Rating Models Mistakes and Implications for the Basel Committee on Banking Regulation

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Abstract

Rating agencies have been key players in various financial crisis not just the current one but also in previous episodes such as the Asian crisis. In this paper we address the following issues: (i) the methodological errors in the agencies rating systems regarding corporate and sovereign debt (ii) Basel Committee banking regulation proposal regarding the agencies' role in establishing the minimum capital requirements. We have analyzed the relationship between ratings and default frequencies for corporate and sovereign bonds in the pre-crisis period and we have identified inconsistencies in the rating system. Another interesting result is that it is not possible to discriminate between issuers with such a large number of rating scales. We concluded that the actual credit risk regulation gravitate around models based on rating systems that cannot be estimated or validated with the guarantees of rigour and allows regulatory arbitrage by banks

Keywords: rating agencies, rating, bonds, credit risk, banking regulation

1. The Importance of Rating Agencies

Credit rating agencies have gained great momentum in the financial markets which has been reinforced in the outbreak and unfolding of the financial crisis. The ratings they assign to issuers and financial instruments are considered relevant information by a majority of investors and have an impact on the behaviour of investors, issuers and governments. There are groups of investors who are prohibited from acquiring financial instruments not rated in the investment grade[4]; also, the rating is a decisive factor to assess the securities' eligibility as collateral in central banks' open market operations with the financial institutions or for liquidity support. What is more, changes in ratings have a strong impact on investors' portfolio preferences. In the presence of any sign, or the evidence of a future possible rating downgrading of an issuer, the holders of those securities engage in sales that can generate a strong downward pressure on prices as well as an increase in spreads. These pro-cyclical movements reinforce bouts of financial instability and constitute the breeding grounds for speculative operations. The reports that agencies draw up on the corporate and sovereign issuers' creditworthiness have a high-impact due to their often self-interested amplification carried out both by the media and the advisory reports of banks, securities firms and hedge funds. Agencies' reports on issuers are riddled with strongly conservative recommendations which in the case of governments point out to the standard neoliberal guidance towards strong fiscal adjustments and public spending cuts. Rating agencies are private companies which elude all public control, regulation and supervision. It is an industry with a strong oligopolistic structure where three US companies, Standard & Poor's, Moody's and Fitch dominate the world market. Their business has spiralled up due to the increased presence of corporate and sovereign issuers in the capital markets but especially due to the unprecedented boom in structured products issuance. These include products originated through asset securitization and structured products linked to financial variables.

2. Agencies' Rating Methodologies Discriminatory Capacity

From 2008 Studies on the rating agencies focused on telling Have Their role in the current crisis. One set of studies have been conducted to study how it impacts a downgrade rating on the spread of European countries in crisis debt or problems in obtaining funding from the European Central Bank by banks linked (Afonso, Furceri and Gomes (2011)5, Ismailescu and Kazemi (2010), Haan and Amtenbrink (2011)6), or the institutionals problems like the problem of incentives of issuers pays model (Pagano and Volpin, 2010). Another problem that has been discussed is the influence of ratings agencies on financial regulation. The European Commission (EC) has identified the need to reduce reliance on rating agencies. The 1060/2009 EC regulation requires financial institutions "to make their own credit risk assessment and not solely and mechanistically rely on credit ratings for assessing the creditworthiness of an entity or financial instrument." Equally, Haan and Amtenbrink (2011) indicate that "the certification of rating agencies may actually increase the reliance on their judgment, as it creates the impression that their ratings can be trusted". In our opinion the problem should not focus on which banks are not dependent on the rating agencies, but to examine whether rating systems can be scientifically validated; since the rating system used by banks is essentially the same system used by the rating agencies. This remains the main problem in our opinion, the regulation is based on pillar 1 and in that context banks can obtain clear regulatory advantages in the IRB method. There is a literature on the inconsistency of the rating, across industries and geographic regions with a variety of conclusions since they depend on the selected data samples7. In this paper we propose a different line of research, which is to analyze the problems of rating systems to question the current system of regulation of credit risk. Specifically, the agencies have defined an excessive number of grades in their rating scales since the available information does not allow building a mesh so thin including so many grades or classes to cover all the obligors.

What really lacks is a theory of default, of the firm's bankruptcy. The reasons a company fails to meet its debt payment commitments are always specific. Automatic inference of a company's future behaviour based on a set of economic and financial ratios is a very risky venture. The connection between the present financial structure of a company and its future payment behaviour is far from being a causal relationship since a lot can happen in the meantime and besides that the ratios provide a static vision which lacks the theory on the dynamics and the environment that sustains the company's activity. The grades defined at the extreme points of the scales, i.e the highest and lowest grades in the agencies' rating systems are the ones that best discriminate based on this type of analysis. The companies which are assigned AAA in the Standard & Poor's terminology or Aaa in Moody's tend to be characterized by a set of extraordinarily positive factors, while at the other end the ones assigned the letter C, with several grades, tend to be on the verge of bankruptcy. However in between these two extremes the agencies attempt to build 15 grades or sometimes more which results in the difficulty to discriminate between a grade and the adjacent one. When comparing two firms, the first one rated A+ (A1) and the second one in the neighbouring A (A2) we can verify that the variables used to rate them do not hold a strictly hierarchical relationship, so that the second company may present better values for some of the variables used in the rating process. The outbreak of Basel II as regulatory framework applied to credit institutions for capital requirements has brought to the fore the concept of probability of default. The probability is a slippery concept when used in the field of economics and in the social sciences in general. It is a concept loaded with subjectivity since it is hardly ever possible to carry out controlled experiments, with repeated tests subject to the necessary and rigorous experimental control, without which the data in use are very far from the criteria determined by the statistical theory. The agencies publish on a regular basis papers on the default frequency of the firms they are rating. We are going to use data coming from the three agencies on the observed behaviour of companies and sovereigns' default.

In the transition matrices that the agencies put together we can observe the default frequencies over a range of horizons. For example for a one-year horizon at the beginning of every year there is a number of companies or sovereigns rated in each grade and at the end of the year the number of those that have defaulted during this period is accounted for. To keep it simple, if Ba1 accounts for 1000 companies at the beginning of the year and 10 of them default then the default frequency within this grade and for this year is 1%. They also publish the cumulative default frequencies that is, from a cohort of corporate or sovereign issuers rated within a certain grade on an initial date they obtain the cumulative default frequency in one, two, etc. years, the average values and the observed values for several years. Tables 1 and 2 show the observed default frequency of Moody´s rated issues for each year and each rating grade during 1983-2008 with an annual time span.

