Internal Ratings Systems, Implied Credit Risk and the Consistency of Banks' Risk Classification Policies.

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Abstract

Although much research has been done on external ratings, much less is known about banks´ internal ratings. This paper aims at improving our understanding of internal risk rating systems at large banks and the way in which they are implemented, to verify if they will provide regulators with a consistent picture of banks' loan portfolio credit risk, as is envisioned in the Basel II Accord. An important property of our work is that we derive our measures of credit risk without making any assumptions about correlations between loans, due to the fact that the size of the data allows us to apply Carey's [16] non-parametric Monte Carlo re-sampling method.

We find that default risk is most likely not homogeneous within rating classes, as regulators whould expect it to be.Our results also reveal substantial differences between the implied loss distributions of the two banks with equal "regulatