercise, only the scores from the automated statistical model are used, based on the most recent financial statements at the time of the assessment. It should be noted that not considering other elements such as the expert judgement of the Full-ICAS BE and the sectoral risk assessment of the Statistical-ICAS BE likely increases the sensitivity to macroeconomic conditions compared with the complete version of the model, in which a higher degree of stability is expected.

— Economic indicators. The database is enriched with several Spanish macroeconomic indicators.[14] ICAS BE assessments made in August are combined with macroeconomic indicators from the previous December. By using this approach, the macroeconomic information is always available at the time of the grade assignment, thus avoiding the practical difficulty mentioned in Section 2.

4.2 Adjusted score

In addition to the ICAS score, the adjusted score is defined as follows:

$$s^*_{i,t} = s_{i,t} - \left(\beta_0 + \beta_1 \times GDP_{t-1} + \beta_2 \times UR_t\right)$$

where β_0, β_1 and β_2 are the coefficients of a linear regression of the series of the original score centrality measure[15] c_t against the year-on-year change in GDP (with one lag) and the year-on-year change in the unemployment rate (UR).

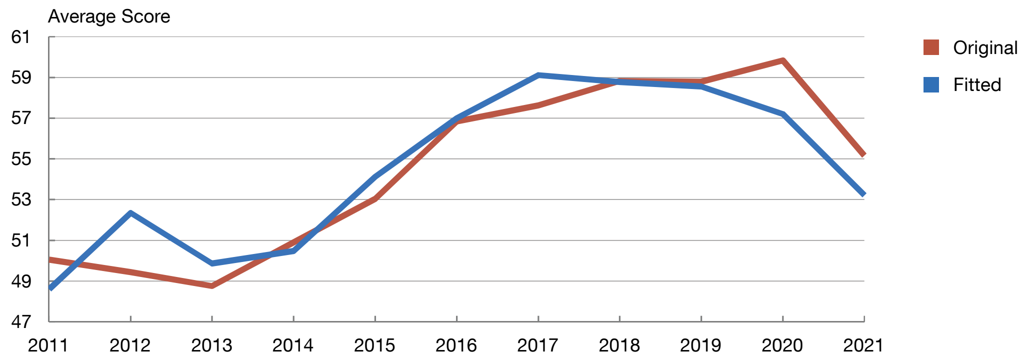
Chart 9 provides more details about the results of the linear regression. It can be observed that the average score series follows a decreasing trend over the period 2011-2013, followed by a steady increasing trend over the period 2013-2020, which is only interrupted by the sharp decrease observed between August 2020 and August 2021. Since higher scores represent better credit quality, at first glance this trend seems to be in line with economic developments in the Spanish economy, where 2014 marked the end of the distressed conditions observed

13 ICAS assessments at August are used for the periodical monitoring of the rating systems.

14 Macroeconomic indicators sourced from the Banco de España time series search engine.

15 In this case, the mean is used as a centrality measure.

Chart 9
Comparison between original and fitted average scores



SOURCE: Banco de España.

since 2008 and the start of a period of economic growth which was interrupted in 2020 with the outbreak of the COVID-19 pandemic.

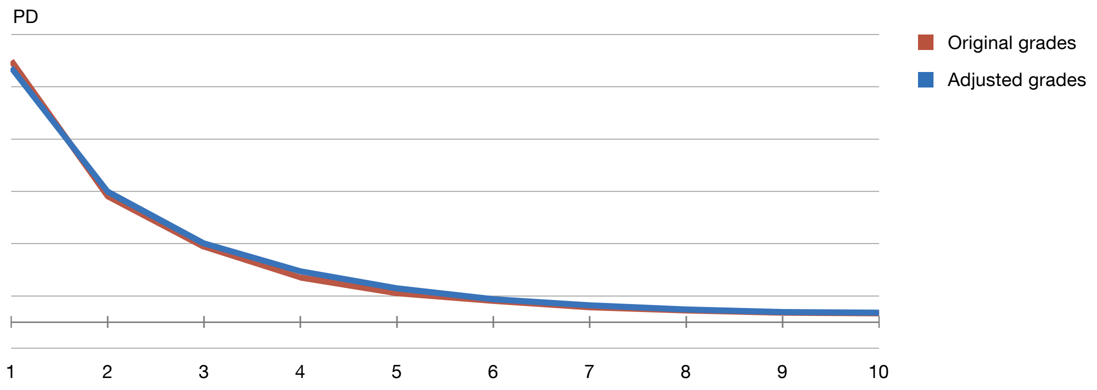
However, it should be stressed that economic developments are not necessarily the only driver of changes in average scores. The composition of the portfolio and other non-cyclical systemic effects might also be a source of changes in the series. Since the aim of this methodology is for these other effects that affect credit quality in a non-cyclical manner to be reflected in changes in capital requirements, they are left untreated in the derivation of s^*.

