Basel and Procyclicality: A comparison of the Standardised and IRB Approaches to an Improved Credit Risk Method

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1. Introduction.

Our procedure here is to try to reconstruct a typical bank portfolio for a country and then, holding the presumed loan book unchanged over time, (i.e. replacing failed loans with loans of a similar quality), to examine how the loan ratings would have shifted, and hence how the capital adequacy requirements (CAR's) for the banks would have varied over time; for other similar exercises see Kashyap and Stein (2003 and 2004) and Gordy and Howells (2004). To do this we use Moody's data on U.S. corporate bonds, included on Moody's Investors Service, Credit Risk Calculator. We can only do this exercise for those countries for which Moody's data on credit ratings has a long enough time series. Unfortunately this rules out most large European countries since adequate Moody's data only go back to 1988 for the U.K., 2001 for Germany; 2002 for France; 2003 for Italy; 2002 for Spain. In practice we also used data provided by the Mexican Financial Regulatory Agency and the Norwegian Central Bank on Corporate Loans for these latter two countries. The Mexican data incorporates statistics between 1995 and 2000 and the Norwegian data incorporates statistics between 1988 and 2001.

For an earlier exercise along these same lines, and using the same Mexican data set, see Segoviano and Lowe, (2002). Amongst the problems are how to reconstruct a `typical' bank portfolio; whether, and how, to deal with the problem of failing loans dropping out of the portfolio; and what account to take of the fact that Basel II is a regime change that may make banks alter their `typical' behaviour. Very briefly, we reconstructed a typical bank portfolio as follows. We assumed that each portfolio consisted of 1000 loans, each one with equal exposure. From each country's data sources, we obtained the *through time* proportion of assets (bonds for the U.S. or corporate loans for Mexico and Norway) that were classified under each of the reported ratings for a given country. With this information we constructed the *benchmark portfolio* that we used to compute capital requirements at each point in time.

By assuming that the initial bank loan book remains unchanged throughout, this is equivalent to assuming that failed loans are replaced by loans of similar initial quality. This is what Kashyap and Stein (2004) did, and seems natural. Gordy and Howells (2004) argue, however, that banks will aim for a higher quality portfolio during recessions, and thus will replace failing loans with credits of higher, than initial, quality. At the macro level it is hard, in most countries, to see where the supply of such higher quality loans would come from during recessions; in discussion of this point at a BIS Conference in May 2004, Michael Gordy noted that in the USA high quality companies tended to shift their borrowing from capital markets, e.g. the commercial paper market, to banks during recessions. In any case, since risk spreads on lower quality loans widen during recessions, any extra benefit to the bank would be slight. So we feel relatively comfortable about our own assumption.

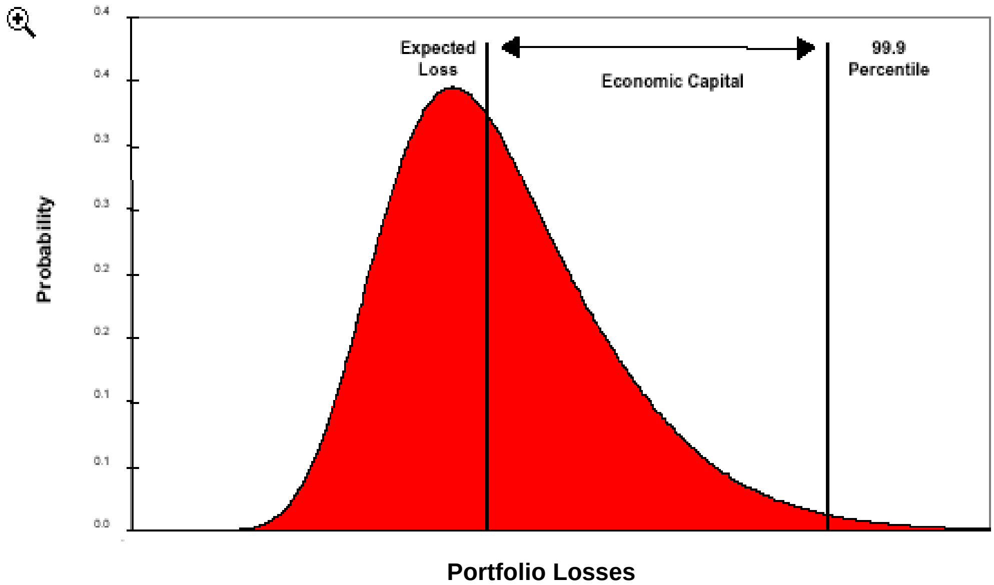
The results of this exercise for the three countries examined are stark. We compared the implied capital requirements for our `typical' bank under three regulatory regimes; first the standardised approach in Basel II, (which is close to that applied in Basel I); second, the Foundations IRB approach, (i.e. assuming a constant Loss Given Default, since we have no good time series in any country for average LGD); and third, an Improved Credit Risk Method (ICRM). This latter uses a Merton approach to model credit quality changes and an indirect approach to model correlations amongst the individual credits in the overall portfolio. The construction of an ICRM is, however, quite complex. The main addition in this note, beyond our associated work, available at Goodhart, Hofmann and Segoviano (2004), is that we spell out in more detail here how we do the exercise of estimating the required capital requirements under an Improved Credit Risk Method (ICRM).

The outline of the paper is as follows. In section 2, we elaborate on the need to measure portfolio effects for proper credit risk quantification. In section 3, we develop the ICRM. In section 4, we present the empirical implementation and results. This section also describes the data and assumptions made to perform the exercise. Finally, our conclusions are summarised in section 5.

2. Why a portfolio Approach?

Since the quality of the credit portfolio of a bank can change at any time in the future, there is a need to make frequent calculations of the expected losses that a bank could suffer under different risk situations. This analysis of uncertainty is the essence of risk management. Therefore, measuring the uncertainty or variability of loss and the related likelihood of the possible levels of unexpected losses in a bank's portfolio is fundamental to the effective management of credit risk. Sufficient earnings should be generated through adequate pricing and provisioning to absorb any expected loss. However, economic capital should be available to cover unexpected credit default losses, because the actual level of credit losses suffered in anyone period could be significantly higher than the expected level. The estimation of the profit and loss distribution of credit portfolios, from which the unexpected losses can be identified (e.g. 99.9 Percentile loss level), represents the issue to be addressed in this document.

Figure 1: Credit Portfolio Profit and Loss Distribution (P&L).



The adoption of the portfolio approach to risk analysis (Markowitz (1959)) has been amply documented and adopted in numerous finance applications[1]. Under this theory, investors seek an optimal risk-return relationship when formulating their investment portfolio.

[1] See Cochrane (2001) for numerous examples on asset pricing.

The model presented in this paper provides a methodology for assessing portfolio risk due to changes in loan value caused by changes in obligor (ie. borrower's) credit quality. Changes in value are caused not only by possible defaults, but also by upgrades and downgrades in credit quality; the correlation of credit quality variations across obligors in the portfolio is also considered. This allows us to calculate the benefits of diversification in the portfolio. Credit risk modellers have already developed risk management techniques that seek to take account of this portfolio diversification effect[2]. In this paper we present a modification to the "Credit-Metrics" and KMV methodologies that have been used to simulate unexpected losses from credit risk in analysed portfolios. For detailed exposition refer to the Credit-Metrics and KMV technical documents. We refer to our modification to the "Credit-Metrics" and KMV methodologies as an Improved Credit Risk Model: ICRM[3].

3. An Improved Credit Risk Method (ICRM).

As already stated, our model assesses portfolio risk arising from changes in loan value caused by changes in obligor credit quality. Given the composition of a particular portfolio, all the possible portfolio values and their probabilities are recorded in the profit and loss (P&L) distribution of the portfolio. This distribution records both, increases and decreases in the value of the portfolio caused by the upgrades and downgrades in the loans' credit qualities. The modelling of the Profit and Loss distribution of the portfolio (P&L) can be broken down into the following steps:

3.1 Modeling the distribution of a single loan.

- 3.1.1 Credit risk migration and the Merton approach.
- 3.1.2 Loan valuation.

3.2 Portfolio risk calculation.

- 3.2.1 Joint probabilities.
- 3.2.2 Indirect approach to model correlations.
- 3.2.3 Simulation of quality scenarios for the credit portfolio.
- 3.2.3 Valuation, P&L distribution and unexpected losses.

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[2]Such approaches may be subject to further improvements, but it is not our intention have to suggest possible improvements to each methodology.

[3] The term "Improved" refers to the fact that this model does take account of the benefits of diversification. This is in contrast to the IRB approaches that use a "simplified, single risk factor model" See Secretariat of the Basel Committee on Banking Supervision, (2001).

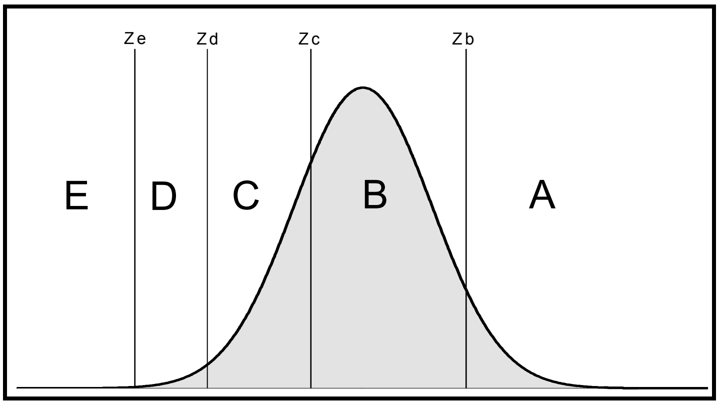
3.1 Modelling the distribution of a single loan.

3.1.1 Credit Risk Migration and the Merton Approach.

The Merton approach assumes that a firm's equity can be viewed as a call option on the firm's assets with a strike price equal to the book value of the firm's debts (Merton (1974)). The intuition behind this assumption is that, given the limited liability of equity, equity holders have the right, but not the obligation to payoff debt-holders and take over the remaining assets of the firm. This approach implies that the credit quality (rating) of a given debtor is related to the difference between the market value of its assets and its debt.

Under this approach, the change in the value of the assets of a given company is related to the change in its rating. So, the distribution of the company's asset returns can be used to calculate the distribution of the probability of the firm's rating change. For the generalisation of this model, it is necessary to include, in addition to the default state, different credit quality states. This is because in this model, risk comes not only from default but also from changes in value due to up(down) grades.

Figure2: The Distribution of Assets' Returns.



The likelihood of any credit rating migration in the coming period is conditioned on the current credit rating of the obligor.

Individual likelihoods of migration are usually represented in matrix form. This table is called a transition matrix. The transition matrix is the table that summarises the migration probabilities from one credit quality to any other.

Table1: Transition Matrix.

	A	B	C	D	E
A	**0.865047**	0.054462	0.011523	0.002826	0.002439
B	0.057558	**0.806042**	0.106912	0.006859	0.014964
C	0.005934	0.052618	**0.812763**	0.060135	0.065386
D	0.001516	0.009098	0.058378	**0.708470**	0.222538
E	0.000000	0.000000	0.000000	0.000001	**0.999999**

To read this table, the credit rating (today) at time t_0 is written on the extreme left column. The possible ratings to which a given loan can migrate at the risk horizon, t_1 are written on the top row. For example, a loan that at t_0 is rated as C has 81.2763% probability of remaining in the same rating at t_1. The table indicates that there is a 6.0135% probability that the loan will migrate to a D rating at t_1 and there is a 6.5386% probability that the loan will default (column E) at t_1. The transition matrix also indicates that there is a 5.2618% that the loan will migrate to a B rating and so on.

