Analysis of procyclical effects on capital requirements derived from a rating system*

Carlos Corcóstegui
Luis González-Mosquera
Antonio Marcelo
Carlos Trucharte

In the new universe of credit risk created on the basis of the current proposal of reform of the 1988 Capital Accord, ratings assessing borrowers' credit quality play an essential role. There is a vast literature on the analysis of ratings obtained from external rating agencies. However, very little has been said and done, so far, with respect to those calculated from internal systems. In this paper we propose a simple quantitative method based on obligors' financial information and default data to estimate a rating system for the Spanish non-financial private-sector firms over the 1993-2000 period (almost an entire business cycle for the Spanish economy). As a consistent implementation demands that risk is measured adequately, special attention is dedicated to the sectoral analysis of the firms included in the sample. Additionally, as macroeconomic considerations are central in the new Basel Capital Accord, we also introduce the underlying economic activity as a fundamental part of the estimated system for the analysis of its impact on the quality of the credit portfolio. The particular transformation of each borrower's financial data regarding its economic activity permits a very intuitive interpretation of the common factor (identified with the business cycle) that equally affects the credit quality condition of every obligor included in the sample. As an additional by-product, and based on the results of the rating system, a crucial element is attained: the transition matrix. These matrices allow for the analysis of the credit migration of the different borrowers included in a credit portfolio. Our paper studies their stability over time by differentiating two separate states: expansions and recessions. Bearing in mind that one of the main fears related to the implementation and use of internal classification systems for the calculation of the regulatory capital requirements is the potential procyclical bias that they are supposed to inherently contain, a study of that effect is also undertaken. This paper quantifies the effect of the migrations of obligors across grades on capital required under the current Basel proposals as a result of the change in their credit quality due to changes in the business cycle. With respect to the previous result, a very simple solution is proposed to mitigate possible repercussions of those cyclical effects without reducing the risk sensitivity of the system. Additionally, that measure can also be used to achieve an objective overall assessment of banking borrowers to reflect an accurate estimate of their credit quality.

1. INTRODUCTION

Gradually, individual banks are integrating into their internal systems own-made models to improve the accuracy and effectiveness when managing the underlying risk of their credit portfolios. This tendency is expected to continue, especially after the publication by the Basel Committee on Banking Supervision (BCBS) of its consultative papers that constitute the current proposal of reform of the 1988 Capital Accord[1]. This proposal, commonly known as Basel II, will not only foster the development and implementation of those risk models, but also will more closely align regulatory capital requirements with economic ones.

The package of consultative papers published by the BCBS in January 2001 establishes that those banks which decide to adopt the Internal Rating-Based (IRB) Approach when calculating their minimum capital requirements will have to meet a series of specific criteria. In particular, they will have to make use of a set of risk weights directly based on a series of probabilities of default (PD) that must be obtained by means of an internal system of classification and qualification (rating

---

* Banco de España (Bank of Spain). The opinions expressed in this paper are the authors' own and they do not necessarily represent those of the Bank of Spain. We gratefully acknowledge the support and helpful comments received from Edward I. Altman as well as those of the seminar participants at CEMFI. We would also like to thank Gorka Sarachu for his excellent data handling. Without his help this work would not have ever been undertaken. All remaining errors are our own.

E-mails: carlos.corcostegui@bde.es; luis.gmosquera@bde.es; antonio.marcelo@bde.es; carlostrucharte@bde.es

[1] BCBS (2001a and 2001b)

system) of their obligors. Consequently, those banks that decide to implement such an approach will have to develop and put into practice those classification systems.

The basic idea included in an internal rating approach is to be more risk sensitive to the key elements that determine a bank's asset credit quality and, as a result, to the economic losses that a bank's portfolio could face. Notwithstanding this, several questions have been raised towards possible inconveniences deriving from that new and groundbreaking approach.

One of the main fears is the potential procyclical bias that it could inherently contain. In particular, and addressed by several authors, one of the main drawbacks when using internal ratings to decide capital allocation is the alleged procyclicality that they may intrinsically incorporate[2]. That procyclicality would basically translate into lower capital requirements when favourable economic conditions prevail and into higher requirements when unfavourable ones do. This effect could have an undesired outcome on the overall economy if banks, according to a more risk sensitive system, are obliged to change their lending behaviour as a result of those procyclical capital requirements. To take an example, if credit institutions during recessions respond by reducing their volume of credits to comply with higher capital ratios, new lending will then diminish making it more difficult for the economic agents (households and firms basically) to recover from the adverse economic conditions. This means that if credit conditions become tighter, this will make more intense the most unfavourable part of the economic cycle and, as a consequence, will aggravate the general economic situation amplifying the economic downturn. The opposite effect will occur when the benign part of the business cycle takes place[3].

It is commonly accepted how the possible existence of procyclicality within a rating system can be recognised. Two different factors have been mainly pointed out as the possible sources that may affect a rating system by the course of the economic cycle[4]. These are the transition of creditors across grades over time (grade migration, i.e. upgrades in booms and downgrades in recessions) and the variations of the estimated PD for each grade. This latter source, whenever the PD is calculated as a long-run average (e.g. over an entire economic cycle), should not pose important problems in terms of cyclical effects on rating systems even though cycles averages are not always identical as economic cycles differ one another. That is, PD’s will vary from one period to the next, but seemingly not in a significant amount leaving the grade migration effect as the main element of concern when talking about cyclicality within a rating system.

Consequently, to be able to analyse and study that above-mentioned migration effect, the first step to be taken will be to estimate a rating system. To obtain the most general and complete outlook of those cyclical consequences, that rating system will be estimated for the whole Spanish credit system, in particular for the non-financial private-sector firms. To meet the requirements of risk sensitivity, it will try to incorporate all elements that should be taken into account when measuring the creditworthiness of each borrower, including macroeconomic considerations as a relevant factor of the level of the latent risk of a credit portfolio. Additionally, the sectoral transformation imposed on the financial data allows us to give an adequate treatment of the ratios included in the classification system as well

[2] Among others, see for example Borio et al (2001). For possible financial stability problems arising from connecting capital requirements to external rating systems see Altman and Saunders (2001). Ervin and Wilde (2001) provide possible approaches to addressing procyclicality as well as an example of the impact on capital ratios of a recession scenario. Additional references can be found in Danielsson et al (2001), DNB (2001), ECB (2001) and Resti (2002)

[3] See Lowe (2002) for a detailed discussion on the relationship between credit in general and the business cycle.

[4] Any possible cyclical effect included in the loss given default (LGD) is not considered in this paper.

as to clearly identify the common factor that equally affects the credit quality of each banking borrower and that is usually associated with the economic cycle.

A crucial element that is derived from the estimated rating system is the transition matrix. This matrix reflects the riskiness of every grade into which every individual obligor is classified. Using that matrix, it will be analysed how borrowers are expected to migrate to different rating grades over time. After estimating the unconditional transition matrix, two different states that depend on the stage of the business cycle are distinguished in order to study the stability of that matrix. On the basis of the previous analysis, it is believed that a certain procyclical bias can exist as the migration pattern of banking borrowers differ depending on whether the general economic conditions are favourable (expansion) or unfavourable (recession). According to that, this paper tries to quantify the effect of the business cycle on the credit quality of the Spanish banking borrowers (firms).

As one of the main worries about internal rating systems is placed on their potential procyclicality when using them to calculate capital requirements, the particular design of the estimated model, will make it possible to analyse the procyclical effects that the system contains. Finally, as certain components of cyclicality are found in the rate of change of capital requirements, some possible courses of action are addressed to try to attenuate that effect. In particular, it is proposed to assign average ratings to banking borrowers as an overall objective assessment of their capability in meeting their credit duties. Additionally, those average ratings clearly attenuate possible cyclical effects without reducing the risk sensitivity of the system.

Once the aforementioned has been established, the rest of the article is structured as follows. The second section briefly introduces the general characteristics of rating systems and, in particular, presents the one developed in this paper. In the third section, a description of the database used to estimate the rating system and the sectoral treatment given to the data utilised take place. The fourth section is devoted to the estimation process, encompassing the description of the potential candidate variables to be included in the final rating system and the results of the multivariate model on which the final classification system is based. The validation process is also incorporated. The fifth section is dedicated to the achievement of the rating system from the scores provided by the multivariate model (particularly, the categories or grades in which every obligor is bucketed, and the probabilities of default of each grade), as well as the analysis of the transition matrix obtained from it. Based on the results obtained from that analysis, the sixth section presents the alleged cyclical effects included in a rating system, in particular, the migration of borrowers across grades over time considered as the main source of procyclicality and describes its effects in terms of variation in capital requirements. Possible measures to tackle those cyclical effects are also presented including a very simple alternative that, in addition to ease the cyclical variation of capital over time, can be used as a reasonably objective evaluation of the overall credit quality of obligors. The last section concludes with a brief summary of the main ideas and results presented in the paper.

