Tests on the Accuracy of Basel II

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Abstract

Basel II rules allow qualified banks to assess the risk in their portfolio of credit exposures with a methodology based on the informational content of credit ratings and two crucial assumptions: (1) the credit risk of individual exposures is driven by one systematic risk factor only and (2) the portfolio is fully diversified. We test the accuracy of the credit risk measures obtained with the new rules by comparing them with benchmark measures derived with a popular ratings-based credit risk model which accounts for multiple risk factors and portfolio concentration. We find that the Basel II assumptions may have a substantial impact on risk assessments and produce deviations from the benchmark that may be economically significant.

Keywords: Basel II, credit rating, credit risk.

JEL classification: G28, G32.

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1. Introduction

From the beginning of 2007 European banks are required to assess the credit risk in their portfolios with a set of new rules collectively known as the New Accord or Basel II. The new regulatory framework has introduced radical changes to the existing regulation and is quickly becoming a benchmark worldwide with all the major non-EU economies and most emerging markets planning to introduce it within the next few years.

Basel II entails a three-pronged approach to bank capital regulation, (1) a comprehensive set of rules designed to measure the risks in banks' portfolios and to produce minimum capital requirements, (2) a supervisory review process setting out the role of bank supervisors in ensuring that the new framework is correctly implemented and (3) disclosure requirements to induce banks to make available more information about the key risks in their books with the objective of improving bank accountability and market monitoring. Under the first "pillar", banks can calculate credit risk capital requirements by choosing one of three approaches. This flexibility was introduced in answer to the criticism levelled at the "one-size-fits-all" approach of Basel I, the previous regulation. All three options fundamentally depart from Basel I in that they employ credit ratings as a way to assess individual exposures' credit risk. The three options are called the standardised approach (SA), the foundation internal rating based approach and the advanced internal rating based approach (collectively called IRBA hereafter). The SA is based on external ratings as assigned by recognised rating institutions whereas the other two approaches, as their names suggest, rely on ratings internally derived by the banks.[1] National supervisors allow banks to adopt the latter approaches only if they are satisfied that the internal rating assignment process is sufficiently accurate.[2]

The Basel Committee have conducted several "quantitative impact studies" to test the effect of the new rules on banks' regulatory capital. However, the main focus of

[1] Krahnen and Weber (2001) and Crouhy et al (2001) describe the principles and technical aspects one should consider when devising an internal rating system. Carey (2001) and Jacobson et al (2006) present some evidence on the consistency of banks' internal credit ratings.

[2] In this respect, the Basel Committee have produced a comprehensive survey of techniques for the validation of internal rating systems (see Basel Committee on Banking Supervision 2005). Carey and Hrycay (2001) on the other hand, investigate the potential pitfalls of internal rating systems and suggest that a combination of several rating methods would help reduce their most common weaknesses.

such studies was to compare the new and the old regulation and to determine whether the new regulation would yield substantially lower capital requirements. On the other hand, most of the available studies on the actual accuracy of Basel II refer to earlier drafts of the new framework which has been substantially modified since the release of the first consultative papers in 1999 and 2001, also to incorporate some of the points made in these studies. Examples are, Altman and Saunders (2001) who show that the risk weights associated with the risk categories in the SA do not accurately represent the credit risk of assets that fall in such categories, and Sironi and Zazzara (2003) who measure the inconsistencies between the asset correlation assumptions in the IRBA and asset correlations implied from empirically observed default correlations. The final version of the New Accord (see Basel Committee on Banking Supervision 2006) indeed presents new risk weights for the SA and a revised treatment of asset correlation in the IRBA. However, following the latest changes, Resti and Sironi (2007a) take another look at the SA and conclude, in agreement with Linnell (2001), that the different treatment of banks and non-bank corporations in the New Accord is not justifiable. Their empirical evidence suggests that the credit risk of banks and non-banks with the same rating are statistically indistinguishable. They also conclude that the current risk categories are too coarse and should be more granular to increase accuracy, and that the risk weight curve across risk categories should be steeper.

Empirical tests on the IRBA focus mainly on the accuracy of the regulatory approach when measuring the risk of loans to small and medium enterprises and/or retail exposures. Perli and Nayda (2004) develop a credit risk model for retail exposures that accounts for future margin income and find that the negative relationship between probability of default and asset correlation established in the IRBA does not necessarily hold empirically. Calem and LaCour-Little (2004) show that geographical diversification, which is not directly addressed in pillar 1 of Basel II, has an important role in determining the economic capital of mortgage loan portfolios. Jacobson, Lindé and Roszbach (2005) through a re-sampling method applied to a large database of bank loans from two major Swedish banks find no evidence in support of the IRBA assumption that SME loans and retail credits are systematically less risky than wholesale corporate loans. With the same data and analytical approach Jacobson, Lindé and Roszbach (2006) show that IRBA capital can be 6 to 9 times higher than economic capital.[3] The re-sampling technique they adopt has the advantage that it allows them to derive portfolio loss distributions without making any of the assumptions (e.g. on correlations) underlying a credit risk model. However, the usefulness of their approach is reduced in portfolios of wholesale corporate loans. First, wholesale credits are larger in size and smaller in number than retail and SME credits in a typical bank portfolio, which will lessen the accuracy and significance of re-sampling. Second, conducting re-sampling on a database where only default losses are recorded (but not losses in loan value arsing from rating downgrades) will not produce meaningful risk measures when there are no or few historical defaults in the sample. Furthermore, the practice of marking-to-market portfolio exposures and hence directly account for downgrade losses is becoming increasingly relevant today with the widespread use of securitisations, also in the retail lending sector.

The contribution of this paper is to provide new ways in which to test the accuracy of SA and IRBA on a portfolio of wholesale corporate exposures. We do so by comparing the regulatory capital obtained from the Basel II approaches with the economic capital resulting from CreditMetrics, a popular credit risk model which provides a natural way to relax the assumptions underlying the IRBA. Furthermore, we single out the effect of correlation and downgrade risk, as well as, loan maturity, probability of default and credit rating on the estimation bias produced by the regulatory models. We do so dynamically over a ten year period on portfolios of eurobonds with different granularity and risk characteristics. We find that the IRBA (as well as the SA) can produce regulatory capital that is as much as three times larger than the economic capital generated with CreditMetrics. This bias has the same order of magnitude as in Jacobson et al (2006) but is smaller, probably because of the explicit inclusion in our analysis of downgrade losses which cause economic capital to rise. The fact that previous findings about the conservativeness of the new capital regulation are broadly confirmed reinforces concerns about the economic impact of the new rules especially in the light of the ongoing debate about the propensity of the New Accord to aggravate credit rationing in recessions (see, for example, Gordy and Howells 2006).

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[3] This result is derived from Table 12 in their paper. A typo in the text of the paper refers to regulatory capital being 6% to 9% higher than economic capital rather than 6 to 9 times higher.

The paper is organised as follows. Section 2 summarises the data used for our analysis. In Section 3 we describe the Basel II models for credit risk. Section 4 introduces the benchmark model that we employ to test the accuracy of the regulatory models. In Section 5 we present our results and Section 6 concludes the paper.

2. Data

The data we use for this study were obtained through Reuters and include US dollar-denominated bonds issued by 502 firms[4]. Our criteria in selecting the bonds are (i) that they were neither callable nor convertible, (ii) that a rating history was available, (iii) that the coupons were constant with a fixed frequency, (iv) that repayment was at par, and (v) that the bond did not possess a sinking fund.

The composition of the total portfolio is shown in Table 1. 46.4% of the obligors are domiciled in the United States. A further 27.5% of the companies are headquartered in Japan, the Netherlands, Germany, France or the United Kingdom. 54% of the companies in our sample are in the financial services or banking sectors.

To implement the benchmark model, we also needed: (i) transition matrices, (ii) default spreads and default-free yield curves over time, (iii) equity index data and (iv) a set of weights linking individual obligors to the equity indices. Transition matrices were sourced from Standard and Poor's (see Vazza, Aurora and Schneck 2005). Default-free interest rates and spreads for different ratings categories were taken from Bloomberg.[5] We also created an equity index dataset going back to 1983 and comprising 243 country and industry-specific MSCI indices. For each obligor, based on the domicile and industry classification provided by Reuters, we then chose one of these indices as the source of systematic risk.

[4] Of these, 90% were eurobonds, the remainder are national bonds from several countries.

[5] We used spreads for United States industrials since these had the longest series and the fewest missing observations.

3. Basel II

In this section we briefly summarise the main features of the alternative approaches to computing credit risk capital requirements in Basel II, the SA and the IRBA. The SA and IRBA are implemented with variations that depend on the type of borrower namely, large corporations, sovereigns, banks and retail borrowers. We shall focus on large corporations and banks only, as the data we employ for the empirical analysis are bonds issued by these types of obligors.