For example in 1983, the first year in the table, no defaults were registered from grade Aaa until the Ba2; the default frequency for grade Ba3 was 2.61%, and so on. The observed default frequencies are the only data we can use to corroborate the quality of the ratings assigned to issuers. Since the rating establishes an ordinal classification it is expected that survival rates follow the same order as the ratings that is, a lower grade must correspond to a lower survival rate or, conversely, to a higher default rate. When the ordering criterion is not fulfilled there is an inconsistency in the rating system. Basel regulation allows banks after an evaluation process to estimate the probabilities of default of the obligors and therefore it raised the need for appropriate methods for such estimates to be available. The information published by the rating agencies on defaults has become highly relevant working material both for the attempt to estimate the probabilities as well as for analysing the difficulties derived from it. When trying to infer estimates of default probabilities from the data at hand new issues emerge: i) identify the hypothesis that must be established so that the default frequencies represent valid information for the estimated probabilities of default ii) verify if the estimates are consistent and iii) corroborate if the agencies' rating grades are indeed clusters of issuers with different probabilities of default or on the contrary, if the rating system is not able to discriminate among notch-level grades.

Table 1: Moody's - Corporate Rating: Default Frequencies 1 Year Horizon. 1983-1995

The data analysis in tables 1 and 2 is focused on detecting the potential inconsistencies present in the assigned ratings. We noticed that the ability to discriminate between grades on the basis of the observed default frequencies is impossible for a large group of ratings since no default was registered in any year of the sample. This is the case for grades Aaa, Aa1, Aa2, A1 and A2. The fact that the default frequency is systematically equal to zero does not imply that the firms rated in these grades have the same probability of default and furthermore, that this probability is equal to zero. The observed null default frequency is a common problem for the higher credit rating grades since, assuming that the true probability of default is very low for example 0.03%, the probability of null frequency for a sample containing a small number of firms is very high. The 0.03% probability of default supposes on average an expected frequency of three defaults over 10,000 firms. The probability of obtaining the null value in 1000 independent attempts with a probability of "success" (default) of 0.03% is 74.1%. The conclusion here is that there is a large group of firms rated in the quoted grades, which is equivalent to not knowing if based on their observed behaviour they are the same or different in terms of probability of default.

Table 2: Moody's - Corporate Rating: Default Frequencies 1 Year Horizon. 1996-2008

Based on the default frequency displayed for each year we encounter a large number of inconsistencies with respect to the hypothesis that the rating system is capable of grading efficiently, which would mean that the rating were in hindsight a robust indicator of the default frequencies. The lack of ascending classification of the default frequencies is observed every year due to the existence of many zeros, but even if we overlook this aspect the phenomenon is confirmed in the years 1983, 1984, 1986, 1987, 1989, 1991, 1993, 1996, 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006 and 2008. It is true however that in some cases the data might be compatible with well-ordered probabilities, i.e a lower probability of default corresponding to a higher rating, given that the results could be interpreted as sampling errors or deviations from the true probabilities, generally due to the small sample size. But the truth is that the only reality is the one we observe based on which it is not possible to assign probabilities using the frequencies without generating the contradiction of assigning a lower probability of default to grades that according to the established rating denote worse credit quality. This leads to a dead-end that can only be resolved by questioning the discriminatory power of a rating system with such a broad number of grades. Taking into account that these abnormal behaviours could be considered, if we are generous in the interpretation, sampling errors due to the small number of firms rated within each grade, we calculate the average default frequencies for the period 1983-2008. Table 3 lists the results for the group known as the investment grade, i.e. from AAA down to Baa3.

Table 3: Moody's - Corporate Rating: Average Default Frequency for Investment Grade. 1983-2008

The results are discouraging given that the frequencies' average behaviour is not the expected one if the rating system was able to discriminate properly. The default frequencies decrease or remain the same from Aa3 up to A3. Chart 1 shows the above.

Chart 1: Moody's - Corporate Rating

Table 4 shows the default frequencies of Standard & Poor's ratings for Mexican issuers. The following inconsistencies are observed:

i) Grades AAA and AA+ have equal frequencies to the one and two years horizon, ii) The default frequencies for AA-, A+, A and A- are lower than for AA to the one year horizon, iii) The default frequency for BB is lower than for BBB+, BBB and BBB-, to the one year horizon, iv) The default frequency for B is lower than for B+ to the one year horizon, v) The default frequency for A+ is lower than or equal to the frequency for AAA, AA+, AA, AA- to the one to five years horizon, vi) The default frequency for A is lower than for AA and AA- to the two years horizon, vii) The default frequency for A- is lower than for AA, AA- and A to the two years horizon, viii) The default frequency for BB+ is lower than for BBB- to the three and four years horizon, ix) The default frequency for BB is lower than for BBB- and BB+ to the two years horizon, lower than for BBB, BBB- and BB+ to the three years horizon and lower than the default frequency for grades BBB+, BBB, BBB and BB+ to the four and five years horizon, x) The default frequency for B is lower than for B+ to the one to five years horizon. The frequency for B- is zero, lower than all previous levels up to grade A to the two to five years horizon.

Table 4: Standard and Poor's - Corporate Rating: Default Frequencies, Mexico: YEARS 1991-2008

Table 5 shows the default frequency of sovereign issuers rated by Fitch for the period 1995-2008.

Table 5: Fitch - Sovereign Rating: Default Frequencies 1 Year Horizon. 1995-2008

The following inconsistencies are noticed:

i) The default frequency is equal to zero for all investment grade rated issuers, ii) The default frequency for BB is lower than for BB+, iii) The default frequency for BB- is lower than for BB+ and BB and the same is true for B- with respect to B, iv) The default frequency for B is lower than for BB+.

Table 6 shows the default frequency of Fitch rated sovereign issuers for the period 1995-2008.

We detect the following inconsistencies:

i) Except for BBB- investment grade rated issuers recorded default frequencies equal to zero, ii) The default frequency for BB- is lower than for BBB-, BB+ and BB, iii) The default frequency for B- is lower than for B.