2. RATING SYSTEMS OF BANKING BORROWERS

The fundamental characteristics of every borrower classification system should be, firstly, its effectiveness to discriminate between good and bad borrowers according to their most relevant economic and financial features, secondly, its ability to classify them into homogeneous risk groups and finally, its capability of providing credit risk measures. A crucial measure that defines these groups is the probability of default (PD), perhaps the most decisive result derived from a classification system. That PD, together with other parameters, can be used to determine the probability density function of economic losses and the required capital measures to cover them.

Classification systems can be of very diverse type, depending fundamentally on the kind of information that is used to estimate them and on the quantitative or qualitative nature of the estimation process. The rating system that is developed in this document is based on statistical estimates of the relationship between the variable to be explained (the event of default of an individual obligor) and a group of financial ratios (balance sheet and profit and loss data). It is necessary to emphasize that this work is not intended to set down the general characteristics that every rating system should possess[5]. It only describes the construction of a system which is based on financial and default information, so that a sensible classification of the obligors (non-financial private-sector firms) that are included in the credit portfolios of the Spanish banks[6] is achieved.

The pioneer works that use financial information to explain, initially, bankruptcies in a group of firms are those of Beaver (1966), based on the univariate analysis of 30 ratios, and the Z-score from Altman et al. (1977). The latter is considered as a cornerstone in this type of analyses since it is the first study that examines the development of firms' bankruptcies classification models using multivariate techniques. Ohlson (1980) and Zavgren (1985) take a step further in the analysis and prediction of the possibility that a company becomes financially distressed, using techniques of logistic regression and, therefore, under less restrictive statistical assumptions than preceding works based on discriminant analysis. On the other hand, Lau (1987) introduces the idea of expanding the existent dichotomy (failure/non-failure) in the classification of firms when enlarging the number of categories or states in which a firm can be classified before it becomes definitively bankrupt. Nonetheless, it has to be noted that the characteristic or condition that all these models try to explain is the fact that a certain firm becomes distressed or, in final terms, bankrupt.

Nowadays, given the importance of reaching an accurate estimate of the potential credit losses faced by banks, their objective variable is the probability that an obligor defaults. Consequently, the most recent models related to the classification of banking borrowers are focused on a different definition of what can be considered as a distressed obligor. In this paper the definition used is similar to the one established by the BCBS when referring to a default event, and it basically refers to those obligors that are past due more than 90 days on any credit obligation, or those that, with a high probability, can be considered unable to pay their credit obligations. This precise event is thought to determine when an obligor becomes an explicit danger that may erode the quality of a bank's credit portfolio. On that basis, capital should be set aside to cover the associated losses and, as proposed by Basel II, calculated according to an internal rating system implemented on the previous premises.

However, before turning to the final achievement of that rating system, it is necessary to establish the terms on which the sample database was constructed. That is explained next.

---

5 In order to obtain a general, detailed and well-developed notion about the main objectives and characteristics that a rating system must have, see the Comptroller's Handbook on rating credit risk (OCC, April 2001).

6 It has to be noted that, in this paper, the term bank is used as a general concept including in its definition every possible credit institution.

3. SAMPLE DATA

3.1. Elaboration of the Database

The main problem with this type of study is the difficulty in getting access to good quality information so that the final results reach the appropriate level of reliability. In order to address this problem, this study combines two different sources of information: on the one hand, the Bank of Spain's Credit Register (CIR), where information about defaulting and other additional credit operation features (existence of requested guarantees and the maturity of the operation among others) can be obtained for each borrower; on the other hand, CBBE-SABE, a mixture of two databases[7] which contains economic and financial information of banking borrowers.

Table 1 summarizes in figures all the relevant characteristics corresponding to each database, as well as the resultant information coming from the combination of both. The first row contains the number of total credit operations included in CIR. In the next row, the previous information is aggregated by obligor, which means gathering together all credit operations that a certain obligor has been conceded by Spanish banks. Additionally, the number of those borrowers that have defaulted, at least in one of its credit operations can be perceived. The detail of the percentage of defaults is provided as well. Table 1 also provides information of the total number of firms for which financial information is available (CBBE-SABE data).

It is interesting to analyse the total exposure coverage of the CBBE-SABE database, defined as the percentage of exposures included in CIR for which information is also included in CBBE-SABE. The average coverage over the period 1992-2000 is around 65%, that is, almost two thirds of the total risk supported by the Spanish banks corresponds to firms for which financial information is available, with a peak of 81% in 1997 and 1998.

Since the financial database is slightly biased to include large firms, the coverage is expected to increase as small firms are left out of the sample. That is, whenever a size threshold is imposed on the process of estimating a rating system, the total exposure coverage is expected to grow. In fact, the sample covers more than 90% of the whole population of firms whenever the threshold of sales equal to € 600,000 is surpassed.

The final rows of Table 1 are devoted to offering information about the sample ultimately used to estimate the classification model. In addition to a series of necessary filters to assure data quality, reliability and integrity (in particular, exclusion of firms with inconsistent values -e.g. negative signs for variables such as total assets or liabilities-, possible inconsistencies in CIR data...), a minimum size threshold in terms of annual volume of sales equal to € 9 million was established based on two types of premises.

The first one refers to the objective of building a classification system for a large part of the so-called *corporate exposures* as an initial approximation to the new demands and proposals that Basel II sets out and that will finally translate into new supervisory operative functions. Since its definition has continuously changed[8], a

[7] Bank of Spain's Central Financial Database (CBBE) complemented with a private database (SABE).

[8] It has to be noted that since the January 2001 BCBS consultative paper was made public, several modifications have taken place, in particular, those included in the November 2001 and the July 2002 BCBS press releases. Basically, the latter is the one that defines a completely new treatment, in terms of capital requirements, for firms' exposures according to their size. With the exception of very small exposures (less than € 1 million, which can be associated with very small firms) that will be included in the category of retail, the rest (large, medium and even small firms) will be considered as corporate exposures. Under that premise, a rating system will be necessary to provide them with a classification in

TABLE 1

DATA

	1992	1993	1994	1995	1996	1997	1998	1999	2000
C.I.R.[1]	1,128,210	1,139,188	1,143,347	1,246,607	1,425,415	1,509,534	1,643,110	1,792,680	1,938,558
No. Obligors[2]	314,337	336,540	357,775	394,067	461,700	491,074	525,983	563,065	603,597
No. Defaults[3]	38,373	51,987	53,208	48,978	50,316	40,578	30,676	27,072	24,955
Percentage of defaults	12.21%	15.45%	14.87%	12.43%	10.90%	8.26%	5.83%	4.81%	4.13%
CBBE-SABE									
No. Firms	40,568	71,837	93,228	116,413	146,726	168,293	187,345	178,525	165,829
Match CBBE / SABE-CIR									
No. Obligors[4]	31,914	57,733	75,938	97,650	127,937	138,309	165,250	158,679	149,218
Total exposure covered[5]	44.58%	55.70%	62.37%	70.11%	78.18%	81.44%	81.65%	69.75%	66.92%
FILTERS[6]									
Obligors	4,585	5,180	6,703	7,701	8,457	9,665	10,835	10,367	10,099
Defaults	108	196	236	291	282	308	347	253	205
Percentage of defaults	2.36%	3.78%	3.52%	3.78%	3.33%	3.19%	3.20%	2.44%	2.03%

[1] Number of credit operations granted to non-financial private-sector firms. Interbank operations and those below € 6,000 are not included.
[2] Number of credit operations aggregated by obligor.
[3] Number of defaulted credit operations aggregated by obligor.
[4] Number of obligors common to both databases (CBBE/SABE - CIR).
[5] Sum of exposures of firms with available information in CBBE/SABE divided by the total sum of the system credit exposures.
[6] The sample only includes public limited firms, limited liability firms, partnerships, commandites and cooperatives whose turnover is above 9 € million. Firms with invalid data have been removed, as well as firms aged less than two years.

small enough threshold was applied so as to include all potential corporate exposures.

The second premise regards the low reliability of financial information in the segment of small firms[9]. After discarding a high proportion of financial statements due to inconsistency of the data, the remaining subset of small firms showed the lowest percentage of defaulted obligors in the entire sample. This result is difficult to justify in the face of other works which analyse the existing negative relationship between size and probability of default[10]. This fact led us to believe that the group of small firms would most probably be the one with the least available financial information and, particularly, the group of small firms that defaults.

3.2. Sectoral Analysis

Before turning to analyse the explanatory power of the available financial information, this section proves the adequacy of transforming that information according to the economic sector into which every obligor is classified. To take an example, one may appreciate in Figure 1 how the values of the *Net Income to Total Assets* ratio seem to differ depending on the economic sector they come from[11]. It is noticeable that more than half of the firms in sector 7 have negative values of the

---

terms of underlying risk, a grade and finally, a probability of default, whatever their final capital requirements will be.

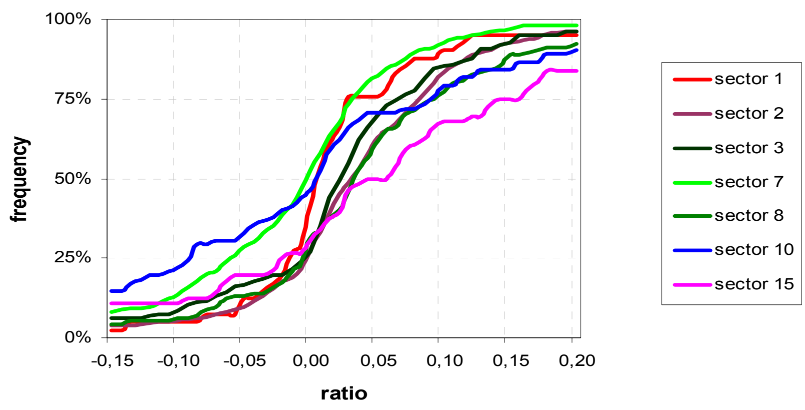
[9] For our purposes, small firms are defined as those with turnover below € 9 million.

[10] See López (2002)

[11] Only seven cumulative distributions have been depicted for intelligibility reasons. The sectors included in this figure and the numbers assigned to them do not necessarily correspond to the sectoral description that appears in Table 2

FIGURE 1

NET INCOME / ASSETS.
SECTORAL CUMULATIVE FREQUENCIES



ratio whereas, less than 20% of firms in sector 3 present values of that ratio below zero. This means that the same value of a certain financial ratio implies a distinct situation conditional to the economic sector. Therefore, if the sectoral component were not accounted for, the final model would assign similar ratings to similar values of the ratio even though they represent different circumstances as already shown. Consequently, this final transformation regarding the economic sector can be considered as essential.

This sectoral approach is possible because economic activity information (NACE codes) of every obligor is available. Such an approach is not only supported by economic reasons, as explained above, but also by statistical tests on the sampling distributions. In particular, the Kolmogorov-Smirnov test for homogeneity of two samples[12] has been implemented to detect whether different sector ratio values are originated by different generating distributions functions. Based on a statistic calculated for each pair of empirical distributions, the null hypothesis that the generating process of both distributions is the same is tested. For our particular case, the null hypothesis is usually rejected (75% of the times) at the 90% level of confidence, confirming the assumption that different sectors have different values of the financial ratios.

Once this sectoral approach has been justified, the financial ratios are transformed. Firstly, 16 different sectors were identified according to the NACE codes (see Table 2). This number satisfies a double objective: it is large enough to capture the idiosyncrasy of different sectors and small enough so that the number of defaults is statistically significant in each group. Next, for each sector and year its median was obtained. Finally, the transformation consisted of calculating the percentage deviation of every financial ratio with respect to its sectoral median per year. As it will be explained later, considering the annual median instead of the one resulting from the whole period delivers the data with a very convenient property. In particular, most of the cyclical component of the financial data is extracted and assigned to the macroeconomic variable of the final model. This will specially serve to the final aim of analysing the potential procyclicality included in internal models.

[12] Source: Siegel and Castellan (1988).

TABLE 2

SECTORAL DESCRIPTION

SECTOR	ACTIVITY	NACE CODE
1	Agriculture, forestry and fishing	01, 02, 05
2	Food and tobacco	15, 16
3	Textiles	17-19
4	Paper	20-22
5	Chemicals	24, 25
6	Metals and electrical machinery and apparatus	27-33
7	Manufacture and sale of motor vehicles	34, 35, 50
8	Energy	10-14, 23, 37-41, 74
9	Construction	26, 45, 70, 90
10	Hotels and restaurants	55, 6330
11	Wholesale and retail trade	36, 51, 52
12	Transport	60-63, 6400-6420
13	Financial intermediation and insurance	65-69
14	Telecommunications and R&D	6420, 72, 73
15	Leisure	92
0	Others	Remaining codes

4. ESTIMATION PROCESS

4.1. Dependent variable

As previously stated, one of the objectives of this paper is to find out the determinants that explain the default of an individual obligor and, based on those factors, to be able to obtain a rating system that classifies banking borrowers according to their credit quality. To achieve that objective, the default event has to be represented by a random variable. It is generally assumed that a firm's default is usually determined by the value of its assets, so that if it falls below the value of its liabilities, default is triggered. However, that "distance to default" is not directly observable. The typical solution consists of using a binary variable that takes value one if default[13] occurs or zero otherwise (the Credit Register database contains that information).

4.2. Independent variables

Once the endogenous variable of the rating system has been defined, the next step is to obtain its determinants from a group of potential eligible candidates. That group of candidates is shown in Table 3 and consists of two main sets of variables.

The larger one contains the usual financial ratios that have been used in the *default* literature, classified by category (profitability, leverage, liquidity…). The expected sign of their relationship with the default variable is the traditional one. For example, large and highly profitable firms are expected to have a lower probability of default than leveraged, illiquid and low productive ones. Given the large number of financial ratios available, a previous univariate analysis was carried out so as to decide which are most significantly related to the event of default.

[13] According to the previous definition of default.

TABLE 3

FINANCIAL *RATIOS*

PROFITABILITY	LIQUIDITY
Profits before taxation / Assets	Cash / Short-term liabilities
Net income / Assets	Cash / Assets
Net income / Sales	Current Assets / Short-term liabilities
Financial profit / Assets	Operating profit / Working capital
	Short-term liabilities / Total liabilities
LEVERAGE	
Total liabilities / Equity	SIZE
Total liabilities / Assets	Assets / Consumer Price Index
(Total liabilities−Cash) / Assets	Sales / Consumer Price Index
Equity / Assets	
CIRBE Exposure / Assets	PRODUCTIVITY
	Financial expenses / Sales
ACTIVITY	Operating profit / Sales
Inventories / Operating Expenses	Staff expenses / Sales
Sales / Assets	Financial expenses / Sales
Sales Growth	Financial expenses / Profits before taxation
	(Financial expenses+Staff expenses) / Sales

OTHER VARIABLES

Maturity	Sectoral dummies
Guarantee	GDP growth rate

The smaller group, but not less important, includes the sectoral dummy variables, two other variables that refer to the characteristics of the credit operations (guarantee and maturity), and a macroeconomic variable (the rate of growth of the GDP).

The sectoral dummy variables account for the proposed classification in terms of economic activity explained in subsection 3.2. In addition to the sectoral transformation of the financial ratios, a dummy variable is required to discriminate among sectors depending on its direct relationship with the default variable. This means that there will exist a negative relationship between the default variable and those sectors whose percentage of defaults are below the average. The opposite relationship will be found for those firms that belong to a sector whose percentage of defaults is above the average default rate.

In order to account for the effect of the guarantee associated to the credit operations, a variable is created so that it takes value one if an obligor is required any type of collateral in any of its credit operations and zero if it is not. Since the fact of being required a guarantee is nothing else than being identified by the bank as highly probable of defaulting, a positive sign is expected. Table 4 shows the frequencies of default of each group and confirms the expectation: firms that are asked to provide a guarantee turn out to default more often.

Another variable that was considered as a potential candidate to explain the event of default was the average maturity of the different credit operations for every obligor. However, no significant relationship was found.