The SA produces a capital requirement with a method similar to that in use in the first Basel Accord (Basel 1988), also called Basel I. Each claim is assigned a risk weight and regulatory capital is given by the sum of the values of all claims, multiplied by their respective risk weights, and a constant factor of 8%. In Basel I weights vary in relation to the type of borrower. In the SA of Basel II, risk weights vary according to both borrower type and the borrower's external credit rating. Different risk charges are applied to un-rated companies.[6] For claims on banks, the SA offers two options and all banks in a country will be subject to one of the two at the discretion of the national supervisor. Under option 1, the risk weight depends on the risk category assigned to the country of incorporation of the borrowing bank. Risk categories are identified by the range of sovereign ratings that attract the same risk weight. So, for example, sovereign ratings from AAA to AA- represent one category as all have a 0% risk weight. Option 1 is particularly suitable for countries whose banks are mostly unrated. Under option 2, the risk weight depends on the borrowing bank's own credit rating.[7] A summary of SA risk weights for large corporations, sovereigns and banks is reported in Table 2.

The credit risk capital charge under the two internal rating based approaches is based on the same analytical framework. However, it is only in the advanced IRBA that banks are responsible for estimating all the four parameters of the model, probability of default (PD), loss given default (LGD), exposure at default (EAD) and effective maturity (M). Banks under the foundation IRBA will have to provide own estimates of the PD, but they are required to follow specific computation rules for the other

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[6] All firms in our sample are rated so the un-rated weight has not been used.
[7] Also paragraph 62 in Basel II states "… a preferential risk weight that is one category more favourable may be applied to claims with an original maturity of three months or less, subject to a floor of 20%. This treatment will be available to both rated and unrated banks, but not to banks risk weighted at 150%".

three parameters. For both approaches, the minimum capital requirement is given by,

$$\text{IRBA Capital} = \sum_{s}^{N} RWA_S \tag{1}$$

where RWA_s denotes the risk weighted value of asset s, and N is the total number of assets in the bank's credit risk portfolio. The RWA_s is defined as follows,

$$RWA_S = UL_S \cdot EAD_S \tag{2}$$

where UL_s is the percent unexpected loss in asset s and EAD_s is the asset's exposure at default. From this formula we can infer that regulatory capital under the IRBA is designed to cover only for unexpected losses. This is because banks systematically set aside provisions for expected losses. UL_s is defined as the difference between the expected loss from borrower s in a downturn scenario and the expected loss under a normal scenario. It is formally defined as,[8]

$$UL_S = CF \cdot MA_S \cdot LGD_S \cdot \left[\Phi\left(\frac{\Phi^{-1}(PD_S) + \Phi^{-1}(0.999)\sqrt{R_S}}{\sqrt{1-R_S}} \right) - PD_S \right] \tag{3}$$

where CF is a calibration factor that was introduced to broadly maintain the aggregate levels of regulatory capital that were in place before the introduction of Basel II. The factor is currently equal to 1.06. Φ denotes a cumulative standard normal. $\Phi(.)$ is an expression for the probability of default in a downturn scenario and is fully derived in the Appendix. MA_s is a maturity adjustment which grows with effective maturity, M, and falls as PD increases. The idea behind it, is that longer maturity bonds, which are riskier, should attract a higher capital charge. However, if PD goes up, the MA_s will fall because lower quality assets are exposed to downgrade risk to a lower extent than higher quality assets. In other words, the

[8] A comprehensive description of the rationale behind the UL formula can be found in Resti and Sironi (2007b), Chapter 20, and Basel Committee on Banking Supervision (2005).

scope for loss in value due to a downgrade is larger for a AAA asset than for an asset with lower credit rating.[9] The maturity adjustment is given by,

$$MA_S = \frac{1 + (M_S - 2.5)b(PD_S)}{1 - 1.5b(PD_S)} \tag{4}$$

where,

$$b(PD_S) = (0.11852 - 0.05478\, ln(PD_S))^2 \tag{5}$$

$b(PD_s)$ has been calibrated on market data to produce the downgrade effect discussed above. M is obtained with a simplified duration formula and is defined as,

$$M_S = \left(\sum_t t \cdot c_t \right) \Big/ \sum_t c_t \tag{6}$$

where c_t denotes the cash flow of asset s at time t. R_s in (3) is a correlation coefficient that measures the dependence between the return of borrower s's assets and the return on a systematic risk factor.[10] By analysing a large database of US, Japanese and European firms Lopez (2004) found R_s to be a decreasing function of the probability of default and an increasing function of the size V of borrower s. These findings have been implemented in the internal rating based approach with the following formula,

$$\begin{aligned} R_S &= 0.12 \cdot (1 - exp(-50 \cdot PD_S))/(1 - exp(-50)) \\ &\quad + 0.24 \cdot [1 - (1 - exp(-50 \cdot PD_S))/(1 - exp(-50))] \\ &\quad - 0.04 \cdot (1 - (\mathrm{V} - 5)/45) \end{aligned} \tag{7}$$

where V is measured in terms of the firm's annual sales in million Euros. The size adjustment does not apply to companies that have a turnover of more than 50 million Euros, and is set at –0.04 for those with annual sales lower than 5 millions. Although

[9] This does not mean however that higher quality exposures will attract higher capital charges. Although they will have a higher MA, their PD, which has a dominant effect on the unexpected loss in (3), will drive down their risk weight. Therefore, the impact of MA as credit quality improves is to make the fall in capital requirement less sharp.

[10] Provided that the systematic risk factor is the same across borrowers, the factor cancels out in the derivation of the UL_s formula and so it need not be explicitly identified, (see the Appendix for details).

we do not have turnover data for the companies in our sample, it is plausible to assume that their size is considerable, since most of them are eurobond issuers. Therefore, we do not apply the size adjustment. If we ignore the size adjustment, (7) indicates that R_s is a weighted average of, i.e. it varies between, 0.12 and 0.24, with the parenthetic values being normalised weights that sum 1. The weights are a function of PD and cause R_s to decline as PD increases.

Interestingly, regulatory capital under the IRBA is additive - as is in the SA and in Basel I - in the sense that to arrive at the total capital requirement one needs to sum the individual capital charge of each asset in the portfolio. However, while additivity in Basel I and the SA in Basel II follows from the implicit assumption that assets in the portfolio are perfectly correlated, the IRBA additivity is the result of the assumptions that the portfolio is perfectly diversified (or infinitely granular) and that only one systematic risk factor drives the correlation among the assets in the portfolio.[11] Therefore, in the IRBA, additivity obtains even though correlation is less than 1.

We implement as closely as possible the advanced IRBA by using the information in our data sample. M is estimated as in (6) and subject to a lower and upper boundary of 1 and 5 years respectively as indicated in Basel II.[12] For the probability of default, as we lack internal rating data, we assume that the bank's internal rating system perfectly replicates that of a recognised rating agency, Standard and Poor's. This is not implausible as Basel II allows banks to map their internal ratings to agency ratings and employ the default probabilities of the latter.[13] The PDs fed into the IRBA model are, at each point in time and for each credit rating, the averages of point-in-time default rates for that rating over the previous five years.[14] As prescribed in Basel II, we constrain default probabilities to be greater than or equal to 0.03%.[15] As we do not have enough information on loss given default for different seniorities over the sample period, we use a flat LGD of 50% across the

[11] See Gordy (2003) for a detailed derivation of this result and an analysis of the properties of the IRBA model.
[12] See BCBS 2006a, para. 320.
[13] See BCSB 2006a, para. 462.
[14] According to Basel II default probabilities should be estimated by taking average default rates over a minimum period of five years (See BCBS 2006a, para. 447, 463).
[15] See BCSB 2006a, para. 285.

whole sample.[16] The exposure at default is equal to 1 for each firm as we aim to form portfolios in which assets are equally weighted.

4. The benchmark

The IRBA in Basel II is derived under some restrictive assumptions, namely that (1) the credit risk of individual exposures is driven by one systematic risk factor only, and that (2) the portfolio of exposures is fully diversified. To remove such assumptions we use CreditMetrics, a popular credit risk model proposed by Bhatia, Finger, and Gupton (1997). The model allows for multiple systematic factors and portfolio concentration. Below we describe its main features.

The main contribution of CreditMetrics is a simple way in which to model the correlation of illiquid credit exposures. Most bank loans are illiquid in the sense that they are not traded, in an exchange or over the counter, and hence their prices are not available. CreditMetrics models the price of a credit exposure as a discrete process. The exposure's future value will depend on the credit rating of the borrower at the chosen horizon (typically one year). The correlation between any two exposures will then depend on how their future rating scenarios are correlated. The idea in CreditMetrics is to model changes in rating scenarios of borrower s with a standard normal latent variable Q_s that represents the return of the assets of that borrower. Positive and large asset returns will push the borrower towards a higher rating, while large negative returns will cause a downgrade and, in severe cases, default. The thresholds $Z_{i,j}$ that determine transitions from an initial rating i to a rating j, are computed by employing the transition probabilities $\pi_{i,j}$ found in rating transition matrices. These are regularly published by all the major rating agencies. The thresholds can be estimated directly using the recursive equations below,

16 More than 70% of our bonds are unsecured, (57.34% of unsecured proper and 14.14% of senior
unsecured) which, according to Carty and Lieberman (1996) have an average recovery rate of 51.13%.
Bonds with lower seniority (that is, subordinated), and hence with a lower recovery rate, account for only 1.55% of the total sample.

$$\begin{cases} \pi_{i,D} = \Phi(Z_{i,D}) \\ \pi_{i,CCC} = \Phi(Z_{i,CCC}) - \Phi(Z_{i,D}) \\ \ldots \\ \pi_{i,AAA} = 1 - \Phi(Z_{i,AA}) \end{cases} \tag{8}$$

Transition probabilities in a given year are estimated by taking the average of the previous 5 years' point-in-time transition matrices. To take into account indirect migration and generate non-zero default probabilities for ratings at the top end of the rating scale we use the "generator" approach introduced by Jarrow, Lando and Turnbull (1997) and refined by Israel, Rosenthal and Wei (2001).

The value of the asset return Q_s is assumed to depend on one or more systematic factors. Under the simplifying assumption that each borrower's asset return depends on one factor only, the asset return will be given by,

$$Q_S = \theta_S X_S + \varepsilon_S \tag{9}$$

where X_S and ε_S denote the standardised return on the factor and the idiosyncratic component of the firm's asset return respectively. Then, the correlation between the asset return of borrower s and v will be $\theta_S \theta_V \rho_{S,V}$ where $\rho_{S,V}$ is the correlation between factors X_S and X_V. In CreditMetrics $\rho_{S,V}$ is proxied with the correlation of the equity indices that most closely represent borrower s and borrower v. Typically, the chosen index is that of the country and industry sector in which a borrower operates. However, it is unclear how the systematic factor loading θ_r should be estimated. For simplicity, we use the approach in the IRBA which expresses θ_S as $\sqrt{R_S}$. This has the additional advantage of simplifying the comparison between the regulatory model and the benchmark, as it eliminates one of the potential sources of difference.

Since the latent variable Q_s is standard normal, one can easily apply Monte Carlo methods to generate correlated rating scenarios for all the loans in the portfolio and derive the distribution of portfolio values[17]. Then, the portfolio loss distribution is obtained by taking the difference between the 1 year forward value of the portfolio

[17] See Bhatia et al (1997), Chapters 10 and 11 for details.

under the assumption that all exposures maintain their current rating and the generated portfolio values.[18] By computing the Value-at-Risk at the 99.9% confidence level on the loss distribution, as prescribed by Basel II, the unexpected loss can then be estimated as the difference between the VaR and the loss mean value. The comparison of the unexpected loss so derived with the regulatory models' capital charge will be the focus of our discussion in the reminder of the paper.

5. Results

In this section we compare the capital charge produced by the benchmark with the capital charges of Basel II's SA and IRBA. The starting point of our analysis is the asymptotic single risk factor model (ASRF) of Gordy (2003), a special case of both, the IRBA and the benchmark. By adding the assumptions that distinguish the two models from the ASRF, one at a time, we will be in a position to study how they diverge and why.

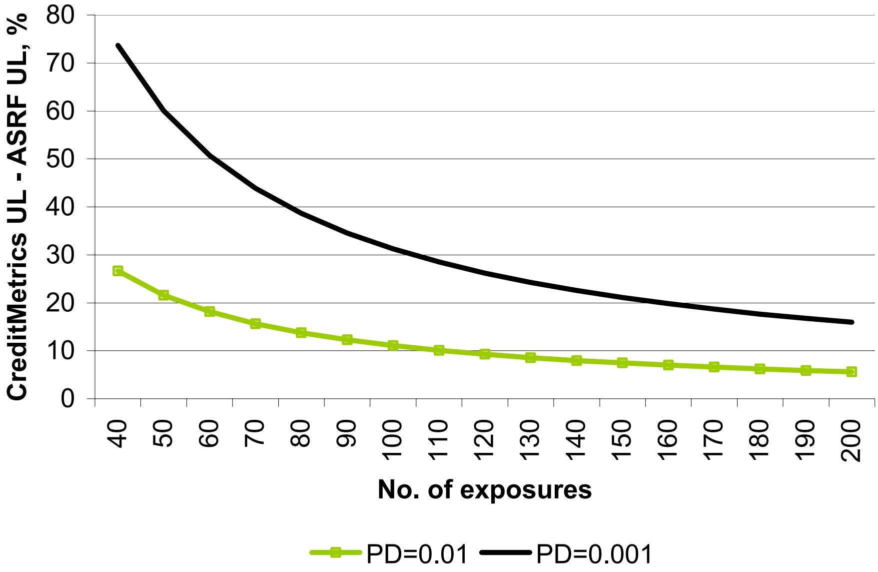
Table 3 summarises our findings. The three features that cause the IRBA to depart from the ASRF are the maturity adjustment, the 0.03% default probability floor and the calibration factor. All of them increase the capital requirement relative to the requirement one obtains with a straightforward application of the ASRF. The maturity adjustment has the largest impact with an average increase in capital of 82.4%. The default probability floor follows with a 50.4% increase, while the calibration factor adds a further 14.0%. The benchmark, on the other hand, introduces granularity effects, (explicit) downgrade risk and multiple systematic risk factors to the basic ASRF. The largest rise in capital is caused by downgrade risk, +108.6%, followed by granularity effects with +36.9%. The introduction of multiple factors on the other hand reduces capital by a substantial 41.5%.[19] The sum total of the above modelling assumptions for the IRBA is +146.8% which is higher than the total for the benchmark (+104.0%). Therefore, from these initial observations it appears that the regulatory model produces more conservative capital requirements

[18] See, for example, Crouhy et al (2000), Section 2.4.

[19] Within the framework of the benchmark model, using a single systematic factor is equivalent to using multiple perfectly correlated factors. Hence, as risk factors are always less than perfectly correlated, it follows that portfolio correlation, and as a result, unexpected losses, go down when multiple factors are introduced in the model.

than the benchmark. Below we shall investigate the causes behind this result in more detail.

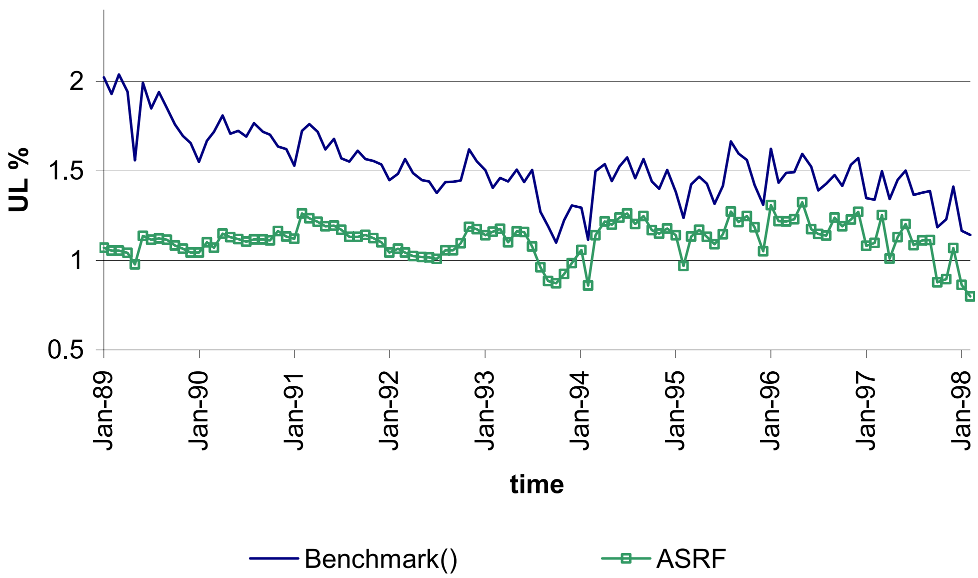
Figure 1: Convergence between CreditMetrics and ASRF



Note: In this graph we report the percentage difference in UL between CreditMetrics and the ASRF model as the number of exposures in the portfolio increases. Results are based on a sample of fictitious exposures with identical default probability and exposure at default, and a loss given default of 50%. The confidence level used to derive UL with both models is 99.9%. CreditMetrics has been implemented without downgrade risk and with a single risk factor.

Figure 1 shows that CreditMetrics with no downgrade risk and a single systematic factor actually converges to the ASRF as portfolio diversification increases. The Figure also reveals two important points. First, credit risk may be hard to diversify. In portfolios with one hundred exposures, the UL of CreditMetrics may still exceed the UL based on full diversification (ASRF) by a non negligible amount, due to concentration effects. Second, in high quality portfolios, convergence is slower. For example, with an average portfolio PD of 0.1%, the discrepancy between CreditMetrics and ASRF is still 15.9% when the number of exposures is as high as 200.

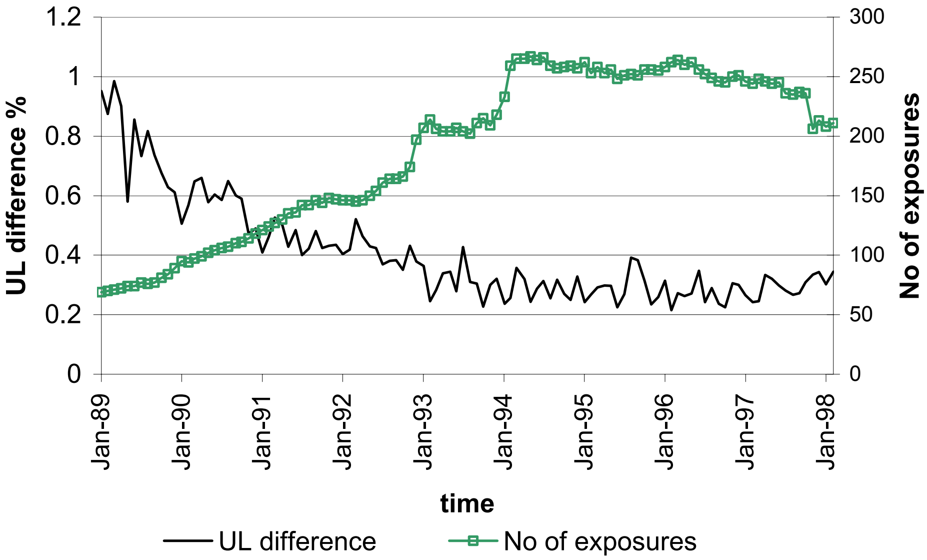
Figure 2: UL comparison with no downgrade risk and a single systematic factor.



Note: The benchmark model is implemented with no downgrade risk and a single factor. ULs are expressed as percentages of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

Figure 2 shows the granularity effect when the benchmark is applied to our bond data. The benchmark is implemented in the simplest way, that is without downgrade risk and with a single systematic risk factor. The difference in unexpected loss is larger at the beginning of the sample period because the sample size increases with time. The negative correlation between the number of exposures and the unexpected loss difference between the two models is easily inferred from Figure 3.

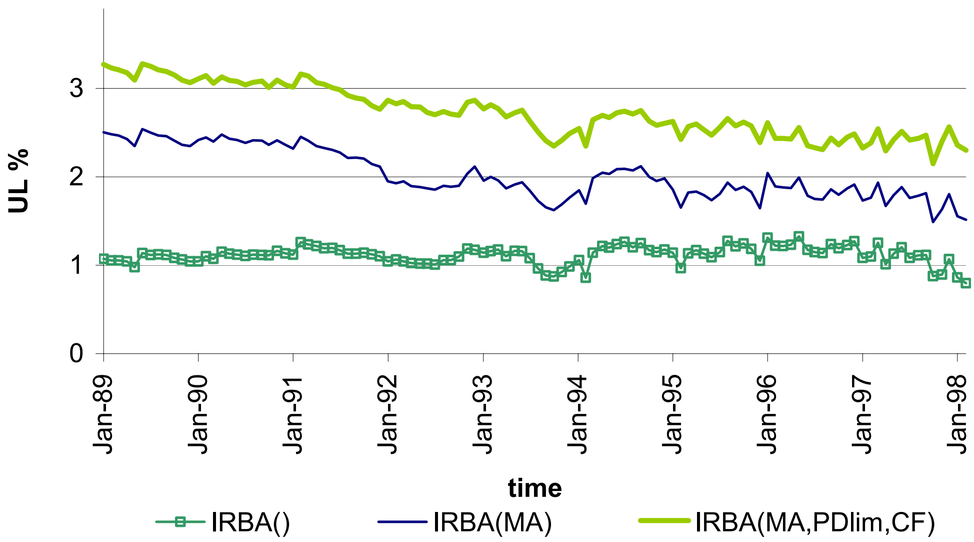
Figure 3. UL difference and granularity.



Note: The UL difference is the difference between the benchmark and the ASRF ULs. ULs are expressed as percentages of expected portfolio value at time t + 1 year. The benchmark model is implemented with no downgrade risk and a single factor. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

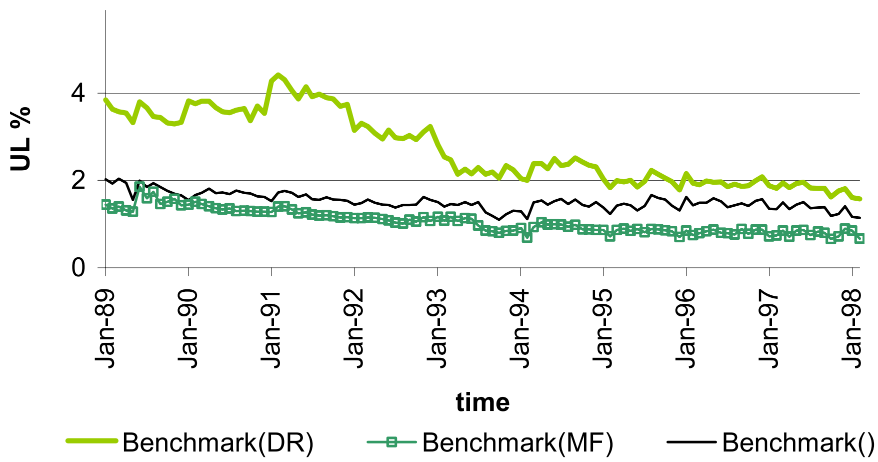
We shall now present a temporal breakdown of the impact on the unexpected loss of those assumptions of the IRBA and the benchmark that differentiate these models from the ASRF and whose average effect was reported in Table 3. Figure 4 shows how the IRBA unexpected loss increases when the maturity adjustment, the PD lower bound and the calibration factor are introduced. The noticeable fall in the capital requirement of the full IRBA is mainly due to a declining average effective maturity of the portfolio which goes from 4.6 years at the beginning of the sample period to 3.2 years at the end of the period. Lower effective maturity directly reduces the maturity adjustment in (3) and (4) thus generating the pattern we observe. Figure 5 illustrates how the benchmark reacts to the introduction of downgrade risk and multiple systematic risk factors. The figure reveals that downgrade risk falls markedly between January 1991 and April 1993 causing the UL to drop by about 50%.

Figure 4. IRBA unexpected loss under different assumptions



Note: In the picture we report the unexpected loss of the IRBA under three scenarios: IRBA(MA,PDlim,CF) which includes maturity adjustment, default probability floor and calibration factor; IRBA(MA) with only the maturity adjustments and IRBA() with none of the above which is the same as the ASRF model. ULs are expressed as percentages of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

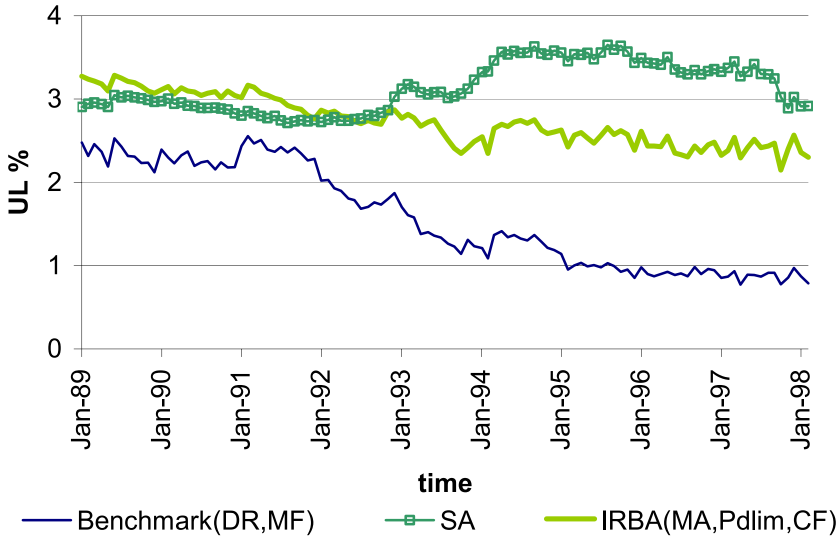
Figure 5. Benchmark unexpected loss under different assumptions



Note: In the picture we report the unexpected loss of the benchmark model under three scenarios: Benchmark(DR) with downgrade risk and one systematic factor, Benchmark(MF) with multiple factors and no downgrade risk and Benchmark() with no downgrade risk and one systematic factor. ULs are expressed as percentages of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

Finally, we investigate the core question of this study which pertains to the difference in capital charges produced by the full implementation of both models as well as the SA. Figure 6 shows that both Basel II approaches yield higher capital requirements than the benchmark and increasingly so as time goes by. The divergence is particularly striking from 1993 onward and peaks in April 1997 when IRBA and SA are about 196% and 322% higher than the benchmark respectively.

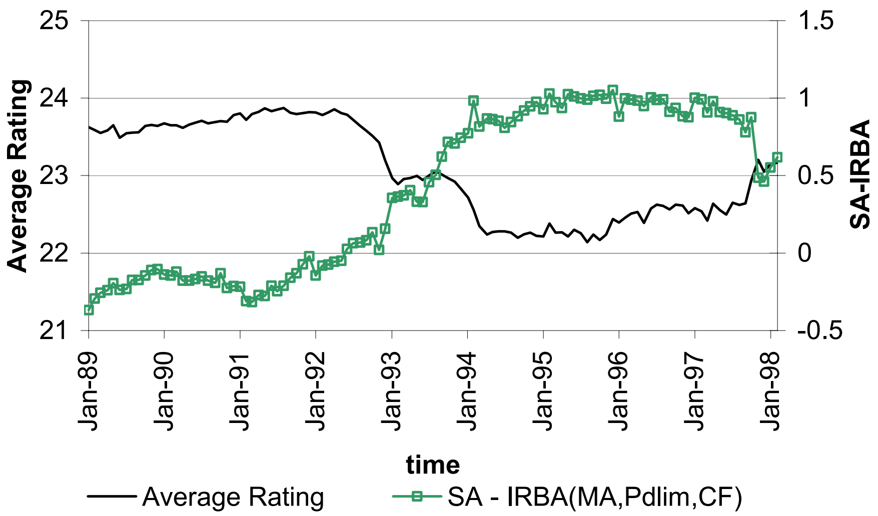
Figure 6. UL comparison: Benchmark, SA and IRBA.



Note. In the Figure the benchmark is implemented with downgrade risk and multiple factors while the IRBA includes the maturity adjustment, the default probability floor and the calibration factor. The UL is expressed as a percentage of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

The Figure also indicates that SA and IRBA start to diverge from the beginning of 1993. The SA may only produce higher capital charges when the average rating of the assets in the portfolio declines. From the above one may infer that the SA may become substantially more conservative than the IRBA as credit quality deteriorates. This point is summarised in Figure 7, which shows how the difference between IRBA and SA appears to be tightly related to the average rating in the portfolio. It should be stressed however, that our sample does not cover the whole rating scale and hence our conclusions may not apply to portfolios that have a very low credit quality. Indeed, Sironi and Resti (2007b)[20] show that for a given maturity (2.5 years) and recovery rate (45%) and given default rates associated with each rating category, the difference between the SA and the (foundation) IRBA may go up or down. In their example, the SA produces increasingly higher capital requirements than the IRBA as the average quality of the portfolio declines from AA to A and from A to BBB, while the distance between SA and IRBA falls as one moves further down the rating scale. Eventually, the IRBA overtakes the SA in portfolios with B and CCC average rating.

Figure 7. Average rating and discrepancy between IRBA and SA



Note. In the Figure the line with squares is the difference in capital charge between SA and the IRBA implemented with all adjustments. The thin line is the average rating in the portfolio. To compute the average rating, numerical values have been assigned to individual rating categories as follows: AAA=27, AA+=25, AA=24, AA-=23, A+=22, A=21 … where each further notch down causes the numerical value to decrease by 1.

Next, we test the performance of the three models in portfolios with different risk profile. We construct a high risk and a low risk portfolio with 40 exposures each, the ones with the lowest and highest ratings respectively among those available in our sample at each point in time. The results are reported in Figures 8 and 9. Although, judging from Figure 1, the effect of portfolio concentration on these small size portfolios should produce a noticeable increase of the benchmark UL relative to

[20] See Figure 20.4, page 617.

the IRBA UL, it turns out that, as before, the IRBA yields, in most cases, capital charges that are higher (and often much higher) than the benchmark. So, the maturity adjustment, PD floor and calibration factor in the IRBA more than compensate for the granularity effect in the benchmark. Also, since the number of assets in the portfolio remains constant over time, it follows that the increasing discrepancy between the regulatory models and the benchmark can not be the result of changes in granularity. We will explore the causes of such differences with regression analysis in the next section.

Figure 8. UL comparison in high risk portfolio

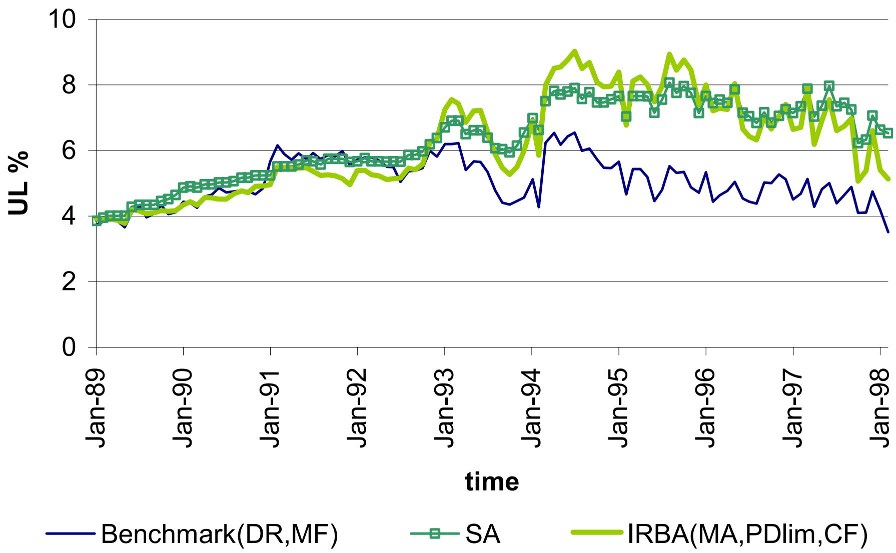
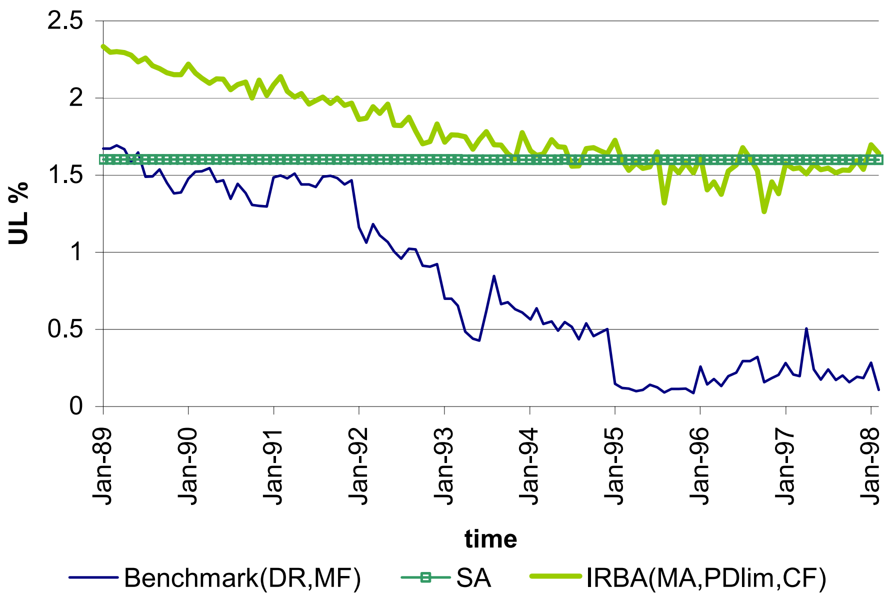


Figure 9. UL comparison in low risk portfolio



Note. In the Figures the benchmark is implemented with downgrade risk and multiple factors while the IRBA includes the maturity adjustment, the default probability floor and the calibration factor. The high (low) risk portfolio includes, at each point in time, the 40 bonds with the lowest (highest) rating in the sample. The UL is expressed as a percentage of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

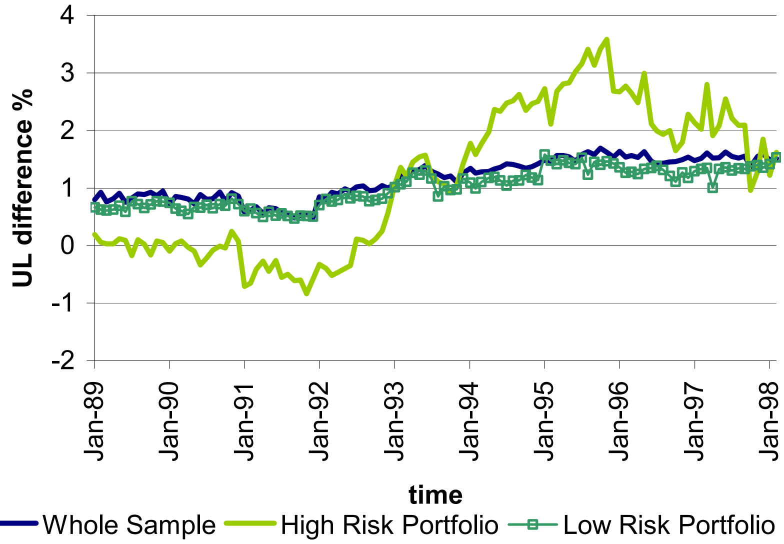
In the low risk portfolio the IRBA systematically overshoots the benchmark. The SA also produces higher capital charges except for the first few months in 1989 when it falls below the benchmark. Also, as the credit quality of the portfolio does not fluctuate much and it always lies in the first rating bucket, the SA capital charge is flat at 1.6%, given by the product of the top rating bucket risk weight (20%) and the 8% Cooke ratio.

