ISSN 1518-3548

BANCO CENTRAL DO BRASIL

Working Paper Series 91

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December, 2004

ISSN 1518-3548
CGC 00.038.166/0001-05

Working Paper Series	Brasília	n. 91	Dec	2004	P. 1-46

Working Paper Series

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The Banco Central do Brasil Working Papers are all evaluated in double blind referee process.

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Credit Risk Measurement and the Regulation of Bank Capital and Provision Requirements in Brazil – A Corporate Analysis[*]

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Abstract

The new Basel II Capital Accord has demanded a lot of attention from regulatory and regulated entities due to its innovations in determining capital requirements, particularly in the area of credit risk. This paper simulates the application of Basel II IRB foundation approach for the computation of total capital requirements for the coverage of credit risk of major Brazilian banks corporate portfolios. The IRB necessary parameters of probabilities of default are estimated from a scoring model that uses explanatory variables derived from the raw data present in the Public Credit Register of the Central Bank of Brazil. IRB requirements are compared with current Brazilian regulatory requirements. By making use of the CreditRisk+ portfolio model this paper shows how it is possible to extend the previous comparison. The main result is that, for the situation analyzed, the IRB approach can be considered more conservative than the current Brazilian prescription.

Keywords: Basel II Accord; Capital requirements; Credit risk modeling; Public Credit Register; Bank regulation; Brazil
JEL Classification: G18; G21; C25

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[*] The authors would like to thank Tom Wilde from CSFB for his assistance in running Creditrisk+, and Luciana Graziela Araujo Cuoco and Plinio Cesar Romanini of the Off-Site Supervision Department for their much appreciated collaboration. The views expressed herein are those of the authors and do not necessarily reflect those of the Brazilian Central Bank or its members. Comments and suggestions are mostly welcome and should be sent to ricardo.schechtman@bcb.gov.br.
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1. Introduction

This study fits within the context of the discussions of the New Basel Capital Accord, the well-known Basel II, promoted by the Basel Committee on Banking Supervision. One of the main innovations of the accord compared to its previous version pertains to the regulation of total capital requirements for credit risk. The new accord aims to approximate the notions of regulatory capital and economic capital, or, in other words, to render regulatory capital more sensitive to the risk profile of bank credit portfolios.

Basel II proposals for the regulation of credit risk comprise three approaches with increasing levels of complexity. At this paper we focus on the intermediary approach, the IRB (Internal Rating Based) foundation approach (Basel 2001), as the simplest approach is not likely to produce major changes in current capital requirements in Brazil and the more advanced one is understood to be too sophisticated for the current stage of development of the Brazilian banking system. In the IRB foundation approach each bank is required to estimate its own set of PD (probability of default) parameters whereas the regulatory entity provides the other inputs. The goal of this paper is to simulate the actual application of this approach by making use of the data present in the Public Credit Register (PCR) of the Central Bank of Brazil. Particularly, PCR data is shown to be useful in PD estimation and therefore a valuable source of information in a country as Brazil, where rating agencies have a very modest scope of coverage.

The simulation of IRB requirements makes it possible a comparison with current Brazilian regulatory requirements, providing an idea of how Basel II IRB is likely to affect the system minimum obligations. However, a more meaningful comparison can be achieved by making use of a third element: a credit risk portfolio model. This issue is explored in the last part of this paper.

The paper is organized as follows. The next section contains a brief description of the current Public Credit Register of the Brazilian Central Bank. We comment on the main features of the data and the market access to them. Section 3 describes the current regulatory approach to provisioning and capital allocation in Brazil (Resolutions 2099 and 2682 issued by the Central Bank of Brazil).

Section 4 initiates the modeling part of the study by deriving potentially explanatory variables of default from the raw data present in the Public Credit Register. Based upon these variables a scoring model is fitted, supplying a probability of default (PD) estimate for each credit exposure identified by the pair borrower-financial institution.

The study then focuses on computing total capital requirements for credit risk for each major bank credit corporate portfolio present in the analysis. Firstly in section 5 this is done according to the IRB foundation approach. We calculate IRB requirements (capital plus provision) using the PD estimates and compare the IRB results with current Brazilian regulatory requirements and existing capital levels.

Section 6 discusses the problems faced by practitioners when trying to apply some influential credit risk portfolio models to the Brazilian context and justify our choice of the CreditRisk+ (CR+) model in the present study. Section 7 presents the results of running CR+ on each bank corporate credit portfolio under the “single systemic factor assumption”. While section 7 compares CR+ results with current regulatory requirements section 8 compares the former with IRB outputs and examines further the fitting between the two. Section 9 concludes the paper with a summary of the main results and some further thoughts.

2. The Brazilian Public Credit Register

Brazil’s Public Credit Register (PCR) was established in the middle of 1997 by the Central Bank with the objective of enhancing banking supervision activities. The PCR was initially conceived to monitor the financial institutions’ credit portfolios and also major borrowers within the financial system. The supervision department was put in charge of managing the database.

So far, the PCR has been able to provide key information on credit risk for supervision, macroeconomic policy makers and banks. It represents an important tool for credit risk management, and could help to reduce spreads in credit transactions.

In general, all financial institutions with credit portfolios are requested to provide information to the PCR[1]. Credit exposures reported embrace loans in general, e.g. revolving credits, auto loans, mortgages, leases, trade finance and guarantees.

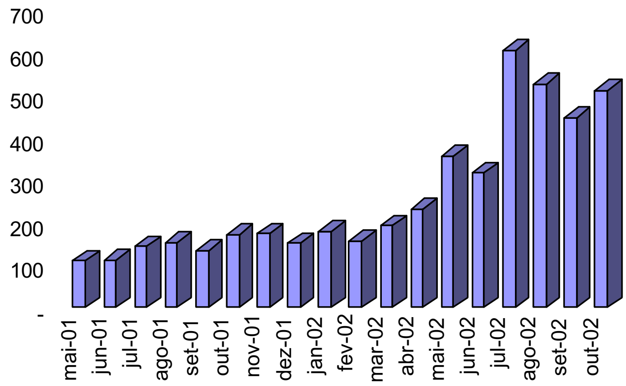
The information available at the PCR is provided by financial institutions on a consolidated basis (by borrower and risk classification). It comprises besides the credit exposure itself, the risk classification and the ranges of maturity[2] and past dues. There are three grades of maturity: up to 180 days, from 181 to 360 days and more than 360 days. As for past due loans, the credits are split into four ranges, according to the days in delay: from 15 to 60 days, from 61 to 180 days, from 181 to 360 days and more than 360 days.

The data sets are provided to the Central Bank on a monthly basis. In order to have access to the PCR information, a financial institution must have express authorization by the borrower, which can also access its own data. Even when this is the case financial institutions have access only to the aggregate debt of a borrower (consolidated throughout the financial system). The available information refers to maturity, past dues, write-offs and guarantees. There is also information on the number of creditors of a borrower within the financial system. The information on the ratings granted by financial institutions is not available.

Banks' consultations to the PCR's database on credit concession processes have been increasing overtime, as graph 1 shows.

[1] Multiple banks, commercial banks, the federal savings and loans banks, investment banks, development banks, real state credit companies, finance companies, leasing companies and credit unions/coops (started providing data in April 2001).
[2] The ranges of maturity comprise the period between the reported month and the final payment of the loan/loans.

Graph 1: Number of financial institutions' access to the system (in 1000)



Since its implementation, the PCR has undergone through several modifications. At the beginning, banks had to monthly report all credit exposures related to individuals or companies which exceeded R$ 50,000. Later on (November 1999) the threshold was lowered to R$ 20,000 and finally to R$ 5,000 in January 2001[3]. Lastly, since March 2000 banks have been requested to provide the risk classifications of their credit exposures, according to Resolution 2682.[4]

As of July 2002, the total numbers of registers in the PCR was more than 7 million: 72% related to individuals (standing for 27% of total credit exposures) and 28% related to companies (standing for 73% of total credit exposures).

3. Current Regulatory Approach for Provisioning and Capital Allocation

The current regulatory framework for credit risk in Brazil comprises the implementation of the 1988 Capital Accord through Resolution 2099 and the regulation for loan classification and provision, established through Resolution 2682. Resolution 2682 provides general guidance for building an asset classification system and has been key in enhancing credit risk management in Brazil.

[3] US$ 1760 (July 2002)
[4] See section about Resolution 2682.