Finally, the GDP growth rate variable accounts for the common factor that underlies credit risk. As one may observe in Table 1, there is a cyclical pattern in the percentage of defaults per year, which resembles very much that of the business

TABLE 4

GUARANTEE.
DEFAULT FREQUENCY

	NO	YES	Total
Non-Defaults	45,723 63.84%	25,899 36.16%	71,622
Defaults	704 35.74%	1,266 64.60%	1,970
Total	46,427	27,165	73,592

cycle[14]. In other words, one can appreciate that the periods with the highest percentage of defaulted obligors are associated with those of an economic downturn and that as the Spanish economy started to recover (1995 onwards), the percentage of defaults started to decline, reaching its lowest point in 2000 at the peak of the economic cycle. Therefore, this variable can be seen as the key one to analyse and quantify the impact of the business cycle on the process of assigning ratings to banking borrowers that will finally translate into capital requirements. Moreover, since the cyclical component of the financial data has been extracted, this time variable will incorporate the whole cyclical effect, making it possible to analyse the allegedly procyclical effects on capital requirements that rating systems incorporate.

4.3. Model

The statistical model selected to estimate the relationship between the default variable and the explanatory variables included in the sample is the logistic one[15]. It should be noted that since one of the most important features in a classification system is its predictive capacity, all the independent variables included in the model are lagged one period (except the sectoral dummies and the guarantee variable, which are contemporaneously observable). The results of the estimated multivariate model can be observed in Table 5, that shows the variables that turned out to be significant in the multivariate analysis as determinants of the default variable as well as their respective signs and coefficients. They can be organized in four different categories:

Financial ratios

- Profitability ratio: *Net income / Total assets*. This variable has a negative sign as initially expected, since the higher the profitability of a firm, the smaller the probability that it defaults.

[14] It can be accepted that the latest Spanish economic cycle ranges from the early nineties to the year 2001. The trough of the business cycle was reached in 1993 while the peak can be positioned near the end of the cycle (2000).

[15] The choice of the logistic model is not only based on the fact that the default condition of an obligor can be reasonably described in probabilistic terms (using probabilities of default) but also on the fact that such a condition is determined by the asset value of the borrower. As this condition is an unobservable latent variable, it can be approximated by a binary one, the endogenous variable in a logistic regression.

TABLE 5

MULTIVARIATE MODEL (a)

Variable	*Coefficient*	*Variable*	*Coefficient*
Constant	-4.268 (0.220)	Equity / Assets	-0.533 (0.029)
GDP growth rate	-0.051 (0.015)	Cash / Assets	-0.107 (0.012)
Sectoral dummies	(b)	Sales / CPI	-0.009 (0.003)
Guarantee	0.815 (0.050)	Short-term liabilities / Total liabilities	-2.375 (0.097)
Net income / Assets	-0.013 (0.002)		

(a) Logistic regression of the *Default* variable on one-period lagged variables. Number of observations: 73,321. Period: 1992-2000. In parenthesis, the standard error of the coefficient. All variables are significant at the 99% confidence level.
(b) 15 dummy variable coefficients have been estimated (one of them has been left out for collinearity reasons) for each economic sector, being 11 of them statistically significant. No estimates are provided for confidentiality reasons.

- Leverage ratio: *Equity / Total assets*. The sign of this ratio is also negative, which means that the higher the proportion of equity over total assets within a firm, the lower its probability of default.

- Liquidity ratios: *Cash / Total assets*. Its negative sign corresponds to what a priori is expected for this variable. This means that, the higher the liquidity the lower the probability of default. However, the *Short-term liabilities / Total liabilities* ratio presents the opposite sign as initially expected. This problem usually occurs in a multivariate context. If two ratios are correlated with one another, then the one that presents the smallest correlation with the independent variable can change its sign. However, this ratio has been maintained in the final model due to its performing contribution.

- Size ratio: *Sales / Consumer Price Index*. This is a very important variable since it accounts for the fact that the size of a firm is a significant determinant of its probability of default. It is commonly accepted that large firms have more alternatives to react against sudden problems than small firms what allows the former to delay the possibility of becoming defaulted. Therefore, the positive sign of the coefficient was expected.

Characteristics of the operation

- *Guarantee*: The positive sign confirms that banks usually demand guarantees from *a posteriori* worst quality borrowers.

Common factor

- *GDP variable:* This variable can be interpreted as the common factor that annually affects in an identical manner the value of the assets of every firm irrespective of other financial features. In this way, this variable can be understood as the annual contribution of the economic cycle to the default condition of each obligor. In other words, it can be interpreted as the existing implicit relationship between the business cycle and the possibility of defaulting. The negative sign implies that the cyclical pattern behaves as initially expected showing that high rates of growth of the GDP are associated with low values of the PD.

Sectoral treatment

- *Sectoral Dummies:* As already described, they represent the economic sector into which every obligor is classified. Positive signs are associated to sectors whose credit quality is worse than that of the sector being excluded for collinearity reasons. Negative signs mean exactly the opposite.

Once the variables that determine an obligor's possibility of defaulting have been established and their coefficients and signs within the multivariate model are known, it is convenient to determine performing measures for the estimated regression model to evaluate its classification power. Table 6 shows the classification table of the final model. One may see in the main diagonal that the model classifies correctly more than 73% of the obligors included in the sample.

TABLE 6

**CLASSIFICATION TABLE.
TRAINING MODEL**

	Observed defaults	Observed non-defaults	Total
Predicted defaults	1,521 **77.40%**	19,487 27.31%	21,008
Predicted non-defaults	444 22.60%	51,869 **72.69%**	52,313
Total	1,965	71,356	73,321

Cut-off: 3% (1,965 / 73,321) . A firm is assigned to the default category if the predicted probability exceeds this value.

It is evident that the previous classification power is obtained for the training sample described in Table 1. In order to test the consistency of the model, a validation sample should be constructed using external data. For that purpose, a database has been extracted for 8,993 firms in the year 2001[16]. The validation process simply consists of calculating the score of every new observation based on the results obtained from the estimated model and comparing it with its observed default event. The classification table is described in Table 7. The main diagonal of the table shows that more than 70% of the firms included in the validation sample were correctly classified, indicating a satisfactory classification power of the estimated model.

[16] It contains default data of the year 2001 and financial information of the year 2000.

TABLE 7

CLASSIFICATION TABLE. VALIDATION MODEL

	Observed defaults	Observed non-defaults	Total
Predicted defaults	135 **70.68%**	2,604 29.59%	2,739
Predicted non-defaults	56 22.60%	6,198 **70.41%**	6,254
Total	191	8,802	8,993

Cut-off: 3% . A firm is assigned to the default category if the predicted probability exceeds this value.

5. RATING SYSTEM

5.1. Calibration

Once the model has been estimated and validated in terms of performing power, it can be used to attain the final objective that it was initially designed for, that is, the completion of a final rating system. For that purpose, it is necessary to establish the PD-homogeneous categories into which the different banking borrowers are to be grouped.

The logistic regression model provides a certain score for each obligor. That score is obtained as the overall sum of the products of each regressor by its respective coefficient. According to those scores, all obligors are sorted out in ascending order and a first tentative classification is produced. Next, the default frequencies of each group are calculated. Using those frequencies as an initial reference, and bearing in mind two fundamental premises, the definitive groups are obtained. The first of these two premises requires that obligors, once being assigned to a group, have to be approximately symmetrically distributed across them. This implicitly assumes that the credit quality of most obligors is neither excellent nor poor. The second one is that the probability of default should increase exponentially as we move from the best to the worst categories. These two features are widely accepted by regulators and practitioners and impose no unusual restriction.

Before turning to the final achievement of the rating grades, a very important remark has to be made on the definition of the PD. No reference has been made, so far, to the situation of a loan in the period *t-1*. This would miss, however, the most important determinant of default, since defaults tend to repeat over time[17]. Therefore, it would be more accurate to talk in terms of conditional PD's being the performance of the loan in period *t-1* the conditioning characteristic. From now on, the PD will refer to the probability of default of an obligor conditional to not having defaulted in the previous period, that is, conditional to belonging to the performing portfolio (PP). Since the estimation of the logistic model did not exclude observations from the non-performing portfolio (NPP), the calculation of the PD's must account for this fact and include only data from performing loans. Table 8 shows very interesting figures. As expected, almost 98% of the obligors belong to

[17] If an index of the default situation in period *t-1* were included in the regression, the model would classify 98% of the data correctly. This, however, shows little interest, since the prediction would be totally determined by this index, with a extremely poor prediction of changes in the default status.

TABLE 8

PROBABILITIES OF DEFAULT

	Performing Loans	Non-Perform. Loans	Total
Non-Defaults	70,723 98.62%	633 39.29%	71,356
Defaults	987 1.38%	978 60.71%	1,965
Total	71,710	1,611	73,321

the PP, whereas the remaining ones belong to the NPP. Within each portfolio, the percentage of default is extremely different: 1.38% and 60.71% in the PP and the NPP respectively. One could interpret them as the average probabilities of default for a typical firm, depending on its performance in the previous period.

Bearing all this in mind, the final rating system obtained had nine categories in addition to the default one as it can be appreciated in Table 9[18]. This table includes not only the grades obtained but also the estimated PD's for each grade. The unconditional probability of 1.38% has been distributed across categories from 0.12% in grade 1 to 11.89% in grade 9. The distribution of obligors across grades is shown in Figure 2. It is approximately symmetrical, with 21% of the obligors in grade 5 and less than 5% of them in the extreme ones. It also shows the exponential increase of the PD as the credit quality of the borrowers deteriorates. Finally, Figure 3 provides information of the distribution of obligors in terms of their default condition. Most defaults concentrate on the worst categories, confirming the explanatory power of the model.

TABLE 9

RATING GRADES AND PD'S

Grade	Score	PD (%)
1	70-100	0.12%
2	64-70	0.21%
3	58-64	0.38%
4	53-58	0.58%
5	47-53	0.94%
6	42-47	1.54%
7	35-42	2.93%
8	27-35	5.76%
9	0-27	11.89%

The column PD represents the probability of default conditional to a particular category. The PD has been calculated over the total performing portfolio.

[18] It has to be noted that the scores assigned to each grade by the logistic model have been re-scaled. They range from 0 (worst quality obligors) to 100 (best quality obligor). The PD column has been calculated as the number of borrowers that default given that in the previous period were performing ones divided by the total number of obligors of that grade.

FIGURE 2

RATING GRADES AND PD

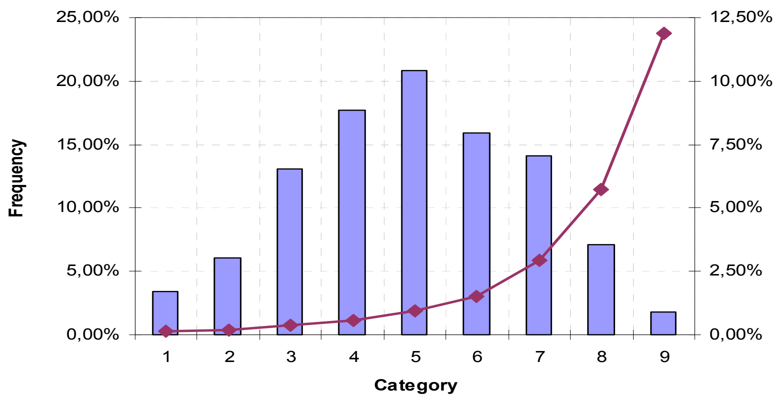
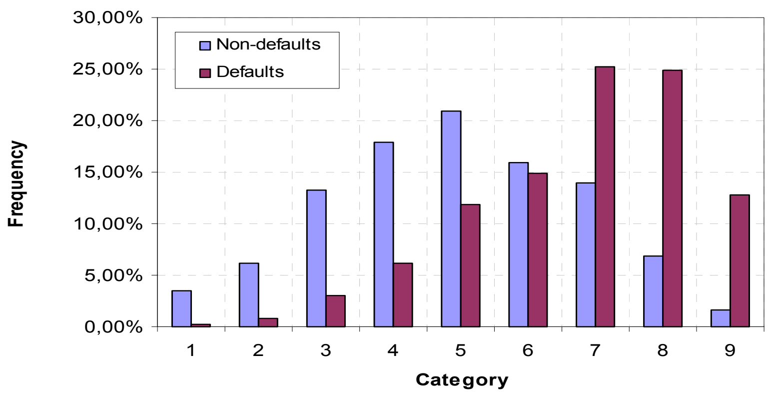


FIGURE 3

RATING DISTRIBUTION OF DEFAULTS AND NON-DEFAULTS



A final remark has be made, however. The calibration process has been carried out with data encompassing a whole business cycle, so that the probabilities in Table 9 refer not to the year in which the rating is assigned, but to a long-run average. The reason is to be found in the suitability of softening capital requirements and avoiding sharp fluctuations that may augment the lending restrictions in recessions. As it has already been noted, this however does not need to be followed by private agents whose objective is the active management of credit risk. The option taken in this study has been derived from the regulatory use that this rating tool is expected to receive.

5.2.- Transition matrix

A crucial element that can also be obtained from the rating system is the transition matrix and its associated probabilities. Table 10 presents the average one-year transition matrix for the sampling period. Before turning to analyse its main

TABLE 10

TRANSITION MATRIX AND TRANSITION PROBABILITIES (%)

Rating at the beginning of the period	Rating at the end of the year									
	1	2	3	4	5	6	7	8	9	Default
1	65.37 (0.96)	19.81 (0.80)	7.90 (0.54)	3.28 (0.36)	1.94 (0.28)	0.97 (0.20)	0.55 (0.15)	0.06 (0.05)	-	0.12 (0.07)
2	13.90 (0.52)	55.24 (0.75)	21.84 (0.63)	5.77 (0.35)	2.00 (0.21)	0.66 (0.12)	0.33 (0.09)	0.07 (0.04)	-	0.21 (0.07)
3	1.95 (0.14)	13.07 (0.35)	58.07 (0.51)	17.64 (0.39)	6.66 (0.26)	1.48 (0.12)	0.53 (0.08)	0.19 (0.05)	0.01 (0.01)	0.38 (0.06)
4	0.34 (0.05)	2.23 (0.13)	17.08 (0.33)	57.03 (0.44)	16.49 (0.33)	4.92 (0.19)	1.11 (0.09)	0.20 (0.04)	0.02 (0.01)	0.58 (0.07)
5	0.13 (0.03)	0.44 (0.05)	4.37 (0.17)	18.77 (0.32)	57.15 (0.40)	13.10 (0.28)	4.56 (0.17)	0.51 (0.06)	0.04 (0.02)	0.94 (0.08)
6	0.04 (0.02)	0.13 (0.03)	0.76 (0.08)	5.38 (0.21)	23.34 (0.40)	52.48 (0.47)	14.13 (0.33)	2.01 (0.13)	0.19 (0.04)	1.54 (0.12)
7	0.01 (0.01)	0.11 (0.03)	0.29 (0.05)	0.92 (0.09)	7.32 (0.26)	22.12 (0.41)	55.70 (0.49)	9.73 (0.29)	0.87 (0.09)	2.93 (0.17)
8	-	0.03 (0.02)	0.08 (0.04)	0.48 (0.10)	1.60 (0.18)	4.68 (0.30)	26.56 (0.62)	55.70 (0.70)	5.11 (0.31)	5.76 (0.33)
9	0.10 (0.09)	-	0.10 (0.09)	0.51 (0.20)	1.13 (0.30)	1.85 (0.38)	7.38 (0.73)	28.72 (1.27)	48.32 (1.40)	11.89 (0.91)

properties, it has to be noted that the basis upon which this matrix was calculated is common to that proposed in Bangia et al. (2002):

- the sample composition of the portfolio is allowed to vary over time helping the sample size to be large enough every year and allowing new firms and sectors to be considered as well as different stages of the business cycle.

- regarding those obligors that move to the so-called non-rated (NR) category[19], the transition probability to the NR state is distributed among all states (except default) in proportion to their respective probability values in the transition matrix. Although this method treats transitions to NR as benign, this is justified by the high coverage of the financial database that leaves the extinction of the debt as the most plausible reason of transition to NR.

Each element of the matrix, a_{ij}, represents the sample proportion of obligors that having started one period in grade *i*, finish it in grade *j*. In brackets, underneath each transition probability, the standard error is also provided. These errors show the precision of the probability estimates and are calculated using the same simplifying assumption as in Nickell et al.(2000) [20].

By taking a look at the elements of the matrix one can observe that, even though the highest values of the matrix appear on the main diagonal, these are much lower than those provided by external rating agencies (S&P's, Moody's...). As stated

[19] It can occur either because their banking debt is extinguished or because no financial information is available for them.

[20] It is assumed that rating transitions are temporally and cross-sectionally independent. Consequently, considering the binomial variable going from rating i to j, the standard error for each sampling transition probability can be calculated as a standard binomial standard error:

$$\sqrt{\text{Probability}_{\text{grade i to j}} * (1 - \text{Probability}_{\text{grade i to j}}) / \text{No. of obligors in grade i}}$$

in Lowe (2002), this is the expected behaviour of internal models employed by banks. Their ratings' assessments are more volatile than those of external agencies, whose qualifications are assigned in the context of adverse economic scenarios to the company's specific circumstances and rarely vary within short periods of time. Additionally, it can also be noted that the second largest probabilities are those next to the main diagonal. This matrix also complies with the general rule of monotonicity, that is, the further a probability is from the main diagonal, the lower its value. The exception to that rule is, as usual, appreciated in the default column of the transition matrix. Another important characteristic that one would expect from a transition matrix is the poorer credit quality of the firms corresponding to the worse rating grades. It can be observed how default probabilities and migration volatilities increase as the quality of the grades decreases.