Having the transition probabilities between different credit qualities, and employing the Merton Approach, it is possible to derive the (market) value of assets that represent the cut-off values between different credit qualities, as shown in Figure 1. These cut-off values fulfil the condition that if the change in the market value of the asset (r) is sufficiently negative, (i.e. smaller than Ze), then the credit falls into default; if Ze < r < Zd, the credit is rated D, and so on. Taking into consideration the empirical transition matrix, the cut-off values are obtained by solving the following equations (e.g. for a loan initially rated as X):

$$\mathrm{Prob}(E|X) = \mathrm{Prob}(r < Ze) = \varphi(Ze) \tag{1}$$
$$\mathrm{Prob}(D|X) = \mathrm{Prob}(Ze < r < Zd) = \varphi(Zd) - \varphi(Ze)$$
$$\mathrm{Prob}(C|X) = \mathrm{Prob}(Zd < r < Zc) = \varphi(Zc) - \varphi(Zd)$$
$$\mathrm{Prob}(B|X) = \mathrm{Prob}(Zc < r < Zb) = \varphi(Zb) - \varphi(Zc)$$
$$\mathrm{Prob}(A|X) = \mathrm{Prob}(Zb < r < Za) = 1 - \varphi(Zb)$$

Where, R is the implied market value of assets, and φ is the Normal Cumulative Density Function (CDF).

3.1.2 Valuation.

In the previous section, we determined the *likelihoods* of migration to any of the possible credit quality states at a given risk horizon. In this section, the *values* at the risk horizon for these credit quality states are determined. Values are calculated for each migration state. These valuations fall into two categories. First, in the event of up(down) grades, only the change in the value of the bond due to migration is considered. To obtain the values at the risk horizon corresponding to rating up(down)grades, a straightforward present value re-valuation is performed. This revaluation upon up(down)grade accounts for the decreasing likelihood that the full amount of the loan will be repaid as the obligor undergoes rating downgrades, and the increasing likelihood of repayment if the obligor is upgraded. Second, in the event of default, the change in the value of the loan due to its downgrade (to the default category) is estimated in the same manner; however, the remaining value of the loan is multiplied by its loss given default (LGD)[4].

Table2: Valuation Table.

	A	B	C	D	E
A	**0.000000**	-0.012525	-0.062947	-0.220099	-0.997560
B	0.012525	**0.000000**	-0.050422	-0.207575	-0.985035
C	0.062947	0.050422	**0.000000**	-0.157152	-0.934613
D	0.220099	0.207575	0.157152	**0.000000**	-0.777461
E	0.997560	0.985035	0.934613	0.777461	**0.000000**

To read this table, the credit rating (today) at time t_0 is written on the extreme left column. The possible ratings to which a given loan can migrate at the risk horizon, t_1, are written on the top row. Changes in the value of the loan due to migration are in the body of the table. For example, if a loan that at t_0 is rated as C, remains at the same rating at t_1, has a zero present value change. If the same loan migrated to a D rating, its present value would be decreased 15.71%. If the loan were upgraded to a B rating, its present value would be increased 5.04%, and so on. This re-valuation upon downgrades/upgrades accounts for the decreasing/increasing likelihood that the full amount of the loan will be repaid as the obligor undergoes migrations.

As already stated, given a current credit rating of the obligor the likelihood of any credit rating migration in the coming period is conditioned on the current credit rating of the obligor.

With the transition probabilities indicated by the transition matrix and the possible values within each migration state indicated by the valuation table, it is possible to obtain the value distribution for each exposure on a stand-alone-basis. Beyond this, portfolio credit risk models[5] then extend this framework to the portfolio as a whole, in order to obtain the distribution of value of the complete portfolio, the so called profit

[4] The loss given default is estimated as LGD= 1-(percentage of recovery value). When databases allow it, the recovery rates and consequently, the LGD's are estimated based on loan characteristics, e.g. credit quality of debtor, geographical area, etc.
[5] See CreditMetrics (1997) and CreditRisk$^+$ (1997) technical documents for specific details.

and loss distribution (P&L) from which we will derive the Value at Risk (VaR) figure used to define capital requirements.

3.2 Portfolio risk calculation.

In section I, we explained the steps followed to obtain the credit risk for a stand-alone exposure. Here we extend the methodology to a “portfolio”. For reasons of parsimony the methodology explained here will refer to a portfolio of just two exposures; however, the methodology applies to a portfolio of any number of elements. In general, the necessary steps are the same as in the previous section, but there is one significant addition. Now it becomes necessary to include the contribution to risk brought about by the effects of credit quality correlations. So, first, we will discuss the joint likelihoods of credit quality co-movements. Second, we extend the credit risk calculation for the stand-alone exposure to the multiple exposure case.

3.2.1 Joint likelihood in credit quality.

Understanding joint likelihoods allow us to account properly for portfolio diversification effects. Correlations determine how often losses occur in multiple exposures at the same time. The portfolio value volatility (risk) will be lower if correlations between credit events are lower.

In theory, a correlation matrix of changes of credit quality between creditors can be computed by developing an explanatory model of the changes in the value of the assets of the borrowers. This approach presents several practical problems for implementation, the most important being the handling of very large correlation matrices. Additionally, it is not possible to obtain the changes in the market value of assets for each particular borrower, since it would be necessary to have specific information about the internal financial structure of each borrower. These two disadvantages make it impossible to implement an ideal correlation matrix; for these reasons we will adopt an indirect (but more manageable) method to introduce the portfolio diversification effect.

3.2.2 Indirect approach to model Correlations.

The referred indirect method for introducing the portfolio diversification effect was first presented in Segoviano (1998). It is based on an assumption made by the CreditMetrics methodology. This methodology makes an a-priori distinction of the factors that determine the changes in the value of the assets of the borrowers. This distinction comes from two basic components: the market component and the idiosyncratic component. By definition, the idiosyncratic component does not correlate with anything, since it refers to those factors unique for the debtor. But the market component can then be further disaggregated into several separate components that allow the portfolio diversification.

$$r_{total} = W_M\, r_{market} + W_I\, r_{Idiosyncratic} \qquad (2)$$

Where:

W_M: Percentage of returns explained by the market component[6].

r_{market}: Market component of returns.

W_I : Percentage of returns explained by the idiosyncratic component.

$I_{idiosyncratic}$: Idiosyncratic component of returns.

Next, the market component of Returns can be defined as:

$$r_{Market}=H_A r_{GDPGeographicallocation}+(1-H_A)r_{GDPSectorComposition} \qquad (3)$$

Where:

H_A: Percentage of the market component explained by the GDP returns of the borrowers' country (geographical location). The determination of H_A will be explained in Section 3.