3.1 Resolution 2099

In Brazil, the 1988 Capital Accord was introduced through the Resolution 2099, issued in August 1994. Later on the Resolution was amended and the current framework used for capital calculation is presented in a table in the appendix. The table provides also a comparison among the current regulation and the 1988 Accord. Although it displays risk weights for all classes of assets, at this paper we focus solely on capital requirements for bank loan portfolios.

The regulatory capital (RC) currently in place in Brazil is given by the following expression:

$$RC = 11\% \sum RWA + \text{Other capital requirements.}$$

where

$\sum RWA$ = sum of risk weighted assets with weights given by the table in the appendix. Loans have 100% risk weight and are evaluated net of provision.

Other capital requirements = capital for credit risk of swaps + capital for interest rate market risk + capital for foreign exchange rate market risk.

Another way to see the above requirement is through the Basel Index (I) that is computed by the Central Bank of Brazil as the ratio $I \equiv 11\% \times (\text{Capital}/RC)$.[5] In this case the requirement that capital should be larger than RC translates equivalently into the requirement that $I \geq 11\%$.

3.2 Resolution 2682

Resolution 2682 from 1999 establishes that financial institutions should classify their credit exposures into nine levels of risk, according to the following grading system: AA (prime companies), A, B, C (normal risk – low probability of default), D (level 1 risk), E, F, G (level 2 risk) and H (level 3 risk – high probability of default).

[5] The capital in the computation of the Basel Index is basically defined as equity + net income + reserves + preferred stocks + subordinated debt + hybrid instruments.

The rating process must be based on:

a) Analysis of the borrower: credit worthiness, indebtedness, capacity to generate cash to repay its debts, quality of earnings, quality of management and internal controls, punctuality, economic activity, commitments;

b) Analysis of the credit transaction: the kind of transaction, the collateral provided, the amount of the debt.

According to regulation, all exposures from a single borrower must be classified according to the higher risk transaction within a financial institution for provisioning, as well as PCR information purposes. In exceptional circumstances (e.g. liquid collaterals) it is allowed to consider more than one rating for a single borrower. Each rating is associated with a specific percentage of provision according to table 1.

Table 1: Structure of Resolution 2682

Classification	AA	A	B	C	D	E	F	G	H
Provision (%)	0	0.5	1	3	10	30	50	70	100
Past-due (days)	-	-	15-30	31-60	61-90	91-120	121-150	151-180	>180

As a general rule, ratings must be reviewed every twelve months. Ratings must also be reviewed every six months when the debt of the borrower or its group is higher than 5% of the actual existing capital. Finally, ratings must be monthly reviewed in case of non-performing transactions, where the grading rules specified in the previous table must be applied.[6]

All documentation related to the credit risk policy and rating process of a financial institution must be available for Central Bank analyses.

[6] After six months the bank must write off the transaction graded H.

4. Estimating Probabilities of Default through a Credit Scoring Model

In this section we estimate annual probabilities of default (PDs) for performing credit exposures provided by large financial institutions to corporate borrowers as of October 2001.[7] Each credit exposure is characterized by the pair borrower-financial institution so that the same borrower may have different estimated PDs in different financial institutions but only one in each single institution. We define corporate borrowers as the ones having at least R$1milion of loans in any financial institution in October 2001, provided they do not belong to the public sector.[8] The analysis is based on the database of the Brazilian PCR and the data used for the estimation comprehends the corporate borrower registers of the period from October 2000 to October 2002. There are 39,946 exposures in existence in October 2001, embracing 8,985 borrowers and 50 financial institutions.[9]

The database used in the model construction is divided in two parts. Registers relative to the period from October 2000 to October 2001 are used to build the explanatory variables of default. Continuous, discrete, dummy and categorical variables are built with this purpose from the PCR raw data. On the other hand, registers relative to the period from November 2001 to October 2002 serve to define the dependent variable characterizing default or non-default status. More specifically, a borrower was considered to be in default in a financial institution if its "mean" credit classification there, according to Resolution 2682, was equal or worse than "E", in any month from November 2001 to October 2002.[10,11] Exposures with classification equal or worse than "E" in October 2001 are directly considered in default and we do not estimate PDs in these cases.[12]

[7] We consider only financial institutions that detain a minimum of 200 credit corporate exposures.
[8] Due to the computational limitations of the database system of the current Public Credit Register this study is restricted only to the universe of corporate borrowers. This is however not too restrictive in terms of a PD model estimation if we assume that information concerning large borrowers is generally more accurate than the one relative to small borrowers.
[9] After excluding exposures with missing registers.
[10] When it was the case that the borrower presented more than one classification in a certain FI its "mean" credit classification in the FI was computed based on the weighted average of the minimum provisioning percentages of the different existing credit classifications.
[11] Exposures that don't last the whole period are recognized as defaulted or non-defaulted based solely on the months of their appearance.
[12] In fact approximately 90% of the exposures bellow or equal "E" in October 2001 maintain this classification in some month of the next year.

In table 2 we show a list of potentially explanatory variables of default that were considered for the estimation of the credit scoring model. Their construction was based on the suggestions by Barren & Saten (2000) and mainly on the hand-on experience of the supervisory departments of the Central Bank. A more detailed characterization of the variables is found on the appendix.

Table 2: Potentially explanatory variables of default

Variable	Expected sign
Classification in 10/2001	+
Worst classification	+
First classification	+
Average classification	+
Frequency of up to date payments	-
Frequency of up to date payments in the system	-
Logarithm of total debt	Undetermined
Logarithm of guarantees	-
Logarithm of guarantees in the system	-
Logarithm of the exposure	Undetermined
Logarithm of the exposure in the system	Undetermined
Frequency of rated credits	-
Frequency of rated credits in the system	-
Time since the first appearance	-
Time since the first appearance in the system	Undetermined
Frequency of total debt in default	+
Frequency of total debt between D and H	+
Frequency of total debt between B and D	Undetermined
Frequency of total debt between B and C	Undetermined
Dummy of delay in 10/2001	+
Dummy of delay in 10/2001 in the system	+
Dummy of any delay	+
Dummy of any delay in the system	+
Dummy of total debt increase	Undetermined
Dummy of total debt increase in the system	+
Dummy of write-offs increase	+
Dummy of write-offs increase in the system	+
Proportion of delay in 10/2001	+
Proportion of delay in 10/2001 in the system	+
Number of FIs	Undetermined
Dummy of single FI	Undetermined
Economic sector	+
Financial conglomerate	+

Two thirds of the exposures (26,631) are selected to constitute a sample for model construction (training sample) and the remaining one third (13,315) is left to comprise a sample for model testing (validation sample). This is done through a sequential sampling procedure controlled by the dependent variable characterizing default, the financial conglomerate provider of the credit and the total debt variable in order to constitute two similar samples in relation to these characteristics. Also preceding the model estimation the Pearson correlation matrix of all non-categorical variables is computed and checked for possible problems of multicolinearity.[13]

The credit scoring model used is a logistic regression and the estimation is conducted through a backward procedure based on the likelihood ratio test. Besides the variables initially built we have also tested for the inclusion of interactions and the discretisation of variables based on the use of a tree classification routine.[14] In most cases these attempts resulted in no additional significant explanatory power. [15] The backward procedure identified at the end 13 significant variables, which are the variables highlighted in the previous table.

Finally, an analysis of residuals was carried out and identified three observations that presented high influence.[16] After their removal the model was readjusted and displayed the coefficients detailed in the table 3.[17] The Hosmer and Lemeshow goodness-of-fit test presents for this final model a statistic value of 8,3701 (p-value = 0.3982), indicating therefore a good level of fitting.

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[13] Due to its high correlation with the variable proportion of total debt between B and D, the variable proportion of total debt between B and C is excluded in order to avoid possible problems of multicolinearity.
[14] The goal of this routine is to form, through the use of classification trees, groups that possess between them the maximum difference in the proportion of defaults.
[15] The only exception refers to the variable worst classification that was modified by the tree routine in order to be constituted by only four categories (AA to B as the basal class, C, D and E to H).
[16] See the D-Cook statistics graph in the appendix.
[17] With respect to the categorical variable conglomerate we display the coefficient only for one financial conglomerate.

Table 3: Model of default prediction

PARAMETER		ESTIMATE	STANDARD ERROR	WALD CHISQUARE	Pr > ChisSq
Intercept		-4.3625	0.5510	62.8208	<.0001
Classification in 10/2001	A	0.3236	0.0941	11.8178	0.0006
Classification in 10/2001	B	0.6311	0.0958	43.3947	<.0001
Classification in 10/2001	C	0.9200	0.1153	63.6227	<.0001
Classification in 10/2001	D	1.7815	0.1326	180.4711	<.0001
Worst classification	C	0.2434	0.093	6.8497	0.0089
Worst classification	D	0.4768	0.1106	18.585	<.0001
Worst classification	E-H	0.6950	0.1493	21.6555	<.0001
Frequency of total debt in default		0.9975	0.3322	9.0163	0.0027
Dummy of delay in 10/2001	1	0.9368	0.0864	117.6562	<.0001
Dummy of delay in 10/2001 in the system	1	0.5974	0.0709	71.0454	<.0001
Dummy of any delay	1	0.2312	0.0856	7.2889	0.0069
Dummy of any delay in the system	1	0.4502	0.0733	37.7064	<.0001
Proportion of delay in 10/2001		0.4500	0.2057	4.7874	0.0287
Proportion of delay in 10/2001 in the system		1.1413	0.1917	35.4289	<.0001
Dummy of total debt increase in the system	1	0.2674	0.065	16.9278	<.0001
Number of FIs		0.0336	0.00574	34.3727	<.0001
Logarithm of the exposure in the system		-0.0984	0.0148	44.4597	<.0001
Conglomerate	2628	1.6523	0.5954	7.7007	0.0055

All the coefficients shown in the previous table are significant with their signs and relative magnitude in conformity with the expected ones.[18] To illustrate this fact take for instance the case of the categorical variable classification in 10/2001 which represents the risk classification of the exposure according to Resolution 2682 as of October 2001 and whose basal level is defined to be "AA", the supposedly less risky classification. All the coefficients of this variable are positive, as expected, indicating that risk classifications other than "AA" translate into higher PDs. Also as we move from "A" to "D" the magnitude of the coefficient increases indicating this is a path of increasing PD, again as expected.

Two variables whose signs we had no prior expectation about appear in the final model: logarithm of the exposure in the system and number of FIs. Their signs indicate that the smaller the size of the borrower (measured by its loan portfolio in the system) and the greater the number of financial institutions in which it holds credits then the larger its probability of default is.

[18] At least for those variables whose effects we have a clear expectation about. See table 2.

It is also interesting to note that relevant characteristics of the exposures are not only those relative to the particular FI but also those relative to the whole financial system. The variables proportion of delay in 10/2001 and dummy of any delay have for example their analogous counterparts in the financial system also included in the final model, namely proportion of delay in 10/2001 in the system and dummy of any delay in the system (and showing larger coefficients). The variable dummy of delay in 10/2001 in the system is also present in the final model, now with a coefficient smaller than the one estimated for its counterpart variable dummy of delay in 10/2001.

Lastly it is useful to pay attention to the variables that do not appear in the final model. Two important variables absent in the final model are the logarithm of guarantees of the borrower and the economic sector of the borrower, so that their effects in PD estimation were found to be statistically insignificant.

5. Simulating Basel II IRB on Brazilian Data

In this section we estimate IRB total capital requirements for the corporate credit portfolios of large financial conglomerates of the Brazilian financial system.[19,20] The analysis still refers to portfolios existing in October 2001 and the term corporate has the same meaning of the previous section. We conduct the analysis at the level of the financial conglomerates holders of the large FIs of the last section. The 28 so chosen conglomerates are hereafter referred as banks. One should note that restricting the analysis only to the larger institutions is consistent with the Basel proposal. In fact only for large banks it’s fair to assume a high degree of diversification and therefore the “single risk factor” assumption embedded in the IRB methodology.[21,22]

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[19] Throughout the remainder of the text, unless clearly specified otherwise, capital means a protection only against unexpected losses. As IRB requirements cover both unexpected and expected losses we have used here the expression “total capital” to convey this latter meaning.

[20] In the latest version of the Accord the Basel committee has decided to move to an unexpected loss-only risk weighting construct. However banks will still be required to compare their actual provisions with expected losses and as a consequence any shortfall will be deducted from capital and any excess may be eligible as capital. Therefore the basic idea that “total capital” should cover both expected losses and unexpected losses remains the same.

[21] See Gordy (2002).

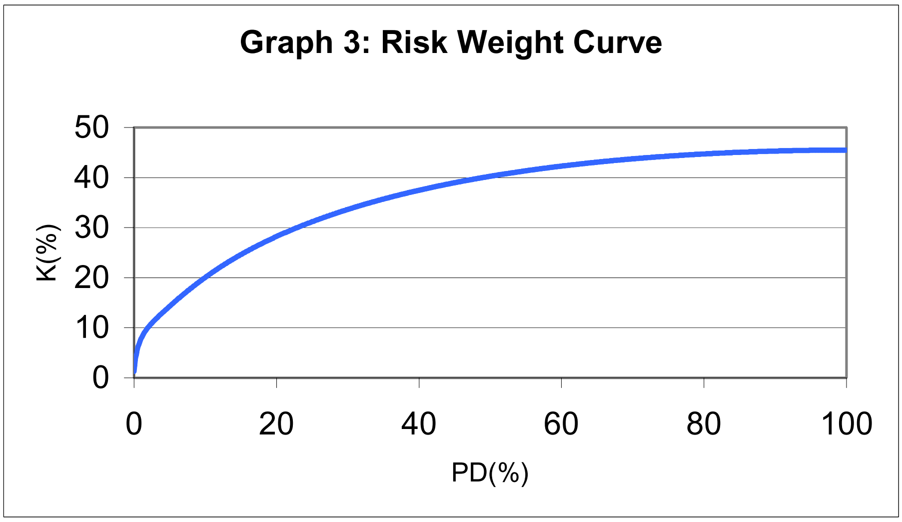
[22] The IRB assumption of an infinitely fine grained portfolio is also more appropriate in the context of large portfolios making the granularity adjustment a less grave problem in this case. See Basel (2001) and Gordy (2002).

To simulate IRB requirements we make use of the scoring model of the previous section. Each performing credit exposure (with classification strictly better than "E"), characterized by a pair borrower-financial institution, is then assigned a probability of default (PD) estimated by the scoring model.[23] Exposures with classification equal or worse than "E" in October 2001 are taken as defaulted and assigned a PD of 100%. The definition of default employed here is consistent with the IRB recommendation that a past due of more than 90 days should be an indication of default since Resolution 2682 indeed characterizes classification "E" in this way.

We follow here the IRB foundation approach as proposed by the third consultative paper on the new accord (Basel 2003), known as CP3. Exposure at Default (EAD) is defined as the sum of due and past-due credits. Guarantees are not included in EAD because their correct consideration would require a deeper analysis than the one that current PCR data can provide. A Loss Given Default (LGD) of 45% and a Maturity (M) of 2.5 years are taken from the CP3 standard prescriptions as there is no detailed information either on collateral or on maturity on the current system.[24]

From the PDs estimates and the values assumed for LGD and M we calculate for each exposure the factor of total capital requirement K according to the formulas provided in the CP3 document.[25] Then we multiply EAD by K and add the product over all exposures arriving at a total capital charge for each bank portfolio.[26] Graph 3 shows K as a function of PD, for a fixed LGD of 45% and a fixed M of 2.5 years, as defined by the IRB curve of the CP3 document.

[23] Since the actual IRB requirement is that the bank should be able to estimate a PD for each rating grade of its internal rating system we may say here that, for each Conglomerate, there are technically as many rating grades as the number of pairs borrower-financial institution.
[24] As the IRB total capital charge is linear on LGD the effect of different values of this parameter is easily estimated in the straightforward manner from the results stated here.
[25] See the appendix about the IRB formulae.
[26] Strictly following IRB, EAD*K should be first multiplied by 12.5 to arrive at a measure of "risk weighted asset" and the sum of the weighted assets should then be multiplied by 8%. As 12.5×8%=1 this doesn't make any difference on the final figures.