In brief, the main properties of this matrix resemble very much to those of the well-known external rating agencies. However, it possesses the inherent properties of a matrix derived from an internal rating system such as the lower values of the main diagonal, what allows for more migrations of obligors.

Although the previous results can be considered pretty relevant, an additional concern of this paper is to analyse and quantify the impact of the economic cycle on the classification of obligors over time as well as on the calculation of capital requirements under the new proposals of Basel II. With the objective of obtaining a first insight into the potential procyclical consequences of using internal models for the calculation of regulatory capital, a previous analysis of the stability of the transition matrices under economic expansions and recessions is carried out first.

Transition matrices are calculated for two different states of the economy, recession and expansion, defined as a function of the value of the rate of variation of the Spanish GDP. It will be possible to determine whether or not those matrices are different and as a result, whether or not the business cycle affects the riskiness of the banking borrowers via grade migrations. The first period comprises the contraction years (from 1993 to 1996) and the second period includes the expansion years (1996 onwards) [21]. Tables 11 and 12 show the cycle-conditional transition matrices and associated probabilities in the contraction and expansionary periods respectively. The entries in shadow are those probabilities that are significantly different at the 5% level from those of the unconditional matrix.

In general, it can be remarked how the quality of the borrowers is lower in contractions than in expansions: default probabilities and downgrades generally increase during recessions and upgrades take place more frequently in expansions. Therefore, it can be concluded that obligors migrate across grades over time and this migration effectively depends on the particular stage of the economic cycle. Knowing that, the next step will consist of quantifying how much of that migration, inherent to the rating system, can be attributed to the business cycle and, finally, how much of that is translated into changes in capital requirements. The objective is to measure the impact of the common factor on the creditworthiness of the banking borrowers and its repercussions in terms of capital variations over time when they are calculated by means of a rating system.

6. PROCYCLICAL EFFECTS ON A RATING SYSTEM

As it can be concluded from the previous stability analysis, rating systems seem to be dependent on the state of the economy, thereby affecting regulatory

[21] See footnote 14.

TABLE 11

RECESSION TRANSITION MATRIX (%)

Rating at the beginning of the period	Rating at the end of the year									
	1	2	3	4	5	6	7	8	9	Default
1	65.78	20.07	7.51	3.33	1.85	0.86	0.49	-	-	0.10
2	12.39	56.43	21.14	6.23	2.45	0.73	0.27	0.07	-	0.29
3	1.65	11.26	57.77	19.35	7.32	1.44	0.50	0.21	-	0.50
4	0.29	2.11	15.24	57.05	18.29	5.42	0.90	0.16	0.04	0.51
5	0.10	0.31	4.13	17.59	56.76	13.72	5.47	0.53	0.08	1.31
6	0.07	0.09	0.68	5.23	22.38	51.67	15.42	2.32	0.18	1.97
7	-	0.09	0.28	1.03	7.54	20.78	55.33	10.58	1.12	3.25
8	-	0.05	0.09	0.55	1.78	5.12	24.70	54.67	6.18	6.86
9	-	-	0.15	0.15	1.22	1.83	7.91	27.55	47.85	13.33

TABLE 12

EXPANSION TRANSITION MATRIX (%)

Rating at the beginning of the period	Rating at the end of the year									
	1	2	3	4	5	6	7	8	9	Default
1	64.97	19.54	8.27	3.24	2.04	1.08	0.60	0.12	-	0.13
2	15.38	54.03	22.52	5.32	1.56	0.58	0.39	0.06	-	0.15
3	2.26		58.35		6.00	1.51	0.56	0.18	0.03	0.31
4	0.41	2.37	19.11	57.04	14.50		1.33	0.25	-	0.63
5	0.16	0.59	4.65		57.48	12.35		0.49		
6	-	0.18	0.86	5.57	24.50	53.28	12.58	1.65	0.21	1.18
7	0.03	0.12	0.30	0.79	7.03	23.86	56.04	8.64	0.55	2.64
8	-	-	0.06	0.38	1.34	4.07	29.15	56.66	3.63	4.70
9	0.31	-	-	1.26	0.94	1.89	6.29	31.13	48.37	9.81

capital calculated with internal models. The way in which the common factor operates within a rating system is two-fold.

6.1. PD-level effect

The level of the portfolio's average PD[22] may vary since the default rate is expected to increase in recessions with respect to periods of expansion. This issue is crucial, since the PD's assigned to the rating categories are just a function of the underlying portfolio's average PD. In order to avoid sharp regulatory capital fluctuations, the BCBS stated in its Consultative Document (January 2001) that "…each estimate of PD must represent a conservative view of a long-run average

[22] The average PD of a portfolio is weighted by the number of obligors in each category. Therefore, it just reflects the default rate of the portfolio in a specified period.

PD for the borrower grade in question…"[23], what in practice could be referred to the previous entire business cycle. As specified at the end of section 5.1, this is the approach adopted in this paper.

However, even though the use of an average calculated over a whole economic cycle can mitigate possible fluctuations in capital, it is certain that economic cycles are not always equal (either in duration or in intensity) and subsequently long-run averages will slightly differ from one period to the next. As a result, every year that the rating is recalibrated, a different cycle is considered and a distinct long-run average is obtained. If, for example, the average default rate of two consecutive cycles were different, due to for example an improved methodology of dealing with defaults, or to a continuous and positive growth rate of the economy, capital would also fluctuate only because of this effect. Notwithstanding that, a separate analysis carried out with the last two cycles in the Spanish economy shows that this effect has a minor impact on capital requirements.

6.2. Migration effect

Once the effect of the changing level of default rates across cycles has been discarded, it is expected that most of the impact on capital will be dominated by the common improvement or worsening of the credit quality of banking borrowers as a consequence of the economic activity fluctuations[24]. That effect will be denominated grade migration and will be the one to which we will pay all of our attention.

The main idea behind this effect is that due to the deterioration of general economic conditions, the qualification given to a certain borrower will inevitably change. It may also change due to variations of its own characteristics, but our analysis of procyclicality focuses only on migrations derived from changes in the macroeconomic variable of the model. The quantification of this effect on regulatory capital variations is carried out next.

Methodology

As estimated in section 5 and presented below in equation (1), the final conditional probability of the rating system possesses two separate halves:

$$\Pr obability\ of\ default_{it} = F\left[\alpha \cdot GDP_{t-1} + \sum_{k=1}^{K} \beta_k \cdot financial\_ratio_{k,i,t-1}\right] \quad (1)$$

where, *Probability of default*$_{it}$ is the predicted probability of default of firm i in year t, $F[\ ]$ is the cumulative standard logistic function, GDP_{t-1} is the GDP rate of growth in year $t-1$ and $financial\_ratio_{k,i,t-1}$ is the k-th sectorally transformed financial ratio for firm i in year $t-1$.

The first half is obviously related to the economic cycle whereas the second half is associated to the individual characteristics of the obligor. In order to quantify the migration effect induced by the state of the economic activity, only the first part of equation (1) will be modified. It could be argued that individual ratios also depend on the state of the economy, and that they may also constitute a source of migration. However, it must be remembered that the sectoral transformation of the financial ratios allows us to isolate the effect of the business cycle in the GDP

[23] See Basel Committee on Banking Supervision (2001, a), paragraph 270

[24] Most migrations are due to changes in the particular situation of each firm. For our purposes, only those caused by changes in the overall level of economic activity are analysed.

variable. Standardization with respect to the annual median reduces the cyclical component included in the financial ratios so that no important effect of the economic cycle is expected to be imposed on them and the previous affirmation can be accepted without major problems.

As changes (entries and exits) in the composition of the examined portfolio could create confusion in identifying real migrations of borrowers, a fixed portfolio will be used to study the cyclical effects. In particular, the year-2000 portfolio is held fixed and taken as the reference pattern[25].

Only three obligors' characteristics are needed to compute capital requirements under the new Basel proposals: their exposure, their rating grade and their corresponding PD[26]. Grade PD's are constant across years (as has already been discussed, the PD-level effect can be discarded) whereas the distribution of exposures across grades will change over time due to migrations of borrowers.