This also has implications for the regression to be performed. As this methodology does not seek to obtain an explanatory model of the series considering all the relevant drivers, a pragmatic approach is adopted, by using a simple ordinary least squares regression rather than more complex time series analysis tools. For instance, it is highly likely that the residuals will show autocorrelation as a result of these missing drivers. But since the aim is just to identify the part of the changes in the series that may be attributed to the economic indicators, this should not be considered an impediment to use the regression results for the purposes of this methodology. Thus, only a minimal assessment of the model fit was performed, to ensure that the sign of the coefficients is meaningful. Overall, the obtained model is considered to properly achieve its aim.

4.3 IRB PD estimation

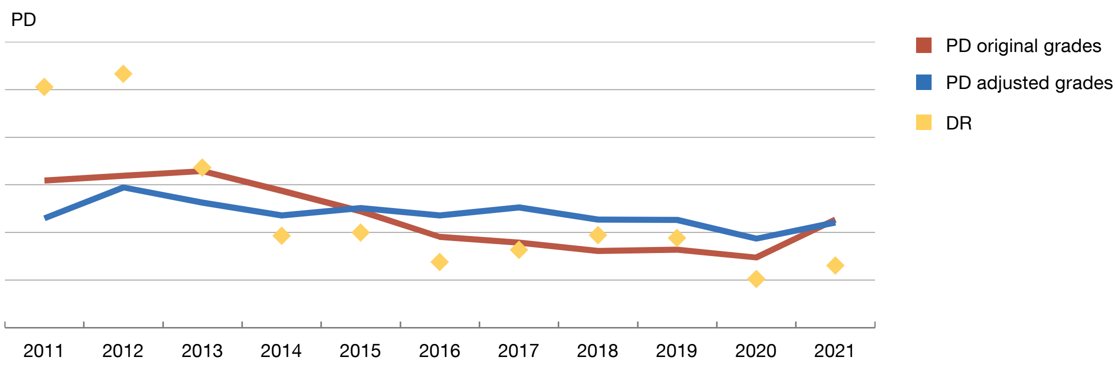
The same process used with the synthetic dataset to obtain two different PD calibrations (with the original and adjusted scores, respectively) (see Section 3) is also followed here. It is important to note that these PD calibrations are solely performed for the purpose of this theoretical analysis and have no relation to the actual PD calibrations applied by the ICAS BE. The obtained default probabilities, and Charts 10 and 11 in particular, provide no information about the ICAS BE's actual calibration.

Chart 10
PDs by grade



SOURCE: Banco de España.

Chart 11
Average PD



SOURCE: Banco de España.

Chart 10 shows the PDs by grade for both calibrations. It can be observed that the resulting PDs are quite similar in both approaches. For confidentiality reasons, the PD scale is omitted.

4.4 IRB PD dynamics

As in the case of the synthetic data, different patterns emerge when the estimates are applied over the available years (see Chart 11). In particular, the (number-weighted) average PD at aggregate level based on the adjusted score calibration is less volatile over time than the (number-weighted) average PD at aggregate level based on the original score calibration.

Table 1
Quantitative assessment of the results. Series of average PD

Statistic (average PD series)	Original	Adjusted
Range	1.8%	1.1%
1st central moment	0.6%	0.2%
Standard deviation	0.7%	0.3%

SOURCE: Banco de España.

Table 2
Quantitative assessment of the results. Series of average RW

Statistic (average RW series)	Original	Adjusted
Range	22.2%	12.1%
1st central moment	7.3%	2.4%
Standard deviation	8.4%	3.2%

SOURCE: Banco de España.

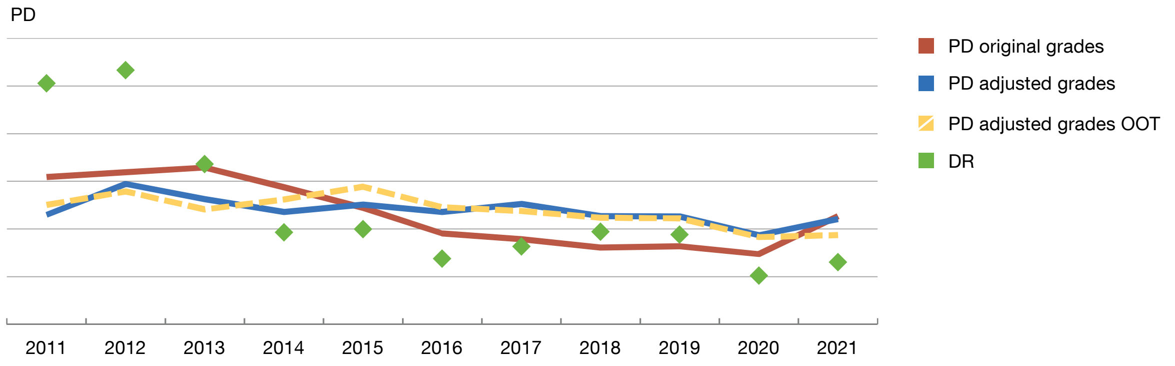
Quantitatively assessing the degree of sensitivity of a grade assignment method to economic conditions is a complex issue, for which there is no generally agreed technique. This article does not attempt to select one of the available metrics to assess the extent to which the adjustment has reduced the sensitivity. Instead, the quantitative assessment is based on the fact that the adjusted scores are the original scores from which a quantity is subtracted. This quantity represents only the effect of the economic indicators on the score average for each year identified through the regression. It can therefore be assumed that any differences between PDs of the two calibrations are solely attributable to their different sensitivity to the economic indicators. Hence, comparing the variability of both PD series provides an indication of how less volatile the adjusted score is. Such reduction can be attributed to the different sensitivities to economic conditions.

Table 1 provides several statistics related to the dispersion of both series. In particular, it shows the PD range (difference between the maximum and minimum PDs of the series), the first central moment (average distance from the PDs in the series to the mean) and the standard deviation. It shows that there is a significant reduction in variability.

The same effect can be obtained by using the series of average RWs[16] instead of the series of average PDs. As expected, the reduction in variability is also significant (see Table 2).

16 For each obligor in the sample, the RW by date is calculated in accordance with Article 153 of Regulation (EU) No 575/2013 by assuming loss given default (LGD)=45%, maturity (M)=2.5 years and sales< €5 million. Once the RW is obtained for each obligor and date, a simple average is calculated to obtain the series of average RWs by date.

Chart 12
Average PD (including OOT exercise)



SOURCE: Banco de España.

It is important to reiterate that the objective is not to remove the variability of the PDs (and RWs) entirely, but to ensure that this variability is driven only by idiosyncratic and/or structural changes and not by changes in economic conditions. These results should therefore be interpreted as the result of applying the method to attempt to remove the score variability due to changes in economic conditions.

4.4.1 Out-of-time (OOT) analysis

The results shown above indicate a relevant reduction in PD variability due to a decrease in its sensitivity to macroeconomic conditions. However, it can be argued that this reduction is observed in the same sample that has been used to develop the regression. Below it is assessed whether the methodology also yields successful results when applied to data not used for the regression.

To this end, the whole process is simply repeated, but this time the regression of the score centrality measure against macroeconomic indicators is performed without the last two available dates (August 2021 and August 2020).[17]

Chart 12 shows the PD series for each calibration process, i.e. (i) the one based on the original grades, (ii) the one based on the adjusted grades where the regression is conducted with the whole sample, and (iii) the one based on the adjusted grades where the regression is conducted without the last two dates. A similar reduction in PD variability is obtained both over the whole period and, more importantly, over the two years excluded from the sample.