Figure 6, 8 and 9 show that none of the Basel II models consistently yields a higher capital charge. However, according to the last quantitative impact study run by the Basel Committee before the final approval of the Basel II framework in 2006 (see BCBS 2006b) the SA yielded on average, across all the 382 banks in the 32 countries that participated in the exercise, a higher capital requirement than either implementation of the IRBA (foundation or advanced)[21]. But, it should be noted that the impact study was done at a particular point in time and hence its result need not

[21] See Table 1 page 2 of BCBS (2006b).

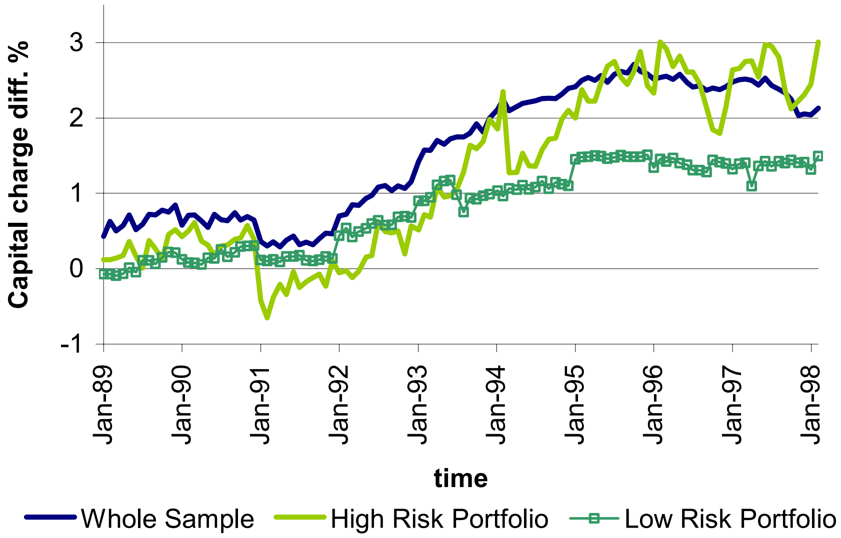
apply in general. The SA will produce higher regulatory capital than the IRBA when economic conditions are particularly benign, as was the case during the last impact study. This is because internally derived default probabilities within each rating category will fall and thus will compress the unexpected loss of the IRBA. On the contrary, the SA capital charges can not reflect such change in PD as they are fixed for each rating category.

Figure 10. IRBA overestimation bias



Note: In the Figure we report the difference between the unexpected loss derived with the IRBA with all the adjustments and the benchmark implemented with downgrade risk and multiple factors. The UL difference is expressed as a percentage of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

Figure 11. SA overestimation bias.



Note: In the Figure we report the difference between the unexpected loss derived with the SA and the benchmark implemented with downgrade risk and multiple factors. The capital charge difference is expressed as a percentage of expected portfolio value at time t + 1 year. Time refers to the date at the VaR horizon, i.e. current time plus 1 year.

Figures 10 and 11 report the difference between the two Basel models and the benchmark and are derived directly from Figures 6,8 and 9. Under the IRBA, the overestimation bias is always positive for the whole portfolio and the low risk sub-portfolio and its average over the sample period is 95% and 82% above the benchmark respectively. In the high risk sub-portfolio the bias is much more volatile and, surprisingly, becomes considerably negative in 1991. The lowest IRBA bias is –0.84% of (expected) portfolio value and occurs in November 1991. This is 37% lower than the benchmark UL. On the other hand, the maximum over-estimation occurs in November 1995 with a whopping 375% increase on the benchmark level.

In the SA the bias exhibits a wider variation than the IRBA bias when we look at the whole portfolio and the low risk sub-portfolio. This is no doubt the result of the lower risk sensitivity of the SA. Indeed the fixed risk weights of the SA do not change when the default probability, asset correlation or downgrade risk vary. So, the SA bias fully reflects the changes in the benchmark due to fluctuations in these factors. On the other hand, the range of variation of the SA bias for the high risk portfolio is comparable to that of the IRBA and is in fact, slightly lower. This indicates that both regulatory models share comparable (and substantial) inaccuracy when measuring the risk in low quality portfolios. Similarly to the IRBA, the lowest and highest SA biases occur in the high risk portfolio. The lowest bias comes about in February 1991 and equals –0.65% of the expected portfolio value, 25% below the benchmark. The highest bias happens in December 1995 and is equal to 3.01%, which is 335% above the benchmark.

In conclusion, Figure 6, 8 and 9 reveal that the regulatory models are closer to each other than to the benchmark. Then, it appears that although the IRBA is a step in the right direction from a fixed risk weight approach such as Basel I and the SA in Basel II, still it has not yet gone half the way towards a full portfolio model. It is also clear that the difference between the two Basel models and the benchmark (Figure 10 and 11) may vary substantially over time, an indication that they exhibit difference sensitivity to mutating economic conditions. This suggests that the extent of the overestimation (and occasional underestimation) can not be simply fixed by a scaling factor. Moreover, the alternating sign of the bias shows that the regulatory models may lead to capital requirements that are not necessarily conservative, as often believed, but could in fact be too low at times.

5.1 Regression Analysis

In this section we explore the causes behind the time variation in the overestimation bias of the Basel II models discussed in the previous section. This will help us to identify the factors that may cause the regulatory models to misrepresent portfolio credit risk. We carry out this analysis by regressing changes in the IRBA and SA biases on changes in the characteristics of the portfolios. These include, (1) average effective maturity, (2) average rating, which denotes both the internal rating for the IRBA and the external rating for the SA,[22] (3) average default probability, (4) portfolio concentration as measured by the Herfindahl index, (5) systematic factor correlation, and (6) the level of downgrade risk. The rating variable has been constructed by assigning a numerical value to each rating as follows, AAA=27, AA+=25, AA=24, AA-=23 and so on. The wider gap between AAA and AA+ was present in conversion tables supplied by Reuters and denotes the absence of the

[22] An interesting area of investigation , which is beyond the purpose of this paper, would be to explore if there are any systematic differences between agency ratings and banks' own ratings and how they impact on SA and IRBA regulatory capital. Differences may occur, for example, because of different emphasis on the rating time horizon (point-in-time or through-the-cycle) and differences in the definition of default.

AAA- rating and probably the greater difference in terms of financial strength between AAA and AA+ than between any other pair of adjacent ratings. Variable (5) is measured indirectly as the impact of changes in factor correlation on the benchmark UL. Downgrade risk is estimated as the difference in the unexpected loss of the benchmark when diagonal rating transition matrices (i.e. without downgrade risk) are replaced with full transition matrices. Regression results are reported in Table 4.

The results indicate that the regulatory models do not share the same sensitivity to all explanatory variables. If the bias of different regulatory models is pushed in different directions by the same variable then banks using different models may be induced, as a result of regulation, to adopt different portfolio allocation and/or lending policies. For instance, the coefficient of effective maturity has a positive sign and is highly significant for the IRBA in the whole portfolio as well as the high and low risk ones. So, banks can decrease the IRBA overestimation bias and hence their capital requirement by decreasing the duration of the assets in their portfolios. This may be achieved for example with policies that favour short term lending or quick amortization of long term loans. On the other hand, the coefficient of effective maturity is either not significant (whole portfolio and high risk sub-portfolio) or negative and highly significant (low risk sub-portfolio) in the SA. This implies that a bank that adopts the SA and has a high quality portfolio can reduce overestimation bias and its capital charge through long term lending, which is exactly the opposite outcome to that obtained with the IRBA.

Higher effective maturity makes the maturity adjustment defined in (4) to go up which ultimately produces higher capital requirements. Given the positive sign of effective maturity in the IRBA regression, higher effective maturity also causes the IRBA estimation bias to increase, an indication that the influence of maturity on portfolio credit risk appears to be over-estimated within the IRBA. This observation is consistent with Kalkbrener and Overbeck (2003) who reached a similar conclusion when investigating the maturity effect in the 2001 version of the New Accord. On the other hand, the negative and highly significant coefficient of effective maturity under the SA in the low risk portfolio results from the influence of maturity on the benchmark model. Longer maturity produces higher volatility of forward bond values and hence higher unexpected loss from the benchmark. Since the SA is not affected by maturity, then when maturity goes up the gap between the

SA and the benchmark will shrink which is the effect captured by the regression coefficient. However, such effect does not seem to be so prominent in the whole sample and in the high risk portfolio.

Downgrade risk has a negative and always significant sign in both the IRBA and SA regression. In other words, when downgrade risk goes up, the benchmark model will reflect the change with higher unexpected losses and the IRBA and SA overestimation bias will fall. It is interesting to note that the maturity adjustment was introduced in the IRBA to account for downgrade risk.[23] But, the fact that the two variables are lowly correlated (0.28 correlation in first differences in the whole sample) and that each can only explain a fraction of the volatility of the other[24] suggest that the maturity adjustment does not accurately capture downgrade risk.