$r_{GDPGeographicalLocation}$: Borrower's country (geographical location) GDP's return.

$(1-H_A)$: Percentage of market component explained by the GDP returns' of the borrower' s sectoral activity.

$r_{GDPSectorComposition}$: Borrower's sectoral activity GDP's return.

[6] In the CreditMetrics technical document, how these weights can be calculated is explained. After empirical implementations, an acceptable value of W_M = 70% is derived. For our exercise, we also assume this value.

Once all the elements that compose the market component of assets' returns have been considered, the next step is to calculate the correlations between the borrowers' loans making up a credit portfolio.

Given a pair of borrowers, classified under ratings X and Y, whose sectoral activities are B and V; located in A and E country groups, and with returns expressed in the following way:

$$r_X = w_{IX} r_{IX} + w_{MX} H_A r_A + w_{MX}(1 - H_A) r_B$$

$$r_Y = w_{IY} r_{IY} + w_{MY} H_E r_E + w_{MY}(1 - H_E) r_V$$

The problem of estimating the correlations among each couple of borrowers in the portfolio is summarised in the following way:

$$\rho_{XY} = w_{MX} H_A w_{MY} H_E \rho_{AE} + w_{MX}(1 - H_A) w_{MY}(1 - H_E) \rho_{BV} \quad (4)$$

Where:
p_{AE}: is the correlation between different country groups.
p_{BV}: is the correlation between different sectoral activities.

This equation is computed for each pair of borrowers making up the portfolio. The results of computing this equation are compiled in a (n x n) square matrix, where n is the number of loans in the portfolio. This matrix is named the correlation matrix between borrowers and is unique for each portfolio. This matrix is a key variable for the simulation of unexpected losses, since it incorporates the necessary elements to quantify the concentration/diversification of the portfolio.

As explained above, the transition matrix indicates the probabilities of quality changes that a stand-alone exposure with a given rating might experience. Additionally, when correlations of quality changes between borrowers are involved, we can compute the joint likelihood of credit up(down)grades between the loans making up a portfolio.

Debtors with similar characteristics will tend to migrate jointly to different credit qualities when hit by economic shocks. Debtors with different characteristics will tend to migrate separately to different credit qualities when hit by economic shocks. This implies that credit portfolios concentrated in credits with similar characteristics will tend to have higher unexpected losses since they will not be diversifying the possible economic risks.

With these components, we show in the following section how quality scenarios for the portfolio are simulated. From these quality scenarios, the loss distribution is built from which it is possible to obtain an estimate of unexpected losses.

3.2.3 Simulation of Quality Scenarios for the Credit Portfolio.

Combining the transition matrix with the correlation matrix between borrowers, and under the Merton framework that assumes lognormal asset returns (see equation (1)), we obtain the joint likelihood of credit quality migration and simulate credit quality scenarios. The simulated quality changes of the components of the portfolio allow us to estimate the losses or profits that determine the P&L distribution of the portfolio.

In order to generate these scenarios, the following process is undertaken:

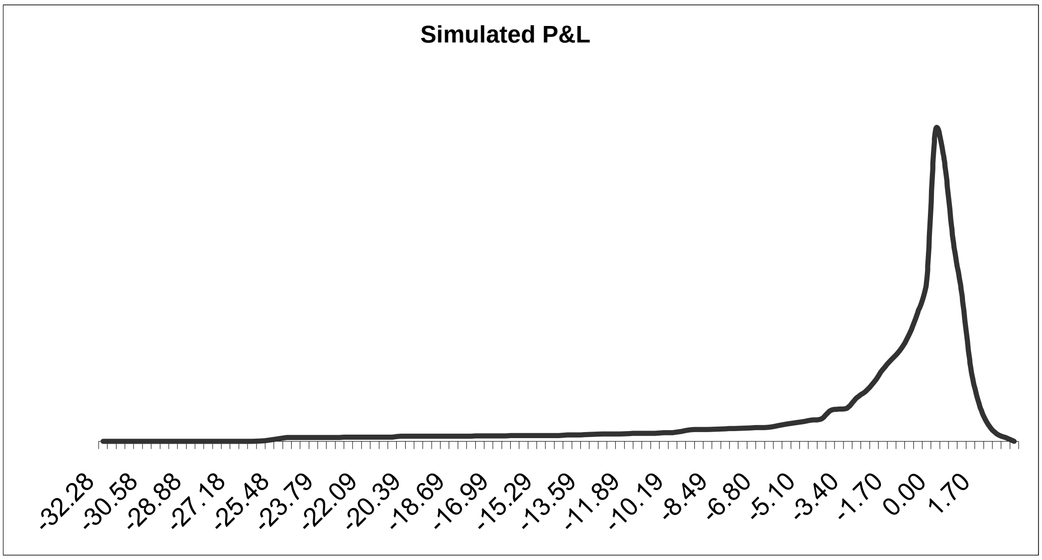
1. Generation of random uniform numbers.
2. Transformation of such random numbers into normal standard random numbers.
3. Transformation of the normal standard random numbers into normal-multivariated random numbers with a correlation matrix defined by the correlations between creditors.

3.2.4 Valuation, P&L Distribution and Unexpected Losses.

Once the credit portfolio quality scenarios have been simulated, we use the simulated credit quality scenarios to re-evaluate the portfolio exposures as explained in section I.2. With the portfolio exposures re-evaluated, we obtain the P&L distribution for the portfolio.

This is done by computing the losses/gains that come from the difference between initial and final credit qualities in the loans making up the portfolio. The losses/gains obtained from the simulation process are used to build a histogram. This histogram summarizes the loss distribution of the credit portfolio.

Figure 3: Credit Portfolio Simulated P&L Distribution.



From this distribution a Value at Risk (VaR) is defined from which we obtain the amount of unexpected losses from the portfolio. The unexpected losses divided by the total amount of the portfolio represent the percentage that with a given probability (defined by the chosen percentile) could be lost in an extreme event. Capital requirements should be such that they can cover these losses.