Table 6: Fitch - Sovereign Rating: Default Frequencies, 5 Years Horizon. 1995-2008

Table 7 presents the default frequencies of corporate issuers to the one year horizon during 1990-2008. In this case the inconsistencies we detected are:

i) The default frequency for AAA, AA and AA+ are the same, ii) The default frequency for A+ is lower than for AA-, iii) The default frequency for BBB is lower than for A- and BBB+, iv) The default frequency for BB is lower than for BB+, v) The default frequency for BB- is lower than for BB+, vi) The default frequency for B+ is lower than for BB+ and BB-, vii) The default frequency for B- is lower than for B.

Table 7: Fitch - Corporate Rating: Default Frequencies, 1 year horizon. 1990-2008

Table 8 shows the cumulative default frequencies of Fitch rated corporate issuers during 1900-2008. The inconsistencies reflected here are:

i) The default frequencies for AAA and AA+ are the same, ii) The default frequency for AA- is lower than for AA, iii) The default frequency for BB- is lower than for BB, iv) The default frequency for B- is lower than for B.

Table 8: Fitch - Corporate Rating: Default Frequencies 5 Years Horizon. 1990-2008

Table 9 shows information about sovereign and corporate rating jointly based on the data provided by Standard & Poor's, indicating the cumulative frequencies to the fifth year observed during 1984-2008. These are therefore average values. In this case a new type of inconsistency emerges when comparing the sovereign default frequencies with those of corporate issuers: Sovereign default frequencies, both in foreign and local currency, are equal to zero from AAA down to BBB+ while default frequencies of corporate issuers recorded non-null values. As established by the agencies the rating scales define, in theory, a homogeneous metric unrelated to the nature of the issuer. For example an A+ rating should mean the same likelihood of compliance with the payment obligations both for a sovereign as for a corporate issuer. If this was not the case agencies should provide the equivalence criteria between the sovereign and corporate scales.
However the description they give for the rating scales is the same both for sovereign and corporate issuers. A conclusion that emerges from the table is that the rating agencies have penalised sovereign issuers.

Table 9: Standard & Poor's Sovereign and Corporate Rating. Cumulative Default Frequencies to the 5th Year. 1984-2008

Sovereign 1975-2008, Corporate 1981-2008.

There are other inconsistencies to be highlighted in the same line with the comments made so far:

1. Sovereign issuers in foreign currency

ii) The default frequency from AAA down to BBB+ is the same, iii) The default frequency for BB+ is lower than for BBB and BBB-, iv) The default frequency for BB is lower than for BBB-, v) The default frequency for B+ is lower than for BB-, vi) The default frequency for B- is lower than for B.

2. Sovereign issuers in local currency

vii) The default frequency from AAA down to BBB is the same, viii) The default frequency for BB+ is lower than for BBB-, ix) The default frequency for BB is lower than for BBB-, x) The default frequency for BB- is lower than for BBB-, xi) The default frequency for B+ is lower than for BBB+, BBB and BBB-, xii) The default frequency for B is lower than for BBB-, BB+, BB and BB-, xiii) The default frequency for B- is lower than for BB-.

3. Corporate issuers

xiv) The default frequency for AA+ is lower than for AA, xv) The default frequency for AA is lower than for AAA, xvi) The default frequency for A+ is the same as for grade A, xvii) The default frequency for BBB is lower than for BBB+.

The main conclusions derived from the previous analysis are:

1) The empirical evidence provided by the agencies themselves reveals a significant number of inconsistencies in the criteria they establish to rate the issuers. This is a breach of the fundamental property of rating systems that is, the ordinal nature of the classification.
2) The agencies rate the issuers following a systematic process that includes meetings with top managers of the companies when they rate corporate issuers or with the senior political leaders when it comes to sovereigns. They also have access to private firms' internal management information. The process is lengthy enough to allow the agencies' employees to return and clarify the topics they consider ambiguous or appear to be more critical. The agencies establish a benchmark for any attempt made by a bank's rating department to assign a rating for their obligors. That is to say that the agencies, who are the best suited to establish the ratings, obtain disappointing results which cannot generally be outperformed by other rating institutions that count with less information, time and ultimately with lower costs.
3) Aware of the inconsistencies the agencies exhibit two arguments in their defence. Actually in most of the transition matrices they publish the grades are grouped and in this way the inconsistencies are being considerably reduced. The first argument is the small number of issuers especially in the higher rating grades. Assuming that the probabilities of default are small the probability to register null values is high. The second argument is the reduced number of years in the sample. In the end both arguments boil down to one which is the small sample size. They never argue however that another possible reason for the inconsistencies is the deficient nature of the rating criteria since they take into consideration factors they believe to be relevant for the greater or lesser likelihood of the default event, when they are not. Or simply that the main goal contains an inherent difficulty impossible to overcome since anticipating the default within the time limits that the agencies establish cannot be achieved based on the information they have available when they assign the rating. That is because the evolution of the issuers' solvency is subject to unknown factors and to the future path that companies or governments will follow as a result of the interaction between the economic environment and the decisions taken by the business or political leaders.

Regarding the sample size, even assuming that the rating criteria were correct the agencies would have to accept that there is not enough available evidence to discriminate among notch-level grades and would thus have to abandon the ambition of trying to fit the issuers into a mesh so thin of so many grades. This means that the distinction they make between for example AAA, AA+, AA and AA- rated sovereign issuers is untenable in terms of the likelihood of default.

3.From the Default Frequency to the Probability of Default

The grades defined by the agencies in their rating scales have an ordinal ambition which is not satisfied according to the analysis carried out in the previous pages and this proves the quality of the work developed by the agencies. The minimum target expected from the ratings is that they be good predictors of the observed rates of default that is the default frequency of a higher credit quality rating should be lower than that of an inferior rating. The reasons why the rating agencies fail are various and one that we consider significant is the attempt to establish an excessively large number of rating grades. Of course another essential factor is the reliability of the criteria established to define the grades, i.e. which variables will ultimately determine if an issuer is assigned one rating or another. Rating methodologies pretend to be able to find the common denominator that allows ranking a heterogeneous group of issuers within the same grade. But this is a highly ambitious goal as there is no reliable theory on the corporate bankruptcy or the sovereign default. Experience shows that defaults are unique events explained mainly by the specific circumstances undergone by the bankrupt firm or the government that has defaulted. There is empirical evidence to attest that the sovereign ratings assigned by the major rating agencies can be explained based on a vector comprising a small number of variables, following Alonso (2009, p. 105-135), which include the GDP per capita, GDP growth, inflation, the public sector and external balance, the external debt, the institutional quality, the corruption level, etc. This means that for the agencies the likelihood of the default is a function of the selected variables. They also apply this type of deterministic default event model to corporate issuers. However two companies with similar economic and financial profile can have considerably different future behaviour patterns when it comes to meet their financial commitments. The characteristics and dimensions of the risks a company is exposed to cannot be drawn directly from its financial statements nor is it possible to determine on this basis its future reaction to an adverse environment or to strategic or tactical errors.