Estimations of regulatory capital will be provided for the 1993-2000 period. To start with, capital requirements for the year 2000 are calculated. The following step is to calculate those requirements for years 1993 to 1999, bearing in mind that migrations only take place via the common factor. To determine the new distribution of exposures per grade for each year, the growth rate of the GDP is substituted for its corresponding value so that a different score is obtained. If the new score falls out of the grade limits, a migration has occurred. To take an example, the new rating of an obligor in year 1999 is obtained by substituting the GDP_{t-1} value in year 2000 by its value in year 1999[27]. Applying the same reasoning for years 1998 to 1993, it is possible to obtain the migration behaviour of each obligor pertaining to the year-2000 portfolio in response to changes in macroeconomic conditions.

A time series of grades is obtained for every borrower and the annual distribution of exposures per grade is also achieved. In conjunction with the PD's obtained from the rating system, minimum capital requirements can be calculated, as well as their annual growth rates. Consequently, it is possible to know how capital requirements change every year because of grade migrations that are the sole consequence of changes in the general economic conditions.

Results

Figure 4 and Table 13 show the annual rates of variation of required capital for corporate exposures as a consequence of migrations caused by changes in the value of the GDP rate of growth under the BCBS January 2001 proposal and the latest October 2002 revision made public for QIS 3 purposes[28]. On the one hand, as the economic conditions worsen (years 1993 and 1994), the amount of capital requirements increases up to 4.5% or 3.1% if the January 2001 or the October 2002

---

[25] The analysis is very robust to the choice of the portfolio.

[26] The assumption of a constant loss given default (LGD) has been maintained throughout the whole paper and no credit risk mitigation techniques have been used to calculate regulatory capital.

[27] $Score_{1999} = Score_{2000} - (\alpha * GDP_{1999}) + (\alpha * GDP_{1998})$. Where α is the estimated parameter for the GDP variable in the logistic regression (Table 5); $\alpha = (-0.051)$. Once the new score is evaluated it is determined if each obligor is classified in their previous grade or has changed grade. If the latter occurs, a migration has taken place.

[28] The October 2002 capital curve varies with respect to the one of January 2001 in the following terms: Capital requirements=LGD* N[(1-R)^(-0.5)*G(PD)+ (R/(1-R))^(0.5)*G(0.999)]*(1- 1.5*b(PD))^(-1)*(1+ (M-2.5)*b(PD)).Where R is the correlation coefficient = 0.12*(1-exp(-50*PD)) / (1-exp(-50))+0.24*[1-(1-exp(-50*PD)) / (1-exp(-50))]; M is the maturity and b is the maturity adjustment=(0.08451-0.05898*log(PD))^2; N(x) denotes the standard normal cumulative distribution function. G(y) denotes the inverse of the standard normal cumulative distribution function. No firm-size adjustment has been considered for simplifying reasons as it will not significantly affect the rates of variation of capital requirements.

TABLE 13

MIGRATION EFFECT.
CAPITAL VARIATIONS AND GDP.

Year	GDP_{t-1}	IRB-Capital requirements January 2001	IRB-Capital requirements October 2002
1994	-1.0%	4.5%	3.1%
1995	2.4%	-8.9%	-6.1%
1996	2.8%	-0.7%	-0.5%
1997	2.4%	0.6%	0.4%
1998	4.0%	-3.3%	-2.3%
1999	4.3%	-0.6%	-0.4%
2000	4.2%	0.2%	-0.1%

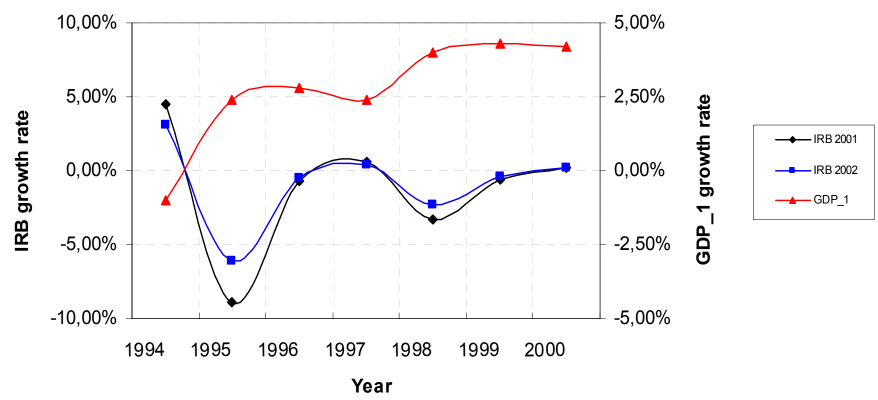
proposed formulae for corporate exposures are respectively considered. On the other hand, when economic conditions improve (1995 onwards), the requirements clearly decrease from one year to the next, especially in 1995 (-8.9% or –6.1% under the January or October proposals respectively).

It is also worth noting how the latest proposed formula for corporate exposures implies a reduction in the cyclical effects included in the computation of capital requirements, as already expected. All variation rates, either positive or negative, are much lower than in the January proposal.

At first sight, the results obtained do not seem to be highly alarming. However, as there is no generalised consensus about cyclicality, the previous annual changes in capital could be considered, either low (if the annual rate of variation is taken into account), or high (if the accumulated rate of change is considered). Consequently, maybe regulatory authorities or even practitioners should not refrain from considering possible ways to tackle the estimated cyclicality included in internal rating systems and its repercussions on capital changes.

FIGURE 4

MIGRATION EFFECT.
CAPITAL VARIATIONS AND GDP.



6.3. Courses of action to tackle cyclical effects

The BCBS has, so far, taken some steps to try to avoid excessive cyclical fluctuations in capital when defining PD estimates as long-run averages or by asking banks to take into account all relevant information and use longer time horizons than one year in assigning ratings to borrowers. The use of stress testing could be considered as a possibility to do this. In the same line, other initiatives could be undertaken such as including variables less vulnerable to changes in general economic conditions as regressors in the rating systems, as for example qualitative variables. In general terms, the final aim is that banks should finally acquire a global perspective of the real capacity of their borrowers to meet their credit debts based on the most appropriate range and type of information that is available for them.

In accordance with that line of thinking a very simple measure is proposed to obtain a reasonable overall assessment of the creditworthiness of each obligor. Additionally, this alternative measure possesses the advantage of mitigating the cyclical effects on capital changes derived from migration, as analysed next.

As the BCBS postulates, PD's in rating systems must be calculated on the basis of long-run averages. In the same way, obligors' ratings could also be calculated using long-run averages. That is, when assessing the capability of borrowers to meet their credit obligations, an average rating could be used for that purpose. Based on that, capital requirements would be calculated utilising average ratings reflecting the average credit quality of each obligor during a certain period of time (e.g. an entire business cycle). This average evaluation would clearly mitigate the cyclical patterns that, due to migration over time, affect internal rating systems and the required capital that is deduced from them. Additionally, it could be a way of objectively taking into account the BCBS requirements regarding the use of longer time horizon and conservative views in assigning ratings.

TABLE 14

MIGRATION EFFECT UNDER AVERAGE RATING. CAPITAL VARIATIONS AND GDP.

Year	GDP_{t-1}	IRB-Capital requirements October 2002 under average rating
1994	-1.0%	1.3%
1995	2.4%	-1.1%
1996	2.8%	-0.6%
1997	2.4%	-0.5%
1998	4.0%	-0.8%
1999	4.3%	-0.5%
2000	4.2%	-1.1%

To prove how the usage of an average rating could ease the cyclical effects included in rating systems, the same exercise as in section 6.2 was carried out to measure the effect of migrations. However, this time a yearly average rating has been constructed for each obligor and used in the analysis[29]. Table 14 and figure 5 present the results obtained when applying that average rating. As can be seen no

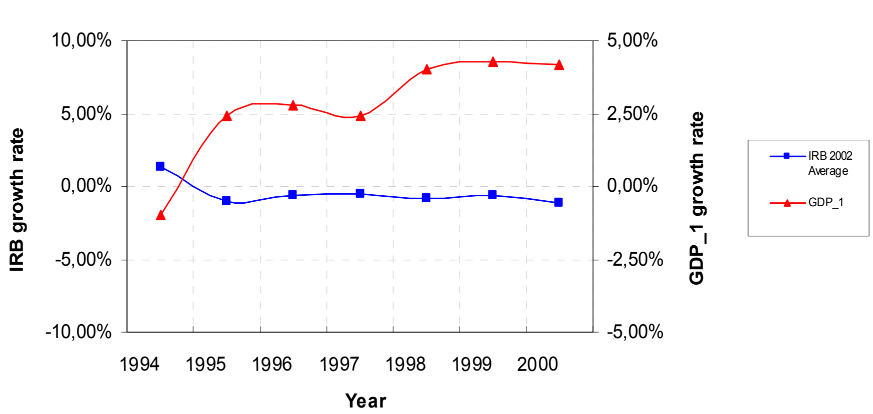
[29] For instance, the average rating of each obligor in year 1996 is calculated as a simple average of previous annual ratings as:

Average $Rating_{1996}$ = ($Rating_{1993}$ + $Rating_{1994}$ + $Rating_{1995}$ + $Rating_{1996}$) / 4.

important fluctuations of requirements will occur over time, being the highest rate of variation for the whole period the one that takes place in 1994 (1.3%)[30].