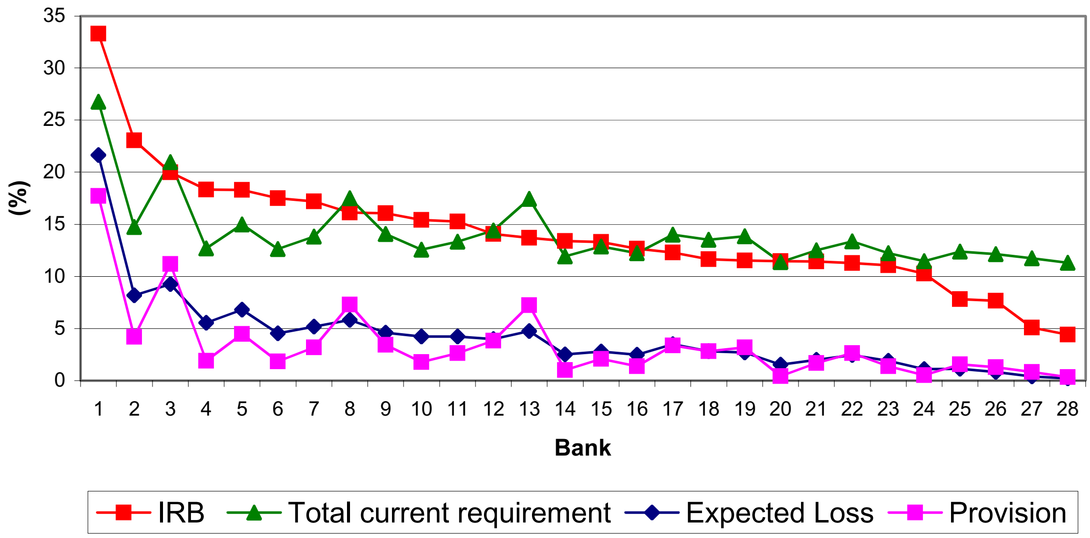


IRB calibration of CP3 was designed to cover both expected and unexpected losses. Therefore the Brazilian regulatory measure to which IRB simulated requirements should be compared with is the sum of capital and provision obligations.[27] IRB requirements and total Brazilian regulatory requirements are plotted in graph 4 for each bank (see the two top lines). To get a view on how the parts constituting total regulatory obligations behave separately in respect to the IRB demand we also plot in the graph the regulatory provision requirements and their theoretical counterparts, expected losses.[28] The vertical distance in the graph between total regulatory requirement and provision is the regulatory capital requirement while the distance between the IRB line and the expected losses line is interpreted here as the IRB implicit capital requirement.

[27] Recall that Brazilian current capital obligation is 11% of exposures net of provision and provision obeys Resolution 2682 which prescripts minimum provisioning percentages according to a classification criteria.

[28] Computed directly as $100 \times LGD \frac{\sum_i EAD_i PD_i}{\sum_i EAD_i}$

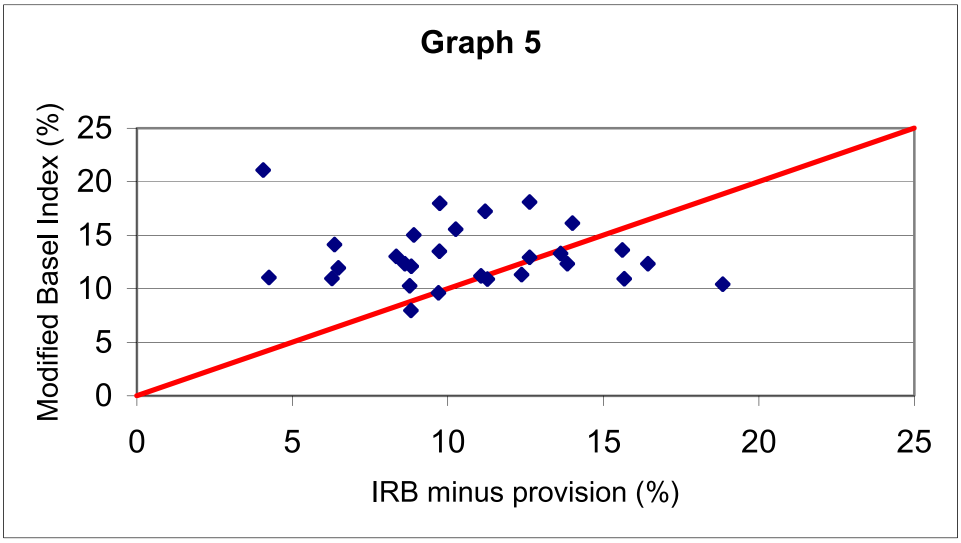
Graph 4: IRB and Current Requirement



The graph illustrates that for 15 out of the 28 banks analyzed the IRB methodology translates into lower total requirements than the current regulatory obligations. For the other group IRB is likely to increase total capital requirements. We also examine the relation between IRB and the current requirement aggregately for the system of the 28 banks. Weighting each bank by the size of its portfolio we find that IRB implies slightly smaller requirements than those currently in place in (-0.52%) and that provisions at the system levels are slightly smaller than the expected losses in (-0.35%). However, more can be said about the relation between IRB and the Brazilian regulatory requirement by making use of a credit risk portfolio model, as discussed in the final part of this paper that initiates with the next section about credit risk models.

An interesting point to note in graph 4 is that, whenever the IRB requirement is greater than the regulatory obligation, their difference is generally largely explained by the difference between expected loss and provision. On the other hand, when the IRB requirement is lower than the regulatory obligation, their difference is generally much larger than the difference between expected loss and provision, meaning that these lower-than-regulatory IRB values are mostly due to the IRB implicit capital requirements lower than regulatory capital.

Another point worth examining is whether Brazilian banks are already sufficiently capitalized to face the new IRB requirements. The context we have in mind is a situation where provision is kept regulated by Resolution 2682 but regulatory capital is redefined as the difference between IRB output and provision. We address the question of sufficient capitalization by examining the Basel Index computed for each financial conglomerate as described in the section about Resolution 2099. This index (with a slight correction) may be compared to the difference between the IRB requirement and the provision to indicate whether existing capital would be adequate in a post-IRB situation (modified Basel Index larger than IRB minus provision) or not (modified Basel Index smaller than IRB minus provision).[29]



In graph 5 each point represents a bank present in our analysis. As most points are located above or approximately along the 45-degree line, the graph suggests that the majority of the banks will not have problems to face the new IRB capital demands. However, caution should be placed in such analysis since Basel Index takes into account regulatory capital for other risks besides the corporate credit risk and therefore the above comparison should be regarded only as an approximation.[30]

[29] The correction is the multiplication of the original Index by 1 minus the mean provision to cope with the fact that current capital regulatory obligation is applied to amounts net of provision.

[30] The approximation is the following:

$$\frac{I \times (1 - provision)}{(IRB - provision)} \cong \frac{Capital}{Risk\ weighted\ assets\ under IRB + Other\ requirements}$$

The greater the percentage of regulatory credit capital for corporate credit exposures in the overall regulatory capital the better is the approximation.

6. Credit Risk Models in the Brazilian Context

In the past decade financial industry has sponsored several credit value-at-risk (VAR) methodologies. Their use in Brazil is, however, severely limited by the amount and type of data they require and the assumptions they make. We briefly comment below on some of the problems faced by practitioners when trying to apply these off-the-shelf models to the Brazilian context.[31]

KMV, one of the first methodologies to bring accuracy to the field of credit risk measurement, is based on the options pricing theory and the ideas of Merton (1974). It is a structural approach where default is endogenous and relates to the capital structure of the firm. The methodology uses inputs parameters from the equity market and for this reason its applicability in Brazil is constrained by the inadequate liquidity of most corporate stocks. For example, KMV's reliance on measures of stock volatility for calculating the probabilities of default represents a limit for equities that are very seldom traded. Therefore, while being a theoretically founded approach, its scope of applicability is possibly limited in Brazil only to the larger firms with trading equities.

Another important methodology in the world of credit risk measurement is CreditMetrics, proposed by JP Morgan. This is a mark-to-market methodology that makes strong use of rating transition probability matrixes to calculate losses arising from both rating downgrades and default events. As it essentially links a set of ratings to different values of spread, an estimation of the credit yield curve is needed. However, Brazil's secondary credit markets are very underdeveloped to provide such an estimate and the alternative of making an estimate based on the sovereign yield curve cannot be considered more than a hunch. Besides, Creditmetrics presumes the existence of a consistent provider of ratings with a reasonable history of rating attribution so that transition matrixes may be appropriately built. That is still not the case in Brazil.

McKinsey also proposes its methodology named CreditPortfolioView, a multi-period model where default probabilities are functions of relevant macroeconomic variables. Transition matrixes are also used but here they possibly change over time according to

[31] These problems are common to many emerging countries, which share a lot of similarities with Brazil. See Balzarotti et. al. (2002) for a more detailed discussion.

the macroeconomic enviroment. Therefore a reasonable amount of data is needed on the chosen explanatory variables so that an appropriate structuring of the macroeconomic effects on the credit portfolio is made possible. However, Brazil's various changes of macroeconomic regimes render the collection and use of this data an extremely hard task.

In this paper we make use of yet another influential model, CrediRisk+, launched in 1997 by Credit Suisse First Boston (CSFB). It is a model of actuarial origin and of default mode type.[32] Defaults follow exogenous and independent Poisson processes, conditionally on a set of systemic factors that are assumed to follow independent Gamma distributions. Besides, the functional form of the model allows an analytical solution so that Monte Carlo simulation is avoided.[33] Relative to others, the model's data requirements are far less demanding to an environment like the Brazilian, characterized by a constrained universe of quoted equity and a small universe of traded corporate debt.[34] We show in this paper how the model may be employed using data from the Public Credit Register of the Brazilian Central Bank and some standard assumptions.[35]

A good introductory description of these four models may be found in Crouhy et. al. (2000). It is also good to remark that, despite their different appearances, some of the models possess very similar underlying mathematical structures. Gordy (2000) shows this is precisely the case in a comparison between CreditRisk+ and a default mode version of CreditMetrics.

7. Description and Application of CreditRisk+ to Brazilian Data

In CreditRisk+ (CR+) framework correlations among default events are due to common sensitivity to the systemic factors and all remaining credit risk is idiosyncratic to

[32] In other words, only default risk is modeled, not the risk of credit quality migration.
[33] An analytical solution is also good because it allows an easy computation of risk contribution measures although this is not the purpose of this paper. See Kurth & Tasche (2002) for an example in the CR+ framework.
[34] At least in its simplified version with only one systemic factor.
[35] We will note however the application is not straightforward.

individual credit exposures.[36] Defining the interpretation of the systemic factors and estimating the sensitivity of each individual exposure to each factor is not an easy task and generally demands considerable data.

We employ here the usually called single factor assumption and interpret the effect of this single factor as representative of the "systemic risk" embedded in the Brazilian economy. This is the most conservative approach as there is no eventual benefit derived from diversification across factors and is consistent with IRB portfolio invariance property as proved in Gordy (2002).[37] A possible alternative with the data currently available from the PCR would be to define a small number of systemic factors as "orthogonal" sets of economic sectors following for instance a procedure of the kind of Boegelien et al. (2002) but this would enlarge very much the data requirements and is possibly left for future analysis.

Below we formally present the model in its simplified version with a single systemic factor. X denotes the systemic factor and D_A the indicator variable of default of exposure A.

$x \sim Gama(\alpha, \beta)$ with $\alpha\beta = E(x) = 1$ and $\beta = \sigma^2 \equiv Var(x)$

Further, for every A, $D_A \mid x \sim Poisson(x_A)$ with $x_A \equiv PD_A x$

And $D_A \mid x$ are independent

The purpose of the model is to compute the probability distribution of the portfolio loss variable $L \equiv \sum EAD_A LGD_A D_A$. To achieve this goal the exposures net of recovery $EAD_A \times LGD_A$ must first be discretised to small integer values, and the probabilities of default may also suffer some approximation to maintain expected losses unaltered. After that and under above assumptions it turns out that the probability generating function of L can be written as:[38]

[36] This framework is indeed common to many default mode credit risk models.

[37] That is the property that the total capital charge on a given exposure depends only on its own characteristics and not on the characteristics of the portfolio in which it is held.

[38] The generating probability function of a discrete random variable L is defined as $G_L(z) \equiv E(z^L)$.

$G_L(z) = \left(1 - \sigma^2 \sum_A \mu_A \left(z^{\nu_A} - 1\right)\right)^{-\alpha}$, where ν_A is an integer representing $EAD_A \times LGD_A$ and μ_A is possibly an approximation to PD_A.

From the properties of a probability generating function one knows that $\Pr ob(L = l) = \frac{1}{l!} \left. \frac{d^l G_L(z)}{dz^l} \right|_{z=0}$, where l is an integer that denotes a possible outcome of loss.

CSFP(1997) provides a recursive relation for the computation of the above derivative from which the probability function of the portfolio loss is calculated and an estimation of quantiles is thus made possible.[39]

Some comments are in order on the methodological choices we have made in the application of the model. First EAD, LGD, PD and the definition of default are the same as those used in the IRB simulation exercise and all considerations there also apply here. Next, the time horizon for which VAR is calculated is set to one year to maintain conformity with Basel proposal, although here we might have used other horizons that we believed more appropriate to the time required by a bank to reconstitute its capital. Yet, the 99.9% quantile is chosen for the computation of the VAR of the portfolio loss distributions, which is in accordance with the confidence level implicit in the CP3 risk weight curve.

CreditRisk+ is run on each bank corporate credit portfolio in analysis. A quantile of the set of exposures net of recovery is used as the unit size that serves to discretise the exposures. A quantile of 25% that was found to be computationally convenient for the largest portfolios is used fixed throughout all portfolios. Although lower quantiles were computationally feasible for the smaller portfolios, we have still used the fixed quantile in those cases in order to give an uniform treatment to all banks.[40]

[39] The recursive relation is in fact due to Panjer (1981).

[40] An adoption of lower values in those cases would mean artificially privileging the smaller banks since the discretization employed here rounds up the exposures net of recovery and therefore typically increases the loss distribution high quantiles.

From the previous presentation of the model one notices that D_A, the indicator variable of default, theoretically a Bernoulli variable, is approximated by a Poisson distribution. This implicit assumption of the model, usually known as the Poisson approximation, is only reasonable when PDs are sufficiently small.[41] However, not all PDs generated by the scoring model satisfy this condition. We cope with this problem by defining a cut-off PD value so that exposures with PDs above it are supposed to generate "deterministic" losses equal to their expected losses and consequently do not enter the CR+ recursive algorithm. These deterministic losses are added to the CR+ quantile of the "non-deterministic" part of the portfolio to arrive at the final quantile figure of the loss distribution.

Previous approach is motivated by the following reasoning. If we believe that default rates that are high on average are likely not to be affected by the economy we may consider them as independent between them and from the others. Then, provided there are many exposures in this situation, we may say, from the law of large numbers, that the total loss resulting from them would not differ much from the their total expected loss. This then leads to our approach in which losses from high PD exposures are modeled as deterministic.[42]

A cut-off PD value of 15% is used fixed across portfolios. Approximately 9% of non-defaulted exposures have PD higher than this value. Although the choice of the above cut-off value has a high degree of subjectivity, we believe our approach to treat high PD exposures as deterministic is preferable than using standard CR+ model without modifications in the sense that it is probably closer to reality.[43]

There is still an important input to the model that deserves comments. Parameter sigma (σ) in the previous presentation is the usually called default rate volatility. Tail probabilities for portfolio losses are quite sensitive to the choice of its value.[44] However, efficiently estimating annual volatility based on just a few years of data present in the PCR is nearly an impossible task. Wilde (2000) suggests the default rate volatility of

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[41] So that terms of degree 2 and higher in the default probabilities can be ignored.

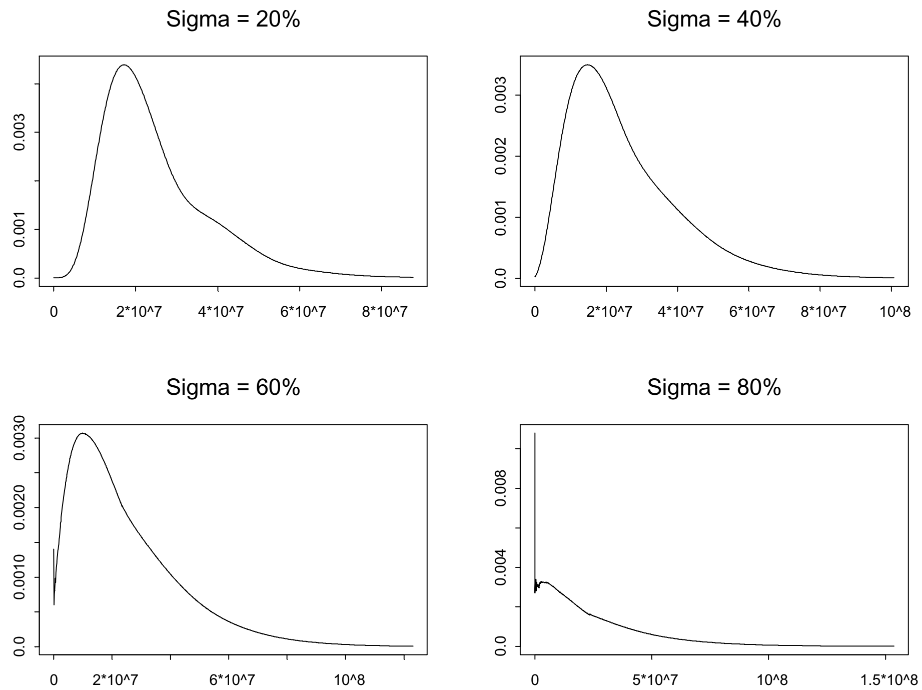
[42] We thank Tom Wilde for suggesting the interpretation of the deterministic approach employed here.

[43] However, further exploration of this issue is left for future analysis.

[44] See Gordy (2001)

100% as part of a robust implementation of the model. At the same time, international estimates of this parameter typically apply to rated firms and therefore the suitableness of these estimates for a country like Brazil is controversial.[45] Therefore here the model is run for values of the default rate volatility varying from 20% to 130% in order to provide an idea of the sensitivity of the results.[46] In graph 6 we illustrate the effect of different values of the parameter on the form of the portfolio loss distribution of a particular bank. We note that tail probabilities increase substantially as we increase sigma.

Graph 6: Probability Function Estimates

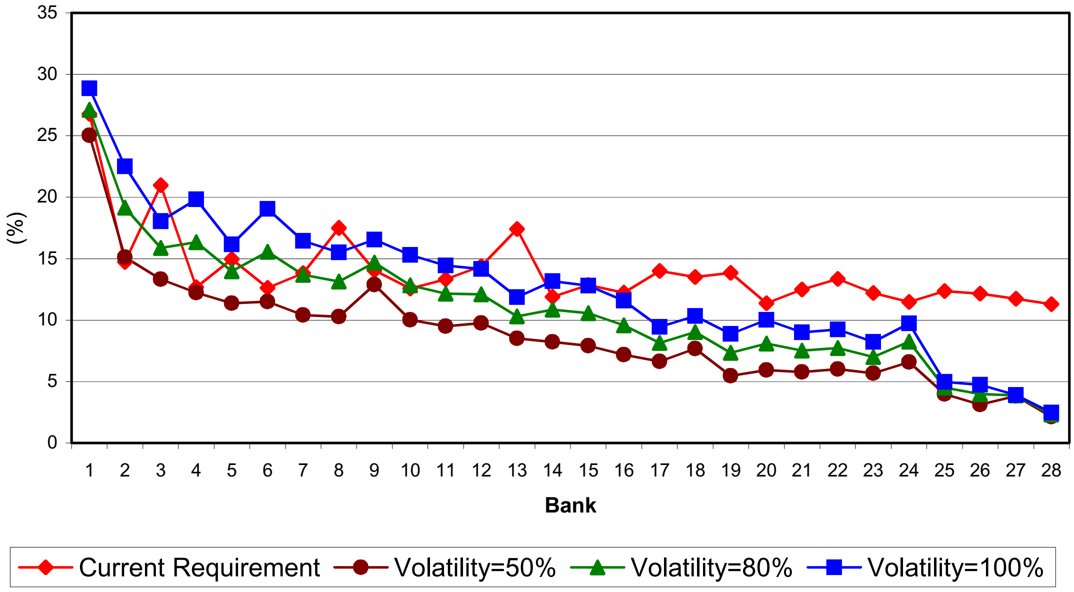


CreditRisk+ and total regulatory requirements (capital plus provision) are depicted in graph 7 for each bank corporate portfolio in analysis. The graph emphasizes once again that increases in the default rate volatility parameter lead to higher CR+ requirements. We show results for volatilities equal to 50%, 80% and 100%. A default rate volatility of 50% is the highest value of the parameter from those tested where current regulatory requirements still exceed or are very close to CR+ requirements for all banks. Increasing volatility to 60% and 70% starts making regulatory requirements look

[45] See Balzarotti et. al. (2003) for a more detailed discussion of the possibilities of estimating default rate volatility in the case of Argentina.

deficient for some banks. With default rate volatility set to 80% we find 6 banks having CR+ estimated requirements violating the upper regulatory limit. With default rate volatility equal to 100% regulatory requirements become still more clearly inadequate.

Graph 7: CreditRisk+ and Current Requirement

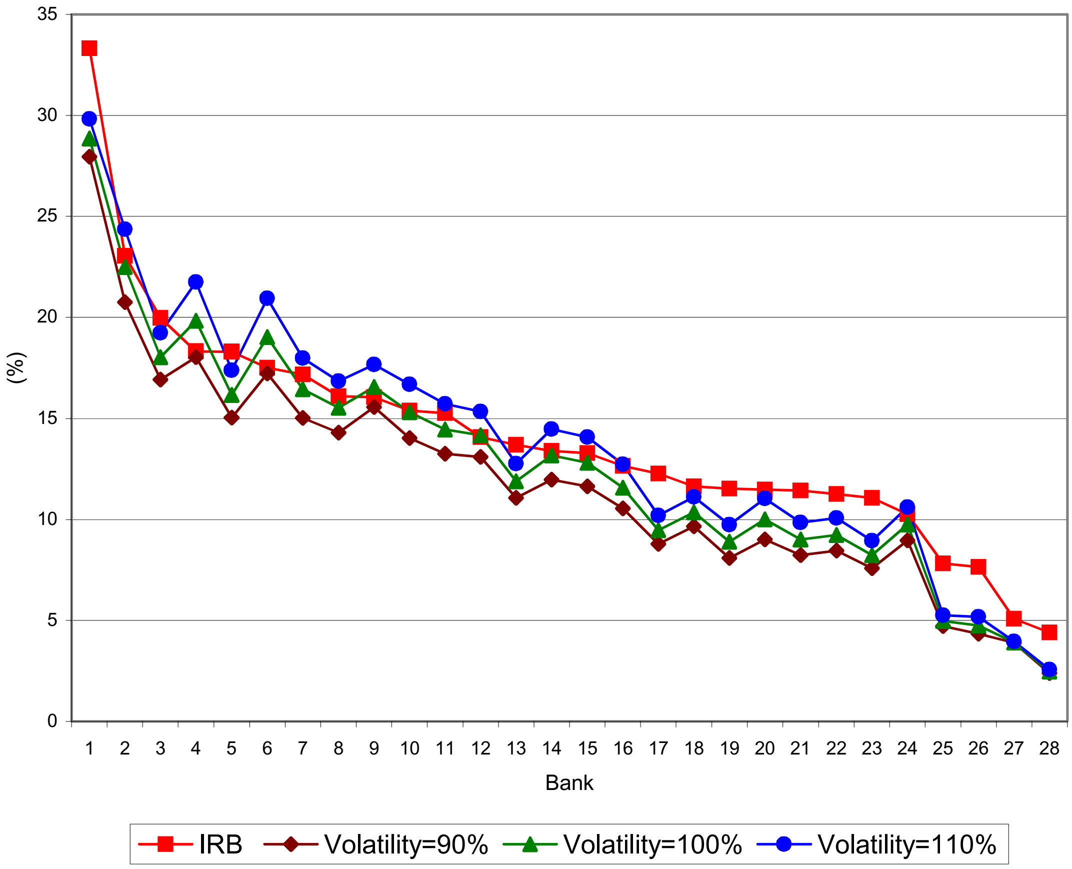


8. Comparing IRB and CR+ Requirements

Now we turn to a comparison between IRB and CR+ requirements. First, interpreting CR+ outputs as proxies to economic requirements we follow an analysis similar to the previous one between IRB and current regulatory requirements. Here we find that a default rate volatility of 90% is the highest value of the parameter from those tested so that CR+ requirements are still below or very close to their IRB counterparts for all banks. With volatility set to 100% we find 4 banks having CR+ quantiles superior to their IRB obligations. With volatility equal to 110% IRB requirements are still more clearly yet deficient from a regulatory perspective. This analysis is illustrated in graph 8.

[46] We have run the model only for volatilities multiple of 10%.

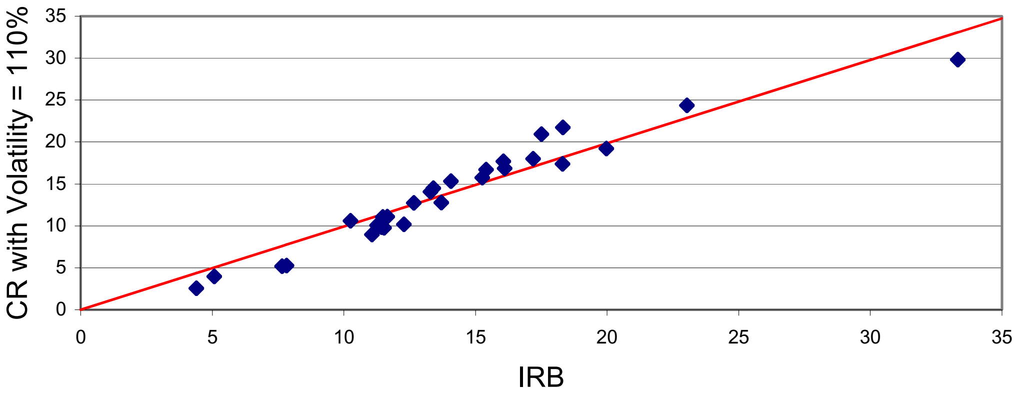
Graph 8: IRB and CreditRisk+



Another kind of analysis is possible when both IRB and CR+ outputs are interpreted as regulatory requirements. A primary concern here is the fitting of the CR+ requirements to the IRB outputs for the corporate Brazilian data of October 2001. Following a suggestion developed by Balzarotti et. al. (2003) we address this issue by running linear regressions across the 28 banks, with constant set to zero, of the CR+ quantiles against the IRB requirements. A different regression is estimated for each value of the volatility parameter. For all values of the volatility we find uncentered R-squared generally extremely high - around 0.98. However, a volatility of 110% is clearly the one that produces the best adjustment in the sense of having the pairs (IRB,CR+) closer to the 45-degree line. The estimated coefficient in this case is 0.992 and the Wald statistic for null hypothesis that the coefficient is equal to the unity is 0.1166 with p-value of 0.733. For all other values tested for the volatility default rate the above null hypothesis is rejected at the 1% confidence level.

The above analysis is illustrated in graph 9 where each point represents a bank. CR+ outputs are graphed against their IRB counterparts for the selected volatility value of 110% and the estimated regression line is shown too.

Graph 9



Other choices for the default rate volatility translate into other values for the estimated coefficient of the regression according to table 4. Based on that table one can propose a recalibration of the IRB risk weight curve through its multiplication by a factor equal to estimated regression coefficient correspondent to the default volatility he has in mind. For instance the inclusion of a multiplicative factor of 0.92 in the IRB formulae is consistent with a perception of a volatility of 100%.

Table 4

Default Rate Volatility (%)	Estimated Regression Coefficient
90	0.86
100	0.92
110	0.99
120	1.07

Nevertheless it should be pointed out, as stated in Balzarotti et. al. (2003), that given the non-linearities involved in credit risk modeling the previous linear regression approach is not theoretically founded. Our choice of a linear adjustment should be mainly justified as addressing the goal of simplicity.

9. Conclusion

At this paper we have illustrated, based on PD estimates, on information about EAD and on some other assumptions, how PCR information can lead to estimations of bank capital and provision requirements. While simulating IRB requirements under the foundation approach has been found to be a more direct task due to its simple and closed package nature, computing CR+ requirements has demanded some subjective choices and reasoning to cope with its recursive nature and its distributional assumptions. In those two both approaches PD estimates played the role of important input parameters and PCR showed its usefulness once again by providing the raw data that was used to build the explanatory variables of default.

For the time period analyzed we have shown that the IRB requirements completely support the performance of corporate credit portfolios for a annual default rate volatility up to 90% while current regulatory requirements accomplish the same achievement only in the case of default volatilities up to 50%. In this way our data suggest that, for the time period analyzed and for the corporate portfolios, the IRB approach can be thought to be more conservative than Brazilian regulatory requirements. That does not mean, however, that the IRB requirements are always higher than their current regulatory counterparts. In fact this paper shows that this is the case for approximately only half of the banks analyzed, the opposite being true for the other group. This paper also shows that the actual existing capital of each bank at the period of analysis are sufficient to cover the new IRB demands for the majority of the banks analyzed. Finally, this paper presents a methodology of recalibration of the IRB risk weight curve based on the CR+ model.

At the same time some caution is needed when interpreting the results of this paper. First, the focus of this paper is exclusively on credit risk of the bank corporate portfolios and, therefore, the total capital requirements computed throughout the text are just the parcels needed to cover this risk. We do not deal with the requirements relative to the credit risk of the other segments of the credit portfolios neither with the relation between credit risk and market risk. Second, the time period used for the analysis (October 2000 to October 2002) comprehends a period where Brazilian currency has experienced a large devaluation due to a number of external and internal factors. The requirement figures shown in this study reflect the environment of that time and, therefore, should not be directly transposed into today's much different macroeconomic conditions.

Finally, it is important to remark that, as the Brazilian Central Bank moves to a new Public Credit Register framework, with a larger scope of information gathering and a more accessible technology infrastructure, a richer set of studies concerning credit risk measurement is made possible. Not only better estimates of PD, EAD, LGD and M become feasible but also the collection and management of the large sets of data is rendered a far less laborious task. For instance, with the new PCR fully in activity, expanding this paper to entail also the bank retail credit portfolios should present no significant data management difficulties.

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Appendix

I. Risk Weights in the Current Brazilian Regulation and the 1988 Accord

	Basel 1988 Accord	Current Brazilian Regulation
0%	(a) Cash (b) Claims on central governments and central banks denominated in national currency and funded in that currency (c) Other claims on OECD central governments and central banks (d) Claims collateralized by cash of OECD central-government securities or guaranteed by OECD central governments	(a) Cash (b) Claims on central government and central bank denominated and funded in national currency (c) Claims collateralised by cash of central-government securities or guaranteed by central government
20%	(a) Claims on multilateral development banks (IBRD, IADB, AsDB, AfDB, EIB) and claims guaranteed by, or collateralised by securities issued by such banks (b) Claims on banks incorporated in the OECD and loans guaranteed by OECD incorporated banks (c) Claims on banks incorporated in countries outside the OECD with a residual maturity of up to one year and loans with a residual maturity of up to one year guaranteed by banks incorporated in countries outside the OECD (d) Claims on non-domestic OECD public-sector entities, excluding central government, and loans guaranteed by such entities (e) Cash items in process of collection	(a) Investments in gold (b) Deposits and investments abroad in foreign currency (c) Cash items in process of collection
50%	(a) Loans fully secured by mortgage on residential property that is or will be occupied by the borrower or that is rented	(a) Claims on banks (b) Loans fully secured by mortgage on residential property (c) Interbank foreign exchange (d) Claims on states and municipalities for their government securities

	Basel 1988 Accord	Current Brazilian Regulation
100%	(a) Claims on the private sector (b) Claims on banks incorporated outside the OECD with a residual maturity of over one year (c) Claims on central governments outside the OECD (unless denominated in national currency - and funded in that currency) (d) Claims on commercial companies owned by the public sector (e) Premises, plant and equipment and other fixed assets (f) Real estate and other investments (including non-consolidated investment participations in other companies) (g) Capital instruments issued by other banks (unless deducted from capital) (h) all other assets banks (unless deducted from capital)	(a) Claims on the private sector (b) Loans (c) Premises, plant and equipment and other fixed assets (d) Real estate and other investments (including non-consolidated investment participations in other companies) (e) all other assets
300%		(a) Tax credit

II. Description of the potentially explanatory variables for default

- **Classification in 10/2001.** Ordinal categorical variable that represents the risk classification attributed by the FI to each borrower according to Resolution 2682 of the Central Bank of Brazil.[47] This variable is decomposed in 4 dummies, each one representing the classifications “A”, “B”, “C” or “D” and we take “AA” as the basal grade. Classifications equal or worse than “E” do not show up in this framework since exposures within this classification range were excluded from the data used in the estimation for being considered already defaulted.

- **Worst classification.** Worst risk classification obtained by the borrower in the FI within the period from October 2000 to October 2001. Similarly to the previous variable this one is decomposed in 3 dummies, representing the risk classifications “C”, ”D” and the classification range “E” to “H”. [48] We take the interval “AA” to “B” as the basal grade.

- **First classification.** First risk classification obtained by the borrower in the FI within the period from October 2000 to October 2001. This variable is decomposed in 8 dummies, each one representing a classification from “A” to “H” and we take “AA” as the basal grade.

- **Average classification.** Average risk classification of the borrower in the FI within the period from October 2000 to October 2001. This timely average classification is computed in the same way as the within-month average classification and is decomposed similarly to the variable first classification.

- **Frequency of up to date payments.** Number of months in which the borrower presents neither past due credits nor write-offs in the FI divided by the number of months the borrower has credits in the FI.[49,50]

- **Frequency of up to date payments in the system.** Number of months in which the borrower presents neither past due credits nor write-offs in the system divided by the number of months the borrower has credits in some FI.[51]

- **Logarithm of total debt.** Logarithm of the total debt of the borrower in the system in October 2001.

[47] For the construction of the variables relative to risk classification it is assumed that each borrower presents only one risk classification within each FI. When that is not the case we assign the borrower a “mean” risk classification as described in a previous footnote.
[48] That categorization has been suggested by the tree classification routine.
[49] We use the expression “the borrower has credits in the FI” to mean the borrower has strictly positive total debt in the FI.
[50] It is important to have in mind that the variables that are built based on data along time comprise information only relative to the period from October 2000 to October 2001. In the case of the variable frequency of up to date payments for instance the months analyzed are constrained to this period.
[51] All the variables are computed based on the restricted database of this study, namely, the one composed by credit exposures provided by financial institutions with at least 200 exposures of borrowers who have at least R$1million in some institution. Consequently the term system should technically convey this precise meaning.

- **Logarithm of guarantees.** Logarithm of the guarantees of the borrower in the FI in October 2001.

- **Logarithm of guarantees in the system.** Logarithm of the guarantees of the borrower in the system in October 2001.

- **Logarithm of the exposure.** Logarithm of the sum of due and past due credits of the borrower in the FI in October 2001.

- **Logarithm of the exposure in the system.** Logarithm of the sum of due and past due credits of the borrower in the system in October 2001.

- **Frequency of rated credits.** Number of months in which the borrower possesses due credits, past due credits or guarantees in the FI divided by the number of months the borrower has credits in the FI. A low frequency indicates a high proportion of months in which the borrower presents just write-offs in the institution, therefore a negative sign is expected.

- **Frequency of rated credits in the system.** Number of months in which the borrower possesses due credits, past due credits or guarantees in the FI divided by the number of months the borrower has credits in some FI. Negative sign again expected.

- **Time since the first appearance.** Number of months since the first month the borrower has credits in the FI up to October 2001. This variable may be interpreted as a proxy for the time of the relationship between the borrower and the institution and therefore a negative sign is expected.

- **Time since the first appearance in the system.** Number of months since the first month the borrower has credits in some FI up to October 2001. Now the previous interpretation doesn't apply and the sign of the coefficient is undetermined.

- **Frequency of total debt in default.** Sum of the total debts relative to the months in which the borrower presents classification between E and H in the FI divided by the sum of total debts of all months the borrower has credits in the FI.

- **Frequency of total debt between D and H.** Similar to the previous variable with the exception that here we consider the classification range between D and H.

- **Frequency of total debt between B and D.** Similar to the previous variable with the exception that here we consider the classification range between B and D.

- **Frequency of total debt between B and C.** Similar to the previous variable with the exception that here we consider the classification range between B and C.

- **Dummy of delay in 10/2001.** The variable assumes 1 if the borrower possesses past due credits or write-offs in the FI in October 2001 and assumes 0 otherwise.

- **Dummy of delay in 10/2001 in the system.** The variable assumes 1 if the borrower possesses past due credits or write-offs in any FI in October 2001 and assumes 0 otherwise.

- **Dummy of any delay.** The variable assumes 1 if the borrower possesses an exposure (past due credits + write-offs) higher than 10% of its total debt in the FI in any month and assumes 0 otherwise.

- **Dummy of any delay in the system.** The variable assumes 1 if the borrower possesses an exposure in the system (past due credits + write-offs) higher than 10% of its system total debt in any month and assumes 0 otherwise.

- **Dummy of total debt increase.** The variable assumes 1 if the increase in the borrower total debt in the FI within the period from October 2000 to October 2001 is superior to 100% and assumes 0 otherwise.

- **Dummy of total debt increase in the system.** The variable assumes 1 if the increase in the borrower total debt in the system within the period from October 2000 to October 2001 is superior to 100% and assumes 0 otherwise.

- **Dummy of write-offs increase.** The variable assumes 1 if the borrower presents write-offs in the FI in October 2001 larger than in the first month the borrower has credits in the FI and assumes 0 otherwise.

- **Dummy of write-offs increase in the system.** The variable assumes 1 if the borrower presents write-offs in the system in October 2001 larger than in the first month the borrower has credits in some FI and assumes 0 otherwise.

- **Proportion of delay in 10/2001.** Sum of past due credits and write-offs of the borrower in the FI divided by the borrower's total debt in the FI, in October 2001.

- **Proportion of delay in 10/2001 in the system.** Sum of past due credits and write-offs of the borrower in the system divided by the borrower's total debt in the system, in October 2001.

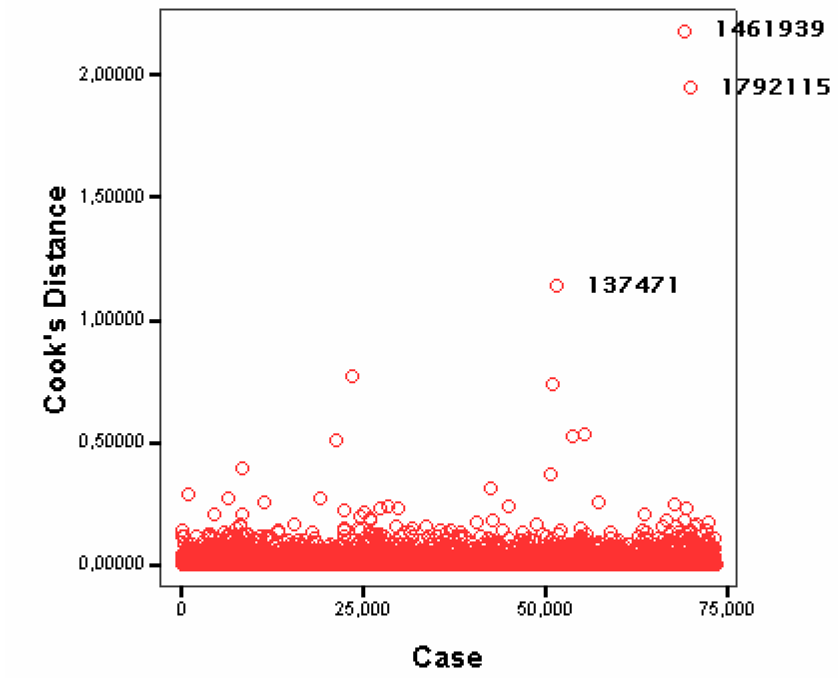
- **Number of FIs.** Number of financial institutions in which the borrower has credits in October 2001.

- **Dummy of single FI.** The variable assumes 1 if the borrower has credits in only one FI in October 2001 and assumes 0 otherwise.

- **Economic sector.** Categorical variable representing the economic sector in which the borrower belongs. It is decomposed in 22 dummies, one for each economic sector. The basal group is taken to be a group with one of the lowest proportions of defaults and therefore a positive sign is expected.

- **Financial conglomerate.** Categorical variable representing the financial conglomerate in which the FI holder of the exposure belongs. It is decomposed in several dummies, one for each conglomerate. The basal conglomerate is taken to a conglomerate with one of the lowest proportions of defaults and therefore a positive sign is expected.

III. Graph of D-Cook statistics of the residuals



IV. IRB formulae as in the CP3 Document

Correlation (R) = $0.12 \times \frac{(1 - \exp(-50 \times PD))}{(1 - \exp(-50))} + 0.24 \times \left[1 - \frac{(1 - \exp(-50 \times PD))}{(1 - \exp(-50))}\right]$

Maturity adjustment (b) = $(0.08451 - 0.05898 \times \log(PD))^2$

Capital requirement (K) =

$$LGD \times N\left[\frac{N^{-1}(PD)}{\sqrt{(1-R)}} + \sqrt{\left(\frac{R}{1-R}\right)} \times N^{-1}(0.999)\right] \times \frac{(1 + (M - 2.5) \times b(PD))}{(1 - 1.5 \times b(PD))}$$

Risk-weighted asset (RW) = K × 12.5 × EAD

The parameters above are computed for each credit exposure separately. N(.) denotes the cumulative distribution function of the standard normal distribution and N^{-1} denotes its inverse. Based upon the previous calculation a final total capital charge for the credit portfolio is achieved as:

Capital Charge = $8\% \times \sum_A RW_A$ where the sum is over all credit exposures.

Under the foundation approach of the IRB methodology LGD is fixed on 45% and M on 2.5 years so that there is only need to input the parameters PD_A and EAD_A for each credit exposure A of the credit portfolio.

For a full description of the version of the IRB methodology used in this study see Basel (2003).

Banco Central do Brasil

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