17 Again, several linear regressions were tested by using different macroeconomic indicators. In this case the model only includes the year-on-year change in the unemployment rate.

5 Conclusions

The cyclicality of capital requirements has been a matter of concern for banking regulators, banking supervisors and the industry for years. Motivated by this concern, this article describes a methodology that intends to take into account plausible changes in economic conditions when assigning exposures to grades or pools. The strategy is to start with an existing grade assignment method and to attempt to remove its sensitivity to economic conditions. To do so, a GAD-control module is added to it. This GAD-control module simply subtracts from the original score an amount which reflects the estimated effect of the economic conditions on the original score. This amount is modelled through a linear regression of a centrality measure of the score against some economic indicators.

This method has several advantages: the order of the original scores is maintained; it enables both the original score and the adjusted score to be kept, allowing the one most suited for its intended purpose to be used; it only affects the scores in a deterministic way depending on the values of the economic indicators, thus respecting any other trend in the scores which cannot be explained in terms of economic developments; it can be combined with additional drivers used for the PD quantification; and finally, its implementation is believed to be quite straightforward.

Once confirmed that the methodology worked with a synthetic dataset designed specifically for this purpose, the methodology was also applied to a real dataset from one of the modules of Banco de España's ICAS for SMEs. The results indicate a significant reduction in the variability of PDs and RWs between the original and the adjusted scores.

Apart from continuing to test this methodology on other datasets, future research may attempt to define methods to obtain centrality measures which neutralise the effect of changes in the portfolio composition on the average score by date. This would make the effect of the economic environment on the centrality measure series more visible, and thus easier to model.

Finally, it should be noted that there may be countless methods to attain the goal of assigning grades in a way that is not overly sensitive to economic conditions. This article will hopefully draw further attention to this matter which, in turn, could contribute to the emergence of new methods.

REFERENCES

Banco de España. (2022). *Memoria de la Central de Información de Riesgos.* https://www.bde.es/f/webbe/Secciones/Publicaciones/PublicacionesAnuales/MemoriaCentralInformacionRiesgos/22/CIR_M2022_Completa.pdf

Basel Committee on Banking Supervision (BCBS). (2004). *International Convergence of Capital Measurement and Capital Standards - A Revised Framework.* https://www.bis.org/publ/bcbs107.pdf

Carlehed, Magnus, and Alexander Petrov. (2012). “A methodology for point-in-time–through-the-cycle probability of default decomposition in risk classification systems”. *Journal of Risk Model Validation,* 6(3), pp. 3–25. https://doi.org/10.21314/JRMV.2012.091

ECB. (2024). *ECB Guide to internal models.* https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisory_guides202402_internalmodels.en.pdf

European Banking Authority. (2017). Guidelines on PD estimation, LGD estimation and treatment of defaulted exposures (EBA/GL/2017/16). https://www.eba.europa.eu/sites/default/documents/files/documents/10180/2192133/f5a2e068-dc4b-4a0e-a10f-378b517ac19c/Guidelines%20on%20PD%20and%20LGD%20estimation%20%28EBA-GL-2017-16%29_EN.pdf?retry=1

European Union. (2013). Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32013R0575&from=EN

Gavilá, Sergio, Alfredo Maldonado and Antonio Marcelo. (2020). “The Banco de España in-house credit assessment system”. *Financial Stability Review - Banco de España,* 38, pp. 95-122. https://repositorio.bde.es/handle/123456789/13555

Rubstov, Mark. (2021). “Calibration of rating grades to point-in-time and through-the-cycle levels of probability of default”. *Journal of Risk Model Validation,* 15(4), pp. 51–74. https://doi.org/10.21314/JRMV.2021.010

Rubstov, Mark, and Alexander Petrov. (2016). “A point-in-time–through-the-cycle approach to rating assignment and probability of default calibration”. *Journal of Risk Model Validation,* 10(2), pp. 83–112. https://doi.org/10.21314/JRMV.2016.154

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