4. Empirical Implementation and Results.

Our objective here is to try to reconstruct a typical bank portfolio for a country and then, holding the presumed loan book unchanged over time, (i.e. replacing failed loans with loans of a similar quality), to examine how the capital adequacy requirements (CAR's) for the banks would have varied over time. We have assumed that each portfolio consisted of 1000 loans, each one with equal exposure. Below we explained the assumptions taken for the additional variables that were needed to perform this exercise. We also indicate the databases from which the necessary information was taken.

4.1 Data and Assumptions.

Geographical distribution of exposures:

From the BIS database on consolidated banking claims for the U.S. and Norway, we obtained the *through time* proportion of assets invested in different geographical areas[7]. Information for Mexico was obtained from the databases provided by the Mexican Financial Regulatory Agency (CNBV).

Credit quality distribution of exposures:

We obtained the *through time* proportion of corporate bonds that were classified under each of the reported ratings for the U.S. from the Moody's investors service database. In the case of Mexico and Norway, we obtained the *through time* proportion of corporate bonds that were classified under each of the reported ratings from the databases provided by the Mexican Financial Regulatory Agency and the Norwegian Central Bank.

Sectoral Activity distribution of exposures:

We assumed that the simulated portfolios consisted of loans evenly distributed across the major sectoral activities that comprise GDP[8].

Transition matrices:

We use Moody's data on U.S. corporate bonds, included on Moody's Investors Service, Credit Risk Calculator. In the event we also used data provided by the Mexican Financial Regulatory Agency and the Norwegian Central Bank on Corporate Loans. The Mexican data incorporates information between 1995 to 2000, and the Norwegian data incorporates information between 1988 to 2001.

Loss Given Default:

We fixed this at 50% in order to make results comparable to the IRB foundation approach developed by the Basel Committee.

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[7] Developing: Africa and the Middle East; Asia and Pacific; developing Europe; Latin America. Developed: EU (non-EMU); EMU; Other Industrial; offshore centres.

[8] We included the following sectoral activities: financial, building, mining, information technology, retail, textile, chemical, energy, pharmaceutical, tobacco, food production, beverages, electrical.

Market component of returns:

In equation (3) we assume that firms' market component of returns are explained by both the firms' sectoral activities and geographical locations. In order to get a proxy of the percentage of the market component of returns that is explained by geographical location ($1-H_A$), we run the following OLS regressions:

$$r_{Market} = C+B\, r_{GDPGeographicalLocation} + \epsilon \qquad (5)$$

Where:

C: is a drift term

r_{Market}: was obtained by estimating the returns of the Morgan Stanley Capital International (MSCI) indexes for major sectoral activities[9].

$r_{GDPGeographicalLocation}$: was obtained by estimating GDP growth rates of the analysed countries.

In general, in regression analysis, the percentage of the total variation of a dependent variable that is explained by the assumed explanatory variables is indicated by the measure of goodness of fit, R^2 (explained sum of squares over total sum of squares). Therefore, we took the R^2 that was obtained by running the regressions specified in equation (5) as proxies for the percentage of market returns that is explained by the GDP growth rates of the analysed countries, e.g., we take $R^2 \sim (1-H_A)$. Consequently, $(1- R^2) \sim H_A$.

Correlations among different country groups and economic activities:

In equation (4), we make use of ρ_{AE}, the correlation between different country groups and ρ_{BV}, the correlation between different sectoral activities. The first were computed using the spreads of syndicated loans for each country group. We assumed that such spreads measure the riskiness of the financial system in each

[9] These indexes are composed as weighted averages of prices of the major corporates in developed economies for specific sectorial activities. The sectorial activities that we considered were: financial, building, mining, information technology, retail, textile, chemical, energy, pharmaceutical, tobacco, food production, beverages, electrical. Source: Datastream.

country group. The latter were computed from indices of the major sectorial activities examined in the exercise[10].

We used the variables and assumptions described in this section to perform the simulation of credit quality scenarios with which we re-evaluated the exposures in the portfolio and computed the P&L of the portfolio.

Simulation:

In this application, we programmed an algorithm to compute 10,000 possible quality scenarios for each of the (n x n) couples of the loans that make up the portfolio. Each quality scenario shows a change in the market value of the borrowers' assets whose loans compose the portfolio. Since it was assumed that the process that generates changes in the assets' log-returns follow a normal distribution, we use a normal-multivariated distribution to generate joint quality migrations.

[10] Idem footnote 9.

4.2 Results.

The results of this exercise for the three countries examined are stark. We have simulated the time paths of CARs under each of our three approaches, standardised, IRB Foundation (IRB F) and ICRM, for our various countries, and the results are set out in Tables 3 to 5, and Charts 1 to 3.

Table 3: CARs for the USA

PERIOD	Standardised	IRB F	ICRM
1982	9.597967	8.591044	8.070189
1983	8.933900	7.185306	6.802057
1984	8.933900	7.624870	7.032411
1985	9.133900	8.024912	7.262765
1986	9.463390	9.989917	8.736384
1987	9.463930	9.824500	8.545390
1988	9.463930	8.659141	6.990717
1989	9.563390	10.804149	6.488127
1990	9.563390	11.677029	7.601025
1991	9.986339	11.434979	7.541649
1992	9.687739	8.064210	6.470195
1993	9.287739	6.468979	4.665018
1994	8.901877	5.395182	3.783256
1995	8.507394	5.561594	4.087216
1996	8.246774	5.646111	4.316443
1997	8.294313	5.940010	4.837646
1998	8.312774	6.508256	5.831926
1999	8.403155	7.810893	6.704727
2000	8.410316	8.126805	7.163834
2001	8.531238	8.245881	7.242604
2002	8.312375	8.180511	6.779526
2003	8.107739	6.603000	6.258685
Average	**8.959430**	**8.016694**	**6.509627**
Variance	**0.339964**	**3.392352**	**1.945790**