FIGURE 5

MIGRATION EFFECT
UNDER AVERAGE RATING.
CAPITAL VARIATIONS AND GDP.



Consequently, the effects of changes in the macroeconomic conditions on required capital are clearly attenuated when assessing the credit quality of each obligor by using its average rating over a long period of time. In any case, it is important to highlight that it does not reduce the risk sensitivity of the model since poorer quality borrowers will continue to have higher PD's and accordingly higher capital requirements than better quality obligors.

Alternative approaches to the use of average ratings are also available such as the use of the worst historical rating of the business cycle or the performance under stress scenarios that reflect specific macroeconomic conditions.

7. SUMMARY

The current proposal of reform of the 1988 Capital Accord designed by the Basel Committee on Banking Supervision and presented in the package of consultative documents published in January 2001, establishes a totally different framework regarding the measurement and management of credit risk. In particular, the innovative proposal of allowing banks to choose the possibility of calculating their minimum capital requirements according to their own risk models will be translated into a further development of internal rating systems and will bring regulatory and economic capital to a closer end.

With the aim of catching up with this new operational environment and of studying some of its properties, this paper presents the estimation of a borrower's classification method of non-financial private-sector firms for the whole Spanish credit system. Its main applications are expected to concentrate on supervisory activities, the unbiased comparison of risk profiles and capital requirements across banks being a crucial one.

[30] It is worth noting that as we get closer to the beginning of the sample, the average to calculate mean ratings takes into account fewer and fewer years. Consequently, the average for those years will be very much affected by the lack of observations to compute that average. If we had had a longer sampling period, we would have observed much smoother averages, and as a result lower rates of change.

According to inconsistency problems and certain lack of available information, a minimum size threshold of annual sales equal to € 9 million has been imposed on a firm to be included in the rating system. Using default data, characteristics of the credit operations, sectorally treated financial data and a variable that accounts for the prevailing macroeconomic conditions, a logistic regression model that determines the probability that a certain obligor defaults is estimated. Therefore, the model has been designed in a flexible way so as to produce not only average ratings but also point-in-time ratings for management purposes. It also permits us to estimate the worst rating of the business cycle and perform stress test exercises considering different macroeconomic environments so as to be used in the assessment of the capital adequacy of banks.

The regression model concludes that the determinants of the event of default are a group of financial ratios (profitability, leverage, liquidity and size), a dummy variable that establishes whether an obligor has been asked for any type of credit guarantee, the economic sector into which every obligor is classified according to their main economic activity and the GDP growth rate interpreted as the common factor that is supposed to equally affect the credit quality of every banking borrower.

Based on the scores derived from the model, a first tentative classification of obligors is obtained. The final rating grades are achieved by imposing two types of premises: first, an exponentially increasing probability of default from best to worst credit quality grades, and second, an approximately symmetrical distribution of obligors across grades. Considering those two premises, a definitive rating system, where nine different categories of risk are distinguished, is obtained.

Once the rating grades and the associated probabilities of default have been attained, the unconditional transition matrix is derived from it. To analyse the stability properties of such matrix, two states, related to the different stages of the business cycle, are considered. The main conclusion of that analysis is that depending on whether the economy is going through a recession or moving into an expansionary period, the transition matrices are different and, as a result the migration of borrowers over time will be affected by those stages. In other words, it is believed that a certain degree of procyclicality may be included in the estimated rating system.

Thanks to the especial design that the regression model possesses it is relatively easy to distinguish between the common factor, usually associated with the economic cycle, and the idiosyncratic factors. Based on the effects of the former it has been analysed how banking borrowers would migrate across grades over time by the sole consequence of changes in the general macroeconomic conditions. Utilising the formulae proposed by the BCBS on its January 2001 consultative paper to calculate minimum capital requirements for corporate exposures and its latest revision (October 2002 for QIS 3 purposes), it studied how those requirements would change over time.

As it is generally agreed, the most comprehensive estimate of every obligor's creditworthiness should be obtained for regulatory purposes. To reach that goal several measures have been intended so far: long-run average PD's, risk assessments of borrowers based on stress scenarios, longer periods for estimation, usage of less sensitive variables to changes in the economic cycle to evaluate credit quality, etc. In accordance with this line of thinking, this paper presents an alternative simple measure that could be used to achieve a reasonable assessment of the riskiness of every obligor. This is the usage of average ratings. This measure also mitigates the cyclical effects included in rating systems derived from migration reasons without reducing their risk sensitivity and facilitates the comparison between banks by using an objective and similar assessment of borrowers for all of them. As analysed in the text, the annual rate of variation of capital is clearly softened by using this average assessment when evaluating the real capacity of every borrower in meeting its debt obligations.

REFERENCES

Altman, E., Haldeman, R. and Narayanan, P., 1977. "ZETA analysis: A new model to identify bankruptcy risk of corporations", *Journal of Banking and Finance*, 1.

Altman, E. and Saunders, A., 2001. "An analysis and critique of the BIS proposal on capital adequacy and ratings", *Journal of Banking and Finance,* vol. 25.

Bangia, A., Diebold, F.X., Kronimus, A., Schagen, C. and Schuermann, T., 2002. "Rating migration and the business cycle, with application to credit portfolio stress testing", *Journal of Banking and Finance*, 26.

Beaver, W., 1966. "Financial ratios as predictors of failure", *Journal of Accounting Research, Supplement on Empirical Research in Accounting*.

Basel Committee on Banking Supervision. January, 2001a. "The new Basel Capital Accord", Consultative Document.

Basel Committee on Banking Supervision. January, 2001b. "The Internal Ratings-Based Approach", Consultative Document.

Borio, C., Furfine, C. and Lowe, P., 2001. "Procyclicality of the financial system and financial stability: issues and policy options". BIS papers, 1. pages 1-57.

Danielsson, J., Embrechts, P., Goodhart, C., Keating, C., Muennich, F., Renault, O. and Song Shin, H., 2001. "An Academic Response to Basel II". Special Paper 130. Financial Markets Group, London School of Economics.

DNB 2001. "Towards a new Basel Capital Accord". Quarterly Bulletin, March, pp. 48-54.

ECB. Monthly Bulletin, May 2001. "The new capital adequacy regime-the ECB perspective", pp. 9-74.

Ervin, W. and Wilde, T., 2001. "Procyclicality in the new Basel Accord", *Credit Risk Special Report, Risk Magazine*, October.

Lau, A., 1987. "A five-state financial distress prediction model", *Journal of Accounting Research,* 25.

López, J.A., April 2002. "The empirical relationship between average asset correlation, firm probability of default and asset size", Federal Reserve Bank of San Francisco, Working paper , No. 23.

Lowe, P., 2002. "Credit risk measurement and procyclicality". BIS papers, No.116.

Nickell, P., Perraudin, W. and Varotto, S., 2000. "Stability of rating transitions", *Journal of Banking and Finance*, 24.

Office of the Comptroller of the Currency (OCC), April 2001. "Rating Credit Risk. Comptroller's Handbook".

Ohlson, J., 1980. "Financial ratios and the probabilistic prediction of Bankruptcy", *Journal of Accounting Research*, 18.

Resti, A., 2002. "The new Basel capital accord: structure, possible changes, micro- and macroeconomic effects". CEPS.

Siegel, S. and Castellan, N.J., 1988. "Nonparametric Statistics for the Behavioural Sciences", 2nd Edition, McGraw-Hill, New York.

Zavgren, C., 1985. "Assessing the vulnerability to failure of American industrial firms: a logistic analysis", *Journal of Business Finance and Accounting*.