Assigning probabilities of default to issuers is a much more ambitious goal than achieving an appropriate ordinal classification. The probability represents a qualitative leap because it seeks to establish a significantly different numeric value for each rating grade. Hence the need to estimate the probabilities using robust procedures. The observed default frequencies are without doubt the available information that *a priori* seems the most suitable to estimate the probabilities and carry out the validation assessment.

A series of hypothesis which need to be made explicit are assumed when using the sample data provided by the default frequencies. The first is accepting that all individuals from the same rating grade, corporate or sovereign, share the same probability of default. For an individual issuer it is impossible to test the hypothesis that the assigned probability of default is correct based on the observed behaviour and regardless of the steps taken to assign that probability. The problem is that it is not possible to perform repeated experimental tests to observe the default frequencies. Given the observed behaviour during for example one year and the probability of default assigned to that time span it is impossible to assess the goodness of fit of the probability no matter if the issuer defaults or not. That is why the agencies will try to estimate the default probability of the entire cohort based on its observed behaviour and accepting the untestable hypothesis that all issuers have the same probability of default. On top of that, in order to choose the criterion for the estimate one must consider as well the hypothesis on the nature of the dependence among the default events within the group. The common hypothesis is to assume that the default events are independent. Any hypothesis that identifies some kind of dependence among them would require us to establish the statistical law that governs the stochastic dependence process. Faced with the difficulty of inferring any dependency pattern from the generally few events of default the common option is to assume the hypothesis of independence. Based on the above hypotheses the defaults can be approximated to the realization of a binomial variable of probability p, probability of default, and assuming N individuals in a given rating grade and n default events, the probability of the observed event is given by:

$$P = \binom{N}{n} p^n (1-p)^{N-n}$$

the maximum likelihood estimator of p is $\hat{p} = \frac{n}{N}$,i.e. the maximum likelihood estimator of the probability of default is given by the observed frequency. Default probabilities estimated based on data the agencies publish are subject to the same type of inconsistencies as those detected for the default frequencies. We will now consider the possibility, in a context of inference, that some inconsistencies can be corrected by paying the price of reducing the discriminating capacity of rating systems that is, drastically reducing the number of grades.

4. *Minimum Number of Obligors to Discriminate between Probabilities of Default*

To test the hypothesis that the probabilities of default are different the appropriate statistical test under the hypothesis that the defaults are independent, Hanson and Schuermann (2006), is the following: let p_i and p_j be the probabilities of default; the null hypothesis $H_0: p_i = p_j$ compared to the alternative hypothesis $H_1: p_i \neq p_j$, is tested by the Z statistic such that if it is likely that Z follows a standard normal distribution the null hypothesis is not rejected. Z is defined in terms of the probabilities of default estimates, based on samples of N_i and N_j number of obligors with n_i observed defaults in grade i and n_j in the grade j, Casella and Berger (2001). The maximum likelihood estimators of the probabilities of default are:

$$\hat{p}_i = \frac{n_i}{N_i} \quad (2) \qquad \hat{p}_j = \frac{n_j}{N_j} \quad (3)$$

And the statistical Z is,

$$Z = \frac{\hat{p}_i - \hat{p}_j}{\sqrt{\frac{N_i + N_j}{N_i N_j}\hat{p}(1-\hat{p})}} \quad (4) \qquad \hat{p} = \frac{N_i \hat{p}_i + N_j \hat{p}_j}{N_i + N_j} \quad (5)$$

Given the estimated probabilities of default it is possible to calculate the minimum number of obligors in each rating grade so that the testing could be able to discriminate if the probabilities of default are different. In analytical terms the matter is finding the combination of N_i and N_j such that:

$$\frac{\left|p_i - p_j\right|}{\sqrt{\frac{N_i + N_j}{N_i N_j}\frac{N_i \hat{p}_i + N_j \hat{p}_j}{N_i + N_j}\left(1 - \frac{N_i \hat{p}_i + N_j \hat{p}_j}{N_i + N_j}\right)}} > z^*_{\alpha/2} \quad (6)$$

Where $z^*_{\alpha/2}$ is the critical value in the standard normal distribution for the chosen confidence level $1-\alpha$. The number of issuers rated by the agencies varies each year. Table 10 shows the number of firms and the corresponding probability of default classified according to rating. In one of their reports Moody's provides data on the number of issuers they rate, grouped in Aa, A, Baa, etc. In order to classify them within the grades from the table the figures have been rounded and distributed as shown. The criterion is not relevant here, what matters is the order of magnitude. On the other hand each rating has been assigned the probability of default obtained from the financial information made public by several banks such as the BBVA and Santander. Although the probabilities of default estimates differ somewhat from one bank to another the differences are not relevant for the following analysis. We should also point out that the default probabilities for higher grades such as AAA, Aa1, Aa2 and Aa3 are established conventionally, not on the basis of the observed defaults. Basel II standards compel them to assign the minimum probability of 0.03% for AAA (Aaa) and from this value onwards probabilities are assigned to the remaining grades since no sample evidence exists, given the small number of issuers within these grades and the low historical rates of default. Using the data in Table 10 we are going to corroborate if it is possible to discriminate among the different rating grades, i.e. contrast if the cohorts' probabilities are different. We start from the A1 rating with the estimated probability $\mathrm{PD(A1)} = 0{,}20\%$ and calculate the probability limit so that:

$$\frac{\left|p_i - p_j\right|}{\sqrt{\frac{N_i + N_j}{N_i N_j}\frac{N_i \hat{p}_i + N_j \hat{p}_j}{N_i + N_j}\left(1 - \frac{N_i \hat{p}_i + N_j \hat{p}_j}{N_i + N_j}\right)}} = 1{,}96 \quad (7)$$

Table 10: Rating, Number of Issuers and Probability of Default

The probability of default we obtain is 1.28 % which means that it is not possible to discriminate between A1, A2, A3 and Baa1 based on data in the table. When a bank estimates default probabilities based on their loan portfolio observed defaults the estimation problems become even more serious. In such cases the estimates' uncertainty increases since they have far less information available. As for sovereign ratings the difficulty of discriminating among grades based on the observed default frequencies increases even further. That is because many frequencies have registered null values for most of the investment grade group and also because the sovereign issuers are considerably fewer than the corporate ones.

5. Basel II: The Irb Approach

The most important change Basel II has introduced compared to Basel I is the calculation of the capital requirements for credit risk using parameters that banks subject to these regulations can estimate internally. Under the IRB approach (internal rating based) the minimum amount of regulatory capital each entity must hold in order to cope with the unexpected losses derived from credit risk is established through a formula where some parameters are banks' internal estimates. There are two IRB approaches, foundation and advanced established under Basel II. Under the foundation approach the banks can only estimate the probability of default of each obligor from their loan portfolio whereas under the advanced approach they can estimate other parameters as well, among which one that stands out due to its impact in calculating the capital requirements is the rate of loss given default, LGD, Basel Committee on Banking Supervision (2006). Banks are allowed to use this approach only subject to explicit approval from their supervisors who undertake a previous evaluation process that presents great difficulties for the regulator. The main conditions to obtain the approval are: (i) the regulator has guarantees that banks' own system for exposures treatment and for parameters estimating is correct, and this refers to the rating's discriminating capacity and the default probability's capacity to predict future default rates ii) banks can demonstrate they have been using for at least three years rating systems consistent with the minimum requirements for measuring the internal risk management iii) banks requesting permission to use their own estimates of the loss given default (LGD) and the conversion factors (CF) should prove that they have been using during those three years estimates consistent with the established minimum requirements.

The minimum regulatory capital required for an obligor i with an exposure EAD_i is given by the following expression:

$$K_i = k \times RW_i \times EAD_i \qquad (8)$$

The capital ratio k maintains the same value as in Basel I, k= 8% and RW_i is the risk weighting factor. The calculation of RW_i is a complete innovation, since it is defined as follows:

$$RW_i = \left[LGD_i \times N\left(\frac{G(PD_i) + \sqrt{R_i}G(0,999)}{\sqrt{1-R_i}} \right) - PD_i \times LGD_i \right] \times$$

$$\times \frac{1+(M_i - 2,5)\times b(PD_i)}{1-1,5\times b(PD_i)} \times 12,5 \times 1,06 \qquad (9)$$

In order to determine the weighting factor RW_i from the expression above, $N(x)$ is the distribution function of a standard normal random variable, $G(z)$ is the inverse function of the standard normal distribution function, i.e. $G = N^{-1}$, which means that $G(0,999)$ is the value of the standard normal random variable that has a cumulative probability of 99.9%, i.e. $G(0,999) = 3,09$. R_i is a correlation coefficient defined in the underlying theoretical model and used to determine the loss over the portfolio. M_i is the effective maturity of the obligor's debt instrument. The correlation coefficient R_i is a function of the probability of default. For central governments, central banks and companies with sales above 50 million euros exposures is given by the following expression:

$$R_i = 0,12\left(\frac{1-e^{-50\times PD_i}}{1-e^{-50}} \right) + 0,24\left(1 - \frac{1-e^{-50\times PD_i}}{1-e^{-50}} \right) \qquad (10)$$

In the IRB methodology the correlation coefficient is not estimated by the financial institutions. Its values are supplied by the regulator who has established different formulas for their calculation. In all of them the higher the probability of default the lower the correlation is. The underlying rationale is that the higher the probability of default the stronger the idiosyncratic risk component is. It is also assumed that credit correlation for large companies is higher than for small and medium-sized entities due to the fact that they relate more closely to the economic cycle.

The loan portfolio consists of instruments with different maturity. The probabilities of default in use have a one-year horizon which is why the Basel Committee decided to introduce a weighting factor referring to the instruments' different maturity. It is assumed that under equal conditions long-term loans have higher risk than short-term ones and a possible rating downgrading is more likely the longer the time span. These distinctive features would be incorporated in a natural way to the model if it worked with probabilities of default for the instruments' different time spans, however this is not possible when choosing a one-year time horizon model. The Basel Committee defines a maturity adjustment called m_i which multiplies each term of the sum that provides the quintile of the distribution.

$$m_i = \frac{1+(M_i - 2,5)b(PD_i)}{1-1,5b(PD_i)} \qquad b(PD_i) = (0,11852 - 0,05478 \times \ln PD_i)^2 \quad (11)$$

M_i is the effective maturity of obligor's debt instrument. This adjustment is only performed for the corporate debt portfolio. The result of the 8% capital ratio multiplied by the risk weighting factor *RW* determines the amount of regulatory capital required in terms of percentage of the exposure. The graph below shows the curves corresponding to three values of the loss given default, namely for LGD=45% which is the value set under the foundation IRB approach, LGD=25% which would fit an institution much more efficient in the recovery process and LGD=65% that corresponds to the opposite case. Given the LGD, each curve represents the amount of minimum capital required based on the probability of default. There is a striking difference in the amount of required capital depending on the PD and LGD estimated values. This paves the way for regulatory arbitrage given that the foundation IRB approach assigns all banks the value of 45% regardless of the greater or lesser efficiency in the recovery process. Imagine two banks for example, the first one highly efficient in terms of recovery with LGD=15% and the second one very inefficient with LGD=85% both subject to the basic IRB approach. Assuming the same portfolio, for example all obligors are BBB+ rated with the probability of default PD=0.80% the two banks would be penalized and rewarded as follows: the first one would be required 7.20% regulatory capital over the exposure when according to its LGD it should only be 2.40%, whereas the second bank would be required the same 7.20% over the exposure when according to its LGD the required capital should be 13.80%. These outstanding differences question the validity to regulate the capital requirements given the difficulty the supervisors encounter to validate the estimates.

Chart 2: Minimum Capital Requirements as a Function of PD and LGD.

Table 11 shows the minimum capital requirements according to the probability of default assigned to each rating grade. There is no official approval between rating grade and probability, but there are numerous banking publications where they assign these probabilities. The table has been created under the hypothesis of LGD=45%.

Table 11: Capital Requirements According to PD with LGD = 45%.

We can see that from AAA down to BBB+ the minimum required capital is lower than 8%. This means that a bank following the new Accord would find favourable the IRB foundation approach with respect to Basel I as long as their portfolio is rated within the grades above. Loan portfolios with lower ratings, from BBB down to CCC would be penalized with a capital ratio higher than 8% compared to Basel I. If a financial institution is able adopt the advanced IRB approach and certainly many large international banks are, the reduction in regulatory capital is much greater compared to Basel I as long as the bank in question can prove an LGD estimate below 45%. For example, assuming LGD=25% we obtain the results in Table 12.

Table 12: Capital Requirements According to PD with LGD = 25%

In this case the number of grades for which the required capital is lower than 8% increases from AAA down to BB+. The entire construction is based on the quality of the probabilities of default estimates, PD, the rates of loss given default, LGD, as well as on the credit risk model according to Gordy (2002, p. 203-227) which are the main components underpinning the formula of capital requirements.

Conclusions

The present paper has tried to highlight the weaknesses in the agencies' credit rating systems and therefore the error of making the entire construction of the credit risk regulation gravitate around models that cannot be estimated or validated with the guarantees of rigour, precision and efficiency that the objective requires. While the market risk models have in their favour the short horizon of their predictions and the availability of sufficient information to estimate the models and perform the desired validations, the circumstances are diametrically opposed for the credit risk models. It is not possible to make individual validations for each obligor, the relevant time spans to measure the risk are one year or above and the information is generally deficient, either due to its characteristics of being generated in a context of asymmetric information or to the limitations imposed by the default numbers. Added to this is the complexity of rating systems designed by the financial institutions and the supervisors' recognized impossibility to make conclusive contrasts on their validity, Basel Committee on Banking Supervision (2005). Throughout the article we have also analyzed the rating systems' weaknesses as basis for calculating the regulatory capital and, therefore, the fragility of Basel II when it comes to credit risk modeling.

Hannoun (2010) pointed out the need to revise the regulatory framework and policies set in place in order to prevent the financial instability in the wake of the crisis but without questioning at any point the whole structure built around credit risk regulation. The Basel Committee has followed a similar line, with Basle III reforms oriented primarily towards increased capital requirements and expanding on the types of risk that must be explicitly regulated, as for example the liquidity risk. However, there has been no questioning of Basel II 's core approach regarding the credit risk, i.e. measuring risk using models based on rating systems designed internally by banks and on estimates of the probabilities of default for each grade in the rating system. Based on the analysis carried on previously throughout the article we believe this is a misguided approach. What is essential to understand is that corroborating the validity of the rating systems and the estimates of the probabilities is a virtually impossible endeavor for the supervisors, and this generates a fully favorable framework where banks can easily underrate the credit risk and 'save up' considerable amounts of regulatory capital. Supervisors should inform about those financial entities that had been evaluated and approved for using the IRB methods but have however suffered far greater losses than those calculated by the internal credit risk models. Reforms should therefore not be based on the alleged improvement in current quantitative methods for credit, liquidity and operational risk, since the uncertainty that underlies the events that govern manifestations of such risks does not allow estimating probability distributions able to tame such risks.

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TABLES AND FIGURES:

TABLES

TABLE 1. MOODY'S - CORPORATE RATING:

DEFAULT FREQUENCIES 1 YEAR HORIZON. 1983-1995

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Aaa	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa3	0,00	0,00	0,00	0,00	0,00	0,00	1,40	0,00	0,00	0,00	0,00	0,00	0,00
A1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
A2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
A3	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Baa1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Baa2	0,00	0,00	0,00	0,00	0,00	0,00	0,80	0,00	0,00	0,00	0,00	0,00	0,00
Baa3	0,00	1,06	0,00	4,82	0,00	0,00	1,07	0,00	0,00	0,00	0,00	0,00	0,00
Ba1	0,00	1,16	0,00	0,88	3,73	0,00	0,79	2,67	1,06	0,00	0,81	0,00	0,00
Ba2	0,00	1,61	1,63	1,20	0,95	0,00	1,82	2,82	0,00	0,00	0,00	0,00	0,00
Ba3	2,61	0,00	3,77	3,44	2,95	2,59	4,71	3,92	9,89	0,74	0,75	0,59	1,72
B1	0,00	5,84	4,38	7,61	4,93	4,34	6,24	8,59	6,04	1,03	3,32	1,90	4,35
B2	10,00	18,75	7,41	16,67	4,30	6,90	8,28	22,09	12,74	1,54	4,96	3,66	6,36
B3	17,91	2,90	13,86	16,07	10,37	9,72	19,55	28,93	28,42	24,54	11,48	8,05	4,10

Source: Moody's Global Credit Policy (2009), pp. 30.

TABLE 2. MOODY'S - CORPORATE RATING:

DEFAULT FREQUENCIES 1 YEAR HORIZON. 1996-2008.

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Aaa	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Aa3	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,48
A1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,99
A2	0,00	0,00	0,00	0,00	0,00	0,41	0,00	0,00	0,00	0,00	0,00	0,00	0,00
A3	0,00	0,00	0,00	0,00	0,00	0,00	0,43	0,00	0,00	0,00	0,00	0,00	0,00
Baa1	0,00	0,00	0,00	0,00	0,29	0,27	1,24	0,00	0,00	0,00	0,00	0,00	0,26
Baa2	0,00	0,00	0,32	0,00	0,00	0,26	0,94	0,00	0,00	0,24	0,00	0,00	0,77
Baa3	0,00	0,00	0,00	0,34	0,98	0,00	1,76	0,00	0,00	0,29	0,00	0,00	0,31
Ba1	0,00	0,00	0,00	0,47	0,91	0,53	1,66	0,55	0,00	0,00	0,00	0,00	0,00
Ba2	0,00	0,00	0,61	0,00	0,66	1,26	1,29	0,69	0,65	0,00	0,50	0,00	0,00
Ba3	0,00	0,47	1,09	2,27	1,51	2,81	1,49	1,33	0,42	0,00	0,00	0,00	2,68
B1	1,17	0,00	2,13	3,08	3,25	3,50	1,81	0,71	0,00	0,00	0,66	0,00	1,72
B2	0,00	1,50	7,57	6,68	3,89	10,05	6,24	2,32	0,58	0,83	0,50	0,00	0,77
B3	3,36	7,41	5,61	9,90	9,92	17,30	8,33	5,29	2,29	2,10	1,93	0,00	3,13

Source: Moody's Global Credit Policy (2009), pp. 30.

TABLE 3. MOODY'S - CORPORATE RATING: AVERAGE DEFAULT FREQUENCY FOR INVESTMENT GRADE. 1983-2008.

Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3
0,00	0,00	0,00	0,11	0,04	0,02	0,02	0,08	0,13	0,41

Source: Moody's Global Credit Policy (2009), pp. 30.

TABLE 4. STANDARD AND POOR'S - CORPORATE RATING:

DEFAULT FREQUENCIES, MEXICO: YEARS 1991-2008.

	Year 1	Year 2	Year 3	Year 4	Year 5
AAA	0,00	0,00	0,00	0,00	0,00
AA+	0,00	0,00	1,02	2,36	4,20
AA	0,37	0,81	1,36	2,07	3,03
AA-	0,00	1,45	1,45	1,45	1,45
A+	0,00	0,00	0,00	0,00	0,00
A	0,00	0,60	1,39	1,39	1,39
A-	0,00	0,55	1,28	1,28	1,28
BBB+	0,34	2,23	4,84	6,63	9,06
BBB	1,42	3,67	5,22	7,39	9,49
BBB-	5,00	12,68	16,84	21,48	21,46
BB+	2,22	8,15	16,14	20,79	27,39
BB	0,00	5,00	5,00	5,00	5,00
BB-	12,50	12,50	12,50	12,50	12,50
B+	27,27	39,39	63,64	75,76	87,88
B	16,67	16,67	16,67	16,67	16,67
B-	0,00	0,00	0,00	0,00	0,00
CCC	31,25	36,98	36,98	36,98	36,98

Note: There is no default frequency for grade B-. After analysing different possibilities the most probable one is that there are no B- rated issuers, which is why it has not been taken into account in the analysis.

Source: Standard & Poor's (2009a), pp. 16.

TABLE 5. FITCH - SOVEREIGN RATING:

DEFAULT FREQUENCIES 1 YEAR HORIZON. 1995-2008.

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BB+	BB	BB-	B+	B	B-	CCC			
2,94	1,82	0,00	0,00	2,13	0,00	23,08			

Source: Fitch IBCA (2009), pp. 10.

TABLE 6. FITCH - SOVEREIGN RATING:

DEFAULT FREQUENCIES, 5 YEARS HORIZON. 1995-2008.

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	10,26
BB+	BB	BB-	B+	B	B-	CCC			
6,67	10,81	0,00	0,00	14,29	13,33	25,00			

Source: Fitch IBCA (2009), pp. 10.

TABLE 7. FITCH - CORPORATE RATING:

DEFAULT FREQUENCIES, 1 year horizon. 1990-2008.

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
0,00	0,00	0,00	0,07	0,00	0,08	0,18	0,20	0,15	0,52
BB+	BB	BB-	B+	B	B-	CCC			
1,57	1,20	1,45	1,39	2,24	1,93	22,30			

Source: Fitch IBCA (2009), pp. 12.

TABLE 8. FITCH - CORPORATE RATING:

DEFAULT FREQUENCIES 5 YEARS HORIZON. 1990-2008

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-
0,00	0,00	0,14	0,00	0,31	0,55	1,03	1,89	2,96	4,06
BB+	BB	BB-	B+	B	B-	CCC			
7,26	10,48	7,27	8,02	10,48	9,32	36,92			

Source: Fitch IBCA (2009), pp. 12.

TABLE 9. STANDARD&POOR'S SOVEREIGN AND CORPORATE RATING.

CUMULATIVE DEFAULT FREQUENCIES TO THE 5^{TH} YEAR. 1984-2008.

SOVEREIGN 1975-2008, CORPORATE 1981-2008.

	Sovereign foreign currency	Sovereign local currency	Corporate
AAA	0,00	0,00	0,27
AA+	0,00	0,00	0,20
AA	0,00	0,00	0,26
AA-	0,00	0,00	0,49
A+	0,00	0,00	0,66
A	0,00	0,00	0,66
A-	0,00	0,00	0,87
BBB+	0,00	0,00	1,62
BBB	3,49	0,00	1,14
BBB-	6,35	12,01	4,09
BB+	1,47	1,82	5,28
BB	3,74	5,96	8,41
BB-	17,58	9,58	11,85
B+	12,49	0,00	17,44
B	14,46	1,72	22,44
B-	13,85	6,25	28,81
CCC/C	75,69	41,15	44,93

Source: Standard&Poor's (2009b), pp. 29.

TABLE 10. RATING, NUMBER OF ISSUERS AND PROBABILITY OF DEFAULT

Rating	Number	PD(%)
Aaa	150	0,03
Aa1	300	0,05
Aa2	300	0,07
Aa3	400	0,14
A1	500	0,20
A2	500	0,35
A3	500	0,50
Baa1	400	1,00
Baa2	400	1,40
Baa3	400	2,55

Source: own elaboration based on data from Moody's.

Table 11. CAPITAL REQUIREMENTS ACCORDING TO PD WITH LGD = 45%.

Rating	PD	b	m	R	G(PD)	G(0,999)	RWA	RPC
AAA	0.03%	0.317	1.573	0.238	-3.432	3.090	15.310	1.225
AA+	0.05%	0.286	1.490	0.237	-3.291	3.090	20.830	1.666
AA	0.07%	0.267	1.442	0.236	-3.195	3.090	25.474	2.038
AA-	0.14%	0.229	1.357	0.232	-2.989	3.090	38.151	3.052
A+	0.20%	0.211	1.320	0.229	-2.878	3.090	46.528	3.722
A	0.35%	0.183	1.267	0.221	-2.697	3.090	62.289	4.983
A-	0.50%	0.167	1.238	0.213	-2.576	3.090	73.788	5.903
BBB+	0.80%	0.147	1.203	0.200	-2.409	3.090	90.010	7.201
BBB	1.40%	0.124	1.167	0.180	-2.197	3.090	109.560	8.765
BBB-	2.55%	0.102	1.133	0.154	-1.951	3.090	130.188	10.415
BB+	4.40%	0.084	1.107	0.133	-1.706	3.090	152.385	12.191
BB	7.80%	0.067	1.083	0.122	-1.419	3.090	186.416	14.913
BB-	10.00%	0.060	1.074	0.121	-1.282	3.090	204.672	16.374
B+	15.00%	0.049	1.060	0.120	-1.036	3.090	234.825	18.786
B	20.00%	0.043	1.052	0.120	-0.842	3.090	252.525	20.202
B-	25.00%	0.038	1.045	0.120	-0.674	3.090	261.399	20.912
CCC	30.00%	0.034	1.041	0.120	-0.524	3.090	263.746	21.100

Source: own elaboration.