Chart 1: CARs for the USA

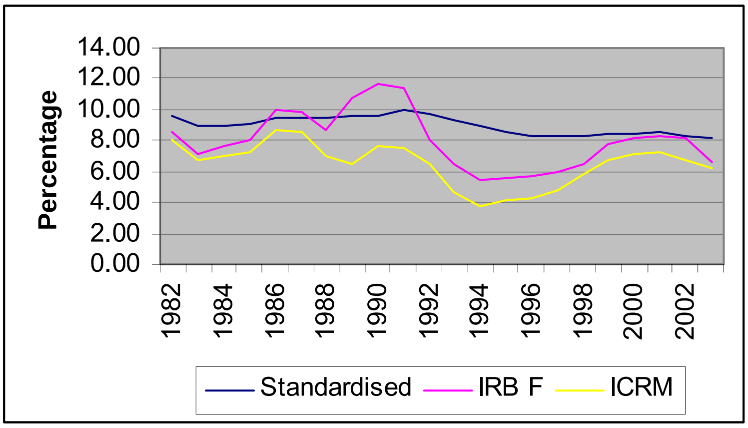


Table 4: CARs for Norway

PERIOD	Standardised	IRB F	ICRM
1989	9.991635	8.311481	7.580115
1990	10.265155	9.275921	8.127573
1991	10.465155	9.781705	8.675031
1992	10.367155	9.929912	9.034373
1993	10.265155	9.523779	9.186305
1994	10.940239	13.235447	9.821542
1995	11.320031	14.066170	11.082487
1996	10.669155	12.141937	9.722593
1997	10.265155	8.857323	7.317353
1998	10.265155	9.001267	7.422621
1999	10.265155	9.218641	7.527889
2000	10.265430	9.486551	7.930505
2001	10.360916	9.648655	8.333122
2002	10.461360	9.764866	8.343509
Average	**10.440489**	**10.160261**	**8.578930**
Variance	**0.113401**	**2.941614**	**1.190491**

Chart 2: CARs for Norway

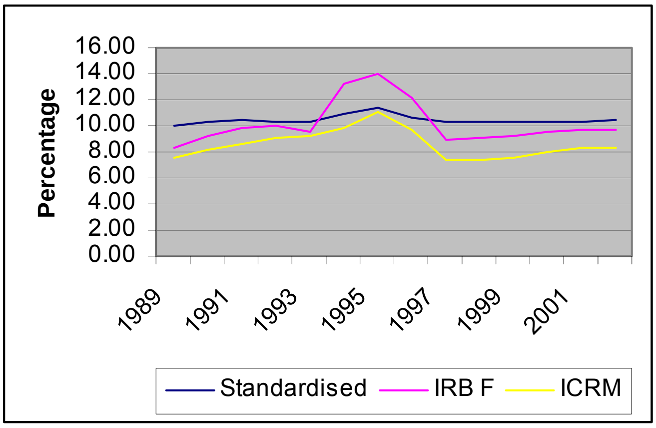
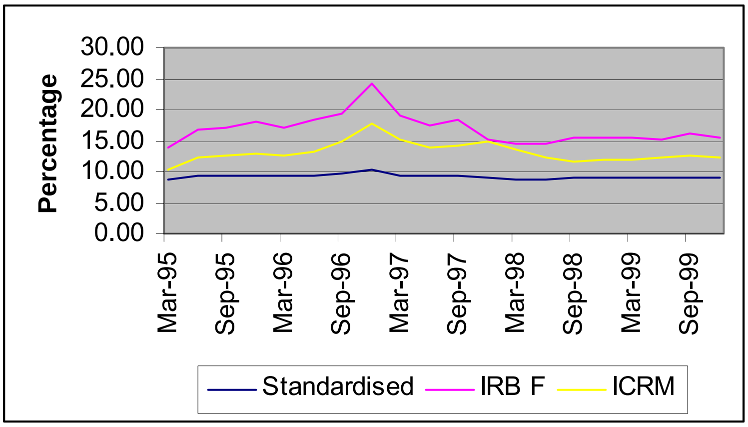


Table 5: CARs for Mexico

PERIOD	Standardised	IRB F	ICRM
Mar-95	8.765096	13.864230	10.462123
Jun-95	9.221855	16.650790	12.285877
Sep-95	9.299730	17.103009	12.714591
Dec-95	9.493498	18.151470	12.820000
Mar-96	9.251044	17.067542	12.589874
Jun-96	9.494958	18.448561	13.248221
Sep-96	9.557249	19.415843	14.891864
Dec-96	10.303734	24.230942	17.645355
Mar-97	9.430354	19.088714	15.153354
Jun-97	9.273425	17.500911	13.895955
Sep-97	9.396601	18.254201	14.344051
Dec-97	8.928781	15.194116	14.796451
Mar-98	8.813186	14.397932	13.673818
Jun-98	8.851211	14.428160	12.256023
Sep-98	9.058278	15.545394	11.622476
Dec-98	9.040916	15.456234	11.797630
Mar-99	9.052107	15.519282	12.003802
Jun-99	8.981783	15.296608	12.251375
Sep-99	9.135013	15.979265	12.725803
Dec-99	8.968905	15.345409	12.100842
Average	**9.215886**	**16.846931**	**13.163974**
Variance	**0.122662**	**5.644965**	**2.588205**

Chart 3: CARs for Mexico



The important result to observe is the much greater variance of the simulated outcomes for the IRB than for the standardised or ICRM approaches. During periods of strong growth, high profits and low NPLs, (USA in the mid 1990s and Norway in 1997), the IRB has a lower CAR than the standardised approach in all our developed countries; whereas in recessions, (e.g. USA in 1990/91, Mexico mid 1995/96 and Norway in 1994/1995), the CAR is markedly higher for the IRB than in the other two approaches. In Mexico, an emerging market economy (EME), the average quality of loan is lower throughout than in developed countries, so the IRB gives a higher CAR in all years, but, as in developed countries, the variance of the CAR (up in recessions as in 1995/96, and lower during the better years) is greater for the IRB than in the other two approaches.

It follows that the % change in the required CAR under the IRB as a country moves from boom to recession (up) and back to boom again (down) will be much more extreme under the IRB than under the other two approaches. This is shown in Table 6.

Table 6: Maximum % Change in CARs

A. IRB	**Upwards**				**Downwards**			
	1 Period	Date	2 Consecutive Periods	Dates	1 Period	Date	2 Consecutive Periods	Dates
USA	0.25	1989	0.33	1989/90	-0.29	1992	-0.49	1992/93
NORWAY	0.39	1994	0.45	1994/95	-0.27	1997	-0.41	1996/97
MEXICO	0.25	Dec 96	0.30	Sep/Dec 96	-0.21	Mar 97	-0.30	Mar/Jun 97

B. ICRM	**Upwards**				**Downwards**			
	1 Period	Date	2 Consecutive Periods	Dates	1 Period	Date	2 Consecutive Periods	Dates
USA	0.21	1998	0.33	1998/99	-0.28	1993	-0.47	1993/94
NORWAY	0.13	1995	0.20	1994/95	-0.25	1997	-0.37	1996/98
MEXICO	0.18	Dec-96	0.30	Sep/Dec 96	-0.14	Mar-97	-0.22	Mar/Jun 97

C. Stand	**Upwards**				**Downwards**			
	1 Period	Date	2 Consecutive Periods	Dates	1 Period	Date	2 Consecutive Periods	Dates
USA	0.04	Jun-05	0.06	1985/86	-0.07	1983	-0.09	1994/95
NORWAY	0.07	Jun-05	0.10	1994/95	-0.06	1997	-0.10	1996/97
MEXICO	0.08	Dec-96	0.08	Sep/Dec 96	-0.08	Mar-97	-0.10	Mar/Jun 97

5. Conclusions.

The implication of the results of this excercise is that procyclicality may well still be a serious problem with Basel II, even after the smoothing of the risk curves that were introduced between Consultative Papers 2 and 3 produced by the Basel Committee to mitigate this problem. However there will be other potentially offsetting factors. Banks normally keep buffers above the required minimum CARs, both for their protection against sanctions should the minimum be infringed and to satisfy ratings agencies, and these buffers are likely to be raised during booms when IRB CARs may fall to extremely low levels. Note, however, that we have used Moody's data for the U.S.A. from1982 to 2003, for Norway from 1988 to 2001 and for Mexico from

1995 to 2000, which are already supposed to be averaged over the cycle, whereas most commercial banks are, so we are told by several of them, likely to use point-in-time ratings, which could worsen pro-cyclicality yet further.

Basel II will be a regime change, and one of the purposes of this is to make bankers more conscious of risk assessment and risk management. It has already succeeded in this. One hope is that it will induce bankers to be more prudent during booms despite declines in CARs. An implication of a move from the standardised to an IRB approach is that the individual bank making this transition will be encouraged to shift its portfolio to higher-quality, higher rated credits, because it then benefits from a lower CAR. This is good of itself, but the higher the quality the credit, the steeper is the risk curve, (relating quality to required risk ratio); so the procyclicality is likely to be enhanced, even if average quality improves.

When a regime change is introduced, no one in truth can predict its ramifications, certainly not us. Nevertheless these simulations suggest that procyclicality could remain a serious concern. It is even possible that with the advent of a serious downturn, if one was to occur, the impact of abiding by the IRB would be too severe for the authorities in some countries to countenance. Perhaps like the Stability and Growth Pact it would only be observed in the breach when it began to bite hard. Possibly an even greater worry might be that the adoption of Basel II, while not being so adverse as to force reconsideration, might yet exacerbate future capital fluctuations.

Certainly there remains a tension between relating CARs more closely to underlying risks in individual banks, and in trying for macro-economic purposes to encourage contra-cyclical variations in bank lending in aggregate. How to square this circle must, however, be a subject for future research.

References

Abiad, A. and A. Mody, (2003), `Financial Reform: What Shapes it? What Shakes it?', IMF Working Paper No. 03/70

Acharya, V.V., Bharath, S.T. and A. Srinivasan, (2003), `Understanding the Recovery Rates on Defaulted Securities', London Business School, Paper in progress, 23 November draft.

Altman, E., (2002), `Altman report on Defaulted Bonds and Bank Loans', Salomon Smith Barney, United States Corporate Bond Research High Yield.

Altman, E., Brady, B., Resti, A. and A. Sironi, (2002), `The link between default and recovery rates: Implications for credit risk models and procyclicality', Working paper, New York University.

Altman E., Elizondo A., Segoviano, M.,(2002), `Medicion Integral del Riesgo de Credito', Editorial Limusa, Mexico.

Bank of England, (1971), Competition and Credit Control, (London: Bank of England), (May).

Basle Committee on Banking Supervision. (1988), `International Convergence of Capital Measurement and Capital Standards', Basel, July 1988.

Basle Committee on Banking Supervision, (1999), `Capital Requirements and Bank Behaviour: The Impact of the Basle Accord', Basle Committee on Banking Supervision Working Paper No. 1.

Berger, A. and G. Udell, (1994), `Did Risk-Based Capital Allocate Bank Credit and Cause a "Credit Crunch" in the United States?', Journal of Money, Credit and Banking, 26, 585-628.

Bernanke, B. and M. Gertler, (1989), `Agency Costs, Collateral and Business Fluctuations', American Economic Review, 79, 14-31.

Bernanke, B. and M. Gertler, (1999), `Monetary Policy and Asset Price Volatility', in New Challenges for Monetary Policy, Proceedings of the Jackson Hole Conference, August 26-28, published by the Federal Reserve Bank of Kansas City, pp [check].

Bernanke, B., Gertler, M. and S. Gilchrist, (1999), `The financial accelerator in a quantitative business cycle framework', in J.B. Taylor and M. Woodford, eds., Handbook of Macroeconomics, Vol. 1C, 1341-1393.

Bordo, M., Eichengreen, B., Klingebiel, D. and M.S. Martinez-Peria, (2001), `Is the crisis problem growing more severe?', Economic Policy, 32, 51-82.

Brennan, M.J., (2004), `How Did It Happen?', Economic Notes, 33:1, 3-22.

Cecchetti, S., Genberg, H., Lipsky, J. and S. Wadhwani, (2000), `Asset Prices and Central Bank Policy', Geneva Reports on the World Economy 2.

Clarida, R., J. Gali and M. Gertler, (1999), `The science of monetary policy: a new Keynesian perspective', Journal of Economic Literature, 37(4), 1661-1707.

Cochrane, J., (2001), `Asset PricingLending', Princeton, N.J., Princeton University Press.