Although the *level* of granularity is important in explaining the difference between IRBA and benchmark (see Figure 2), regression results show that *changes* in granularity are not significant in explaining changes in such difference, probably because they have been gradual over time and hence overshadowed by the effect of other variables. Even though the sign of the concentration variable, which is a measure of granularity, is not significant, still, as one might expect, it is negative. This means that higher concentration pushes the UL of the benchmark higher and closer to the regulatory models' ULs (as the latter remain unaffected by concentration).

The correlation between the external rating and default probability variables is negative, as expected.[25] However, the level of correlation is not as high as to cause concern for multicollinearity (-41% in the whole portfolio, -79% in the high risk portfolio and –61% in the low risk portfolio). The reason for including both variables in the regression is that default probability may change within the same rating category over time. So default probability and rating need not move in unison. Also, changes in the external rating produce an impact on SA while changes in default probability do not.

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[23] See, for example, Resti and Sironi (2007b), p. 611.

[24] When we regress one variable on the other, plus a constant, for the whole sample we find the adjusted R-squared to be 7.2%.

[25] The correlation was estimated on the first difference of the variables.

The rating variable influences both the IRBA and the benchmark in a similar way since a change in rating brings about a change in the rating's associated default probability. However, the negative sign of the variable's coefficient suggests that the distance between the IRBA and the benchmark increases as the rating deteriorates. This may follow because of the parameterisation of the IRBA which appears to become more and more conservative as credit quality goes down.

Similarly, higher values of the default probability variable bring about higher IRBA overestimation bias in the whole (average quality) portfolio. The direction of the relationship is the same as in the high risk portfolio but the default probability coefficient in that instance is not significant. The result in the low risk portfolio is more curious as the default probability coefficient is negative and highly significant. This implies that higher credit quality (i.e. lower PD) causes the gap between IRBA and benchmark to grow, which appears to contradict our previous conclusions. In fact, the finding seems to be the result of the PD floor of 0.03% in the IRBA. As the credit quality improves and the probability of default keeps falling below the 0.03% limit, the benchmark UL will fall while the IRBA UL will not be affected. Hence, the gap between the two opens up. According to this line of reasoning, however, the rating's coefficient in the low risk portfolio should be positive, while it is negative and highly significant. The reason for it, is that the rating variable for the low risk portfolio only changes in the first two years of the sample period, when the usual negative relationship between credit quality and overestimation bias still applies. After that, the average rating of the portfolio is flat at the AAA level (as all assets in the high risk portfolio are AAA rated from January 1991). Therefore, the negative relationship between credit quality and overestimation bias does not carry into the remaining years (i.e. most of the sample period) when the PD limit effect kicks in.

Unlike in the IRBA, in the SA both the rating and default probability coefficients are always negative. The two variables have the same sign because the SA is only affected by ratings and not by default probability. The negative sign of the rating variable means that, similarly to the IRBA, the SA appears to become more conservative than the benchmark as the credit rating deteriorates. On the other hand, a higher value of the default probability variable causes the benchmark unexpected loss to increase while leaving the SA unexpected loss unaffected, which results in a lower SA overestimation bias.

The factor correlation variable is significant only in the high risk portfolio under both regulatory models. Its sign is negative in the high risk portfolio because if factor correlation goes up (down) the benchmark UL will go up and the overestimation bias will have to fall (increase) as the variable does not have any bearing on the regulatory models.

It should be noted that the low risk portfolio under both IRBA and SA produces coefficients for all the explanatory variables, with the exception of effective maturity, that have very similar values (often identical up to three digits). This is because the IRBA and SA overestimation biases in the low risk portfolio are highly correlated (65% on first differences) as they are overwhelmingly influenced by the behaviour of the benchmark model (see Figure 9).[26]

6. Conclusion

In this paper we test the accuracy of the new credit risk measurement techniques introduced with Basel II. We do so by comparing the credit risk measures produced by the new regulatory framework with those obtained with a benchmark model that removes several of the restrictive assumptions of the former. We find that the discrepancies between regulatory models and the benchmark may be large. Our results may be summarised as follows: (1) The regulatory models are typically more conservative than the benchmark and may occasionally produce risk estimates that are more than three times higher than the benchmark level. This should raise some concern as the finding combined with the higher risk sensitivity of the new regulation may well exacerbate credit rationing in periods of economic recession. (2) Credit risk underestimation is also possible although its magnitude during our observation period is small compared to the overestimation bias (37% and 25% below the benchmark under the IRBA and the SA respectively). The implication is that banks may at times be over-exposed to credit risk, despite the conservative approach taken in devising the new rules. (3) Contrary to the evidence presented in the last quantitative impact study undertaken by the Basel Committee (see BCBS 2006) we find that the standardised approach may yield lower capital requirements

[26] The SA unexpected loss is constant over the sample period so the SA bias is entirely driven by the benchmark loss. In the case of the IRBA, although its unexpected loss changes, it does so with little volatility, so again the IRBA bias is dominated by the benchmark loss.

than the internal rating based approach, when default rates are high and the portfolio has long duration. (4) The difference between the regulatory models and the benchmark depends on the combined effect of several variables. As a result, the discrepancy could not be corrected easily, for example with the use of a constant scaling factor. (5) We find the more advanced internal rating based model (IRBA) to yield risk measures that are on average closer to the standardised approach than to the benchmark model. This suggests that although the IRBA and the benchmark are both portfolio models, the simplifying assumptions in the IRBA offset a large proportion of the benefits of a portfolio approach to credit risk modelling. (6) Different regulatory models can produce different incentives and, as a consequence, different portfolio allocation distortions in banks. For instance, the adoption of the IRBA may induce banks to shorten the duration of their assets to attract lower capital requirements and align regulatory capital with economic capital. On the other hand, the SA has little sensitivity to asset duration. So, banks could successfully engage in regulatory capital arbitrage by investing in assets with longer duration. (7) Finally, we find that the maturity adjustment appears to be a poor proxy for downgrade risk.

We should emphasise that our conclusions are based on the benchmark we employ in this study. Although the chosen benchmark provides a natural way to relax the assumptions in Basel II and is a widely popular model, its predictive ability has not been thoroughly investigated yet, partly due to data availability issues which make backtesting problematic.[27] Furthermore, in this work we do not consider possible generalisations of the benchmark in which recovery risk and credit spread risk are accounted for as suggested by Kiesel et al (2001). These generalisations are likely to increase the capital requirements implied by the benchmark. However, this will not necessarily result in a greater consistency between the regulatory models and the benchmark as the additional risks, which are not captured by the regulatory models, will create further points of departure between the two. Moreover, the introduction of these risks leaves open the question of how to model the dependence between credit spreads, recovery rates and transition rates. We leave the investigation of these issues to future research.

[27] For a first analysis of the out-of-sample performance of such benchmark see Nickell et al (2007).

Appendix. Derivation of downturn probability of default in the internal rating based approach

Following Vasicek (2002), let us assume that the asset return Q_S of any borrower s in a loan portfolio depends on one systematic risk factor only, X, and that the asset correlation between any two borrowers is constant and equal to R. Also, assume that the variables Q_S for s=1,2,… are jointly standard normal. Then, Q_S will be

$$Q_S = X\sqrt{R} + Z_S\sqrt{1-R}$$

where X and Z_1, Z_2, … are mutually independent standard normals. The unconditional probability of default for borrower s is simply,

$$PD_S = P(Q_S < Q_{S,d}) = \Phi(Q_{S,d})$$

where $Q_{S,d}$ is the default threshold for borrower s. On the other hand, the conditional probability of default depends on the value taken by the systematic factor X. Let us denote such value as x. Then, the conditional probability can be written as,

$$PD(X = x)_S = P(Q_S < Q_{S,d} \mid X = x) = P\left(x\sqrt{R} + Z_S\sqrt{1-R} < Q_{S,d}\right)$$

which yields,

$$PD(X = x)_S = P\left(Z_S < \frac{Q_{S,d} - x\sqrt{R}}{\sqrt{1-R}}\right) = \Phi\left(\frac{Q_{S,d} - x\sqrt{R}}{\sqrt{1-R}}\right)$$

In a downturn X will be very low (that is very negative). Let us call the value of X in a downturn, x_{down}. Basel II assumes a downturn scenario that occurs once every 1000 years. Then, x_{down} in Basel II will be,

$$x_{down} = \Phi^{-1}(0.001)$$

So, the probability of default of borrower s conditional on a downturn that occurs with the above frequency will be,

$$PD(X < x_{down})_s = \Phi\left(\frac{Q_{s,d} - \Phi^{-1}(0.001)\sqrt{R}}{\sqrt{1-R}}\right)$$

or, equivalently,

$$PD(X < x_{down})_s = \Phi\left(\frac{\Phi^{-1}(PD_s) + \Phi^{-1}(0.999)\sqrt{R}}{\sqrt{1-R}}\right)$$

which is the expression we find in Basel II documents.

References

Altman Edward I. and Anthony Saunders (2001) "An analysis and critique of the BIS proposal on capital adequacy and ratings", Journal of Banking & Finance 25 (2001) 25-46.

Basel Committee on Banking Supervision, (1988) “International Convergence of Capital Measurement and Capital Standards”, Bank for International Settlements, Basel.

Basel Committee on Banking Supervision, (2005) “Studies on the Validation of Internal Rating Systems”, Bank for International Settlements working paper No.14, Basel.

Basel Committee on Banking Supervision, (2006a) “International Convergence of Capital Measurement and Capital Standards”, Bank for International Settlements, Basel.

Basel Committee on Banking Supervision, (2006b) “Results of the fifth quantitative impact study”, Bank for International Settlements, Basel.

Bhatia, M., Finger, C. C. and Gupton, G. M., (1997) "Creditmetrics-Technical Document," JP Morgan, New York.

Calem, Paul S. and Michael LaCour-Little (2004) “Risk-based capital requirements for mortgage loans” Journal of Banking and Finance 28, 647–672

Carey, Mark (2001) “Some evidence on the consistency of banks’ internal credit ratings” Federal Reserve Board working paper, Washington.

Carey, Mark and Mark Hrycay (2001) “Parameterizing credit risk models with rating data”, Journal of Banking and Finance 25, 197-270.

Carty, L. V. and Lieberman, D. (1996) "Corporate bond default and default rates 1938-1995," Moody’s Investors Service, Global Credit Research, January.

Crouhy, Michel, Dan Galai and Robert Mark. (2000) "A Comparative Analysis Of Current Credit Risk Models," Journal of Banking and Finance, v24(1-2), 59-117.

Gordy, Michael B. (2003) “A Risk-Factor Model Foundation for Ratings-Based Bank Capital Rules” Journal of Financial Intermediation v12, n3 (July), pp. 199-232.

Gordy, Michael B. and Bradley Howells (2006) “Procyclicality in Basel II: Can we treat the disease without killing the patient?” Journal of Financial Intermediation 15, 395–417.

Israel, Robert B., Jeffrey S. Rosenthal and Jason Z. Wei. "Finding Generators For Markov Chains Via Empirical Transition Matrices, With Applications To Credit Ratings," Mathematical Finance, 2001, v11(2,Apr), 245-265.

Jacobson, Tor, Jesper Lindé and Kasper Roszbach (2005) “Credit Risk Versus Capital Requirements Under Basel II: Are SME Loans and Retail Credit Really Different?” Sveriges Riksbank working paper, Stockholm.

Jacobson, Tor, Jesper Lindé and Kasper Roszbach (2006) “Internal ratings systems, implied credit risk and the consistency of banks’ risk classification policies” Journal of Banking & Finance 30, 1899–1926.

Jarrow, R. A., D. Lando and S. M. Turnbull. "A Markov Model For The Term Structure Of Credit Risk Spreads," Review of Financial Studies, 1997, v10(2,Summer), 481-523.

Kalkbrener, M. and L. Overbeck (2003) “The Maturity Effect on Credit Risk Capital” in Credit Risk Modelling, the Cutting Edge Collection, edited by Michael Gordy, Risk Books, London.

Kiesel, Rudiger, William Perraudin and Alex Taylor (2001) “The structure of credit risk: spread volatility and ratings transitions” Bank of England working paper.

Krahnen, Jan Pieter and Martin Weber (2001) "Generally accepted rating principles: A primer" Journal of Banking & Finance 25, 3-23.

Linnell, Ian (2001) "A critical review of the new capital adequacy framework paper issued by the Basle Committee on Banking Supervision and its implications for the rating agency industry" Journal of Banking & Finance 25, 187-196.

Lopez, Jose A. (2004) “The empirical relationship between average asset correlation, firm probability of default, and asset size”, The Journal of Financial Intermediation, Volume 13, Issue 2 (April), 265-283.

Nickell, P., Perraudin, W. and Varotto, S. (2007) “Rating-based Credit Risk Modelling: An Empirical Analysis”, forthcoming in the International Review of Financial Analysis.

Perli, Roberto and William I. Nayda (2004) “Economic and regulatory capital allocation
for revolving retail exposures” Journal of Banking and Finance 28, 789–809.

Resti, A. and A. Sironi (2007a) “The risk weights in the New Basel Capital Accord: Lessons from bond spreads based on a simple structural model”, Journal of Financial Intermediation, 16(1), 64-90.

Resti, A. and A. Sironi (2007b) Risk Management and Shareholders’ Value in Banking. From Risk Measurement Models to Capital Allocation Policies. Wiley Finance, Chichester (England).

Sironi, Andrea and Cristiano Zazzara, (2003) “The Basel Committee proposals for a new capital accord: implications for Italian banks” Review of Financial Economics 12, 99–126.

Vasicek, O.A. (2002). The distribution of loan portfolio value. Risk.

Vazza, D., D. Aurora and R. Schneck (2005) "Annual 2005 Global Corporate Default Study And Rating Transitions" Global Fixed Income Research, S&P’s.

Table 1. Portfolio Characteristics

Country	No. of firms	%
United States	233	46.4
Japan	42	8.4
Netherlands	36	7.2
United Kingdom	27	5.4
Germany	17	3.4
France	16	3.2
Other	131	26.1

Industry	No. of firms	%
Financial Services	160	31.9
Banking	111	22.1
Utilities	27	5.4
Energy	20	4.0
Merchandising	15	3.0
Telecoms	15	3.0
Other	154	30.7
Total	502	

Table 2. Risk Weights under the Standardised Approach in Basel II

Rating	Sovereign	Banks (Option 1)	Banks (Option 2)	Corporates
AAA	0	0.2	0.2	0.2
AA+	0	0.2	0.2	0.2
AA	0	0.2	0.2	0.2
AA-	0	0.2	0.2	0.2
A+	0.2	0.5	0.5	0.5
A	0.2	0.5	0.5	0.5
A-	0.2	0.5	0.5	0.5
BBB+	0.5	1	0.5	1
BBB	0.5	1	0.5	1
BBB-	0.5	1	0.5	1
BB+	1	1	1	1
BB	1	1	1	1
BB-	1	1	1	1
B+	1	1	1	1.5
B	1	1	1	1.5
B-	1	1	1	1.5
<B-	1.5	1.5	1.5	1.5
Unrated	1	1	0.5	1

Table 3. Impact of IRBA and the Benchmark models' assumptions on Capital Charge

This table reports the marginal capital charges produced by the various assumptions underlying the IRBA model in Basel II and the benchmark model. Estimates are averages over the sample period based on the implementation of the models on our bond data. Marginal effects are percentages expressed in terms of the capital charge of the ASRF model of Gordy (2003).

Assumptions	Marginal Capital Charges, % of ASRF
	IRBA
Maturity Adjustment	82.4
PD floor	50.4
Calibration factor	14.0
IRBA Total	146.8
	Benchmark
Granularity	36.9
Multiple Factors	-41.5
Downgrade Risk	108.6
Benchmark Total	104.0

Table 4. Regression of changes in Basel II overestimation biases on changes of portfolio characteristics

The table reports the estimation results of regressions that aim to explain changes in the overestimation bias in Basel II's internal rating based approach (IRBA) and standardised approach (SA) relative to the benchmark model. The estimation bias is measured as the difference between the unexpected loss obtained from one of the Basel II approaches and that of the benchmark model. The benchmark model is CreditMetrics implemented with the inclusion of downgrade risk and multiple systematic factors. The sample includes monthly observations over the period from January 1989 to February 1998. Explanatory variables are in first differences and include: portfolio "Concentration" as measured by the Herfindahl index; average "rating"; average "default probability"; average "effective maturity"; "downgrade risk" which is estimated as the difference in unexpected loss of the benchmark model when diagonal rating transition matrices (i.e. without downgrade risk) are replaced with full transition matrices; and the variable that measures systematic "factor correlation". The "high risk portfolio" ("low risk portfolio") columns denote a portion of the sample including, at each point in time, the 40 firms with the lowest (highest) rating. Parameters are estimated with ordinary least squares. ***,**,* indicate significance at the 1%, 5% and 10% confidence level respectively. Confidence intervals are estimated with standard errors adjusted for autocorrelation and heteroscedasticity.

	IRBA overestimation bias			SA overestimation bias		
	Whole Portfolio	High Risk Portfolio	Low Risk Portfolio	Whole Portfolio	High Risk Portfolio	Low Risk Portfolio
Constant	0.006	-0.007	0.002	0.001	0.017	0.002
Concentration	-10.32	-	-	-80.77	-	-
Rating	-0.162	-0.541***	-1.111***	-0.357***	-0.154	-1.111***
Default Prob.	21.74***	0.147	-23680.2***	-52.14***	-40.69***	-23685.6***
Effective Maturity	0.482***	0.411**	0.319***	0.010	-0.093	-0.112***
Downgrade Risk	-0.565***	-0.233*	-0.331***	-0.649***	-0.332***	-0.331***
Factor Correlation	0.016	-0.287***	-0.226	0.055	-0.195***	-0.226
Adj. R-squared	0.452	0.609	0.644	0.481	0.387	0.531