TABLE 12. CAPITAL REQUIREMENTS ACCORDING TO PD WITH LGD = 25%

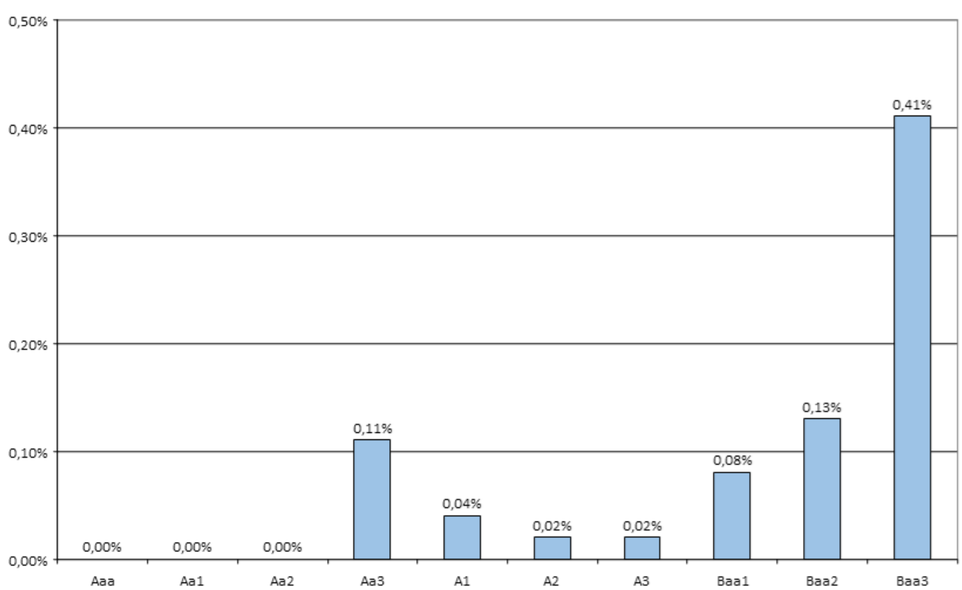
Rating	PD	b	m	R	G(PD)	G(0,999)	RWA	RPC
AAA	0.03%	0.317	1.573	0.238	-3.432	3.090	8.506	0.680
AA+	0.05%	0.286	1.490	0.237	-3.291	3.090	11.572	0.926
AA	0.07%	0.267	1.442	0.236	-3.195	3.090	14.152	1.132
AA-	0.14%	0.229	1.357	0.232	-2.989	3.090	21.195	1.696
A+	0.20%	0.211	1.320	0.229	-2.878	3.090	25.849	2.068
A	0.35%	0.183	1.267	0.221	-2.697	3.090	34.605	2.768
A-	0.50%	0.167	1.238	0.213	-2.576	3.090	40.994	3.279
BBB+	0.80%	0.147	1.203	0.200	-2.409	3.090	50.006	4.000
BBB	1.40%	0.124	1.167	0.180	-2.197	3.090	60.867	4.869
BBB-	2.55%	0.102	1.133	0.154	-1.951	3.090	72.327	5.786
BB+	4.40%	0.084	1.107	0.133	-1.706	3.090	84.659	6.773
BB	7.80%	0.067	1.083	0.122	-1.419	3.090	103.565	8.285
BB-	10.00%	0.060	1.074	0.121	-1.282	3.090	113.707	9.097
B+	15.00%	0.049	1.060	0.120	-1.036	3.090	130.459	10.437
B	20.00%	0.043	1.052	0.120	-0.842	3.090	140.292	11.223
B-	25.00%	0.038	1.045	0.120	-0.674	3.090	145.222	11.618
CCC	30.00%	0.034	1.041	0.120	-0.524	3.090	146.525	11.722

Source: own elaboration.

CHARTS

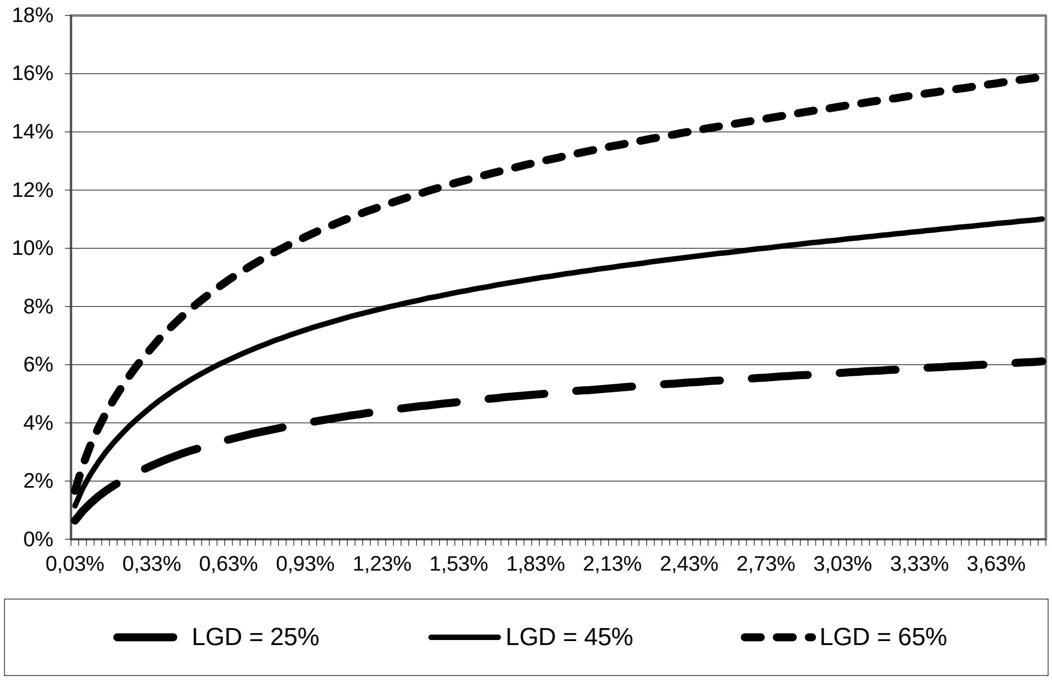
CHART 1. MOODY'S - CORPORATE RATING:

AVERAGE DEFAULT FREQUENCIES FOR INVESTMENT GRADE.



Source: Moody's Global Credit Policy (2009).

CHART 2. MINIMUM CAPITAL REQUIREMENTS AS A FUNCTION OF PD AND LGD.



Source: own elaboration.