Collyns, C. and A. Senhadji, (2002), `Lending Booms, Real Estate Bubbles and the Asian Crisis', IMF Working Paper 02/20.

Credit Suisse First Boston International, (1997), `CreditRisk+ Technical Document'.

Demirgüc-Kunt, A. and E. Detriagiache, (1998), `Financial Liberalization and Financial Fragility', IMF Working Paper No. 98/83.

Dickey, D. and W. Fuller, (1981), `Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root', Econometrica, 60, 423-433.

Drees, B. and C. Pazarbasioglu, (1998), `The Nordic Banking Crises. Pitfalls in Financial Liberalization?', IMF Occasional Paper No. 161.

Eichengreen, B. and M. Bordo, (2003), `Crises now and then: What lessons from the last era of financial globalisation', Chapter 3 in Monetary History, Exchange Rates and Financial Markets; Essays in honour of Charles Goodhart, (Vol 2), ed. P. Mizen, (Cheltenham, UK: Edward Elgar), 52-91.

Elsinger, H., Lehar, A. and M. Summer, (2002), `Risk Assessment of Banking Systems', Mimeo, Oesterreichische Nationalbank, August.

Furfine, C., (1999), `Interbank Exposures: Quantifying the Risk of Contagion', BIS Paper, No. 70, June.

Gertler, M., Goodfriend, M., Issing, O. and L. Spaventa, (1998), Asset Prices and Monetary Policy: Four Views, Centre for Economic Policy Research (CEPR) and Bank for International Settlements (BIS), booklet, (CEPR: London).

Glick, R. and M. Hutchison, (1999), `Banking and Currency Crises: How Common are the Twins?', Federal Reserve Bank of San Francisco Pacific Basin Working Paper No. PB 99-07.

Goodhart, C.A.E., (2004), `The Bank of England, 1970-2000', Chapter 17 in The British Government and the City of London in the Twentieth Century, ed. R. Michie, (Cambridge, UK: Cambridge University Press), 340-371.

Goodhart, C., Hofmann, B. and M. Segoviano, (2004), `Bank Regulation and Macroeconomic Fluctuations' in Oxford Review of Economic Policy, 20 (4), (Winter), Special issue on European Financial Integration, eds. X. Freixas, P. Hartmann and C. Mayer.

Goodhart, C.A.E., Sunirand, P. and D.P. Tsomocos, (2003), `A Model to Analyse Financial Fragility', Oxford Financial Research Centre Working Paper No. 2003fe13.

Gordy, M.B. and B. Howells, (2004), `Procyclicality in Basel II: Can we Treat the Disease without Killing the Patient?', Board of Governors of the Federal Reserve System, Paper in Progress, May 12 draft.

J.P. Morgan & Co Incorporated, (1997), `Creditmetrics Technical Document'.

Kaminsky, G. and C. Reinhart, (1999), `The Twin Crisis: The Causes of Banking and Balance-of-Payments Problems', American Economic Review, 89, 473-500.

Kaminsky, G. and S. Schmukler, (2002), `Short-Run Pain, Long-Run Gain: The Effects of Financial Liberalization', George Washington University , mimeo.

Kashyap, A.K. and C. Stein, (2003), `Cyclical Implications of the Basel-II Capital Standards', [check and complete].

Kashyap, A.K. and C. Stein, (2004), `Cyclical Implications of the Basel-II Capital Standard', Federal Reserve Bank of Chicago Economic Perspectives, First Quarter, pp 18-31.

Kiyotaki, N. and J. Moore, (1997), `Credit Cycles', Journal of Political Economy, 105, pp 211-248.

Leahy, M., S. Schich, G. Wehinger, F. Pelgrin and T. Thorgeirsson, (2001), `Contributions of Financial Systems to Growth in OECD countries', OECD Economics Department Working Paper No. 280.

Levine, R., (1997), `Financial Development and Economic Growth: Views and Agendas', Journal of Economic Literature, 35, 688-726.

MacKinnon, J., (1991), `Critical Values for Cointegration Tests', in: R. Engle C. Granger (Eds.), Long-Run Economic Relationships: Readings in Cointegration, Oxford University Press.

Markowitz, Harry, (1959), `Portfolio Selection: Efficient Diversification of Investments', John Wiley and Sons.

Merton, Robert C., (1974), `On the pricing of corporate debt: The risk structure of interest rates', The Journal of finance, Vol 29, pp449-470

Perron, P., (1989), `The Great Crash, the Oil Price Shock and the Unit Root Hypothesis', Econometrica, 57, 1361-1401.

Perron, P., (1990), `Testing for a Unit Root in a Time Series Regression with a Changing Mean', Journal of Business and Economic Statistics, 8, 153-162.

Perron, P., (1997), `Further Evidence from Breaking Trend Functions in Macroeconomic Variables', Journal of Econometrics, 80, 355-385.

Reid, M., (1982), `The Secondary Banking Crisis, 1973-75: Its Causes and Course', (London: Macmillan).

Reinhart, C. and I. Tokatlidis, (2001), `Before and After Financial Liberalization', University of Maryland, mimeo.

Secretariat of the Basel Committee on Banking Supervision, (2001), `The New Basel Capital Accord: An Explanatory Note', (Basel: BIS).

Segoviano, M., (1998), `Basel II v.s. Creditmetrics', London School of Economics, MSc in Economics dissertation.

Segoviano, M., Lowe P.,(2002), `Internal ratings, the business cycle and capital requirements: some evidence from an emerging market economy', Monetary and Economic Department, BIS Working papers, 117.

Upper, C. and A. Worms, (2001), `Estimating Bilateral Exposures in the German Interbank Market: Is there a Danger of Contagion?', BIS Paper, No. 1, March.

Walsh, C. and J. Wilcox, (1995), `Bank Credit and Economic Activity', in: J. Peek and E. Rosengreen (eds.), Is Bank Lending Important for the Transmission of Monetary Policy?, Federal Reserve Bank of Boston Conference Series No. 39.

Wells, S., (2002), `UK Interbank Exposures: Systemic Risk Implications', Financial Stability Review, Bank of England, December, pp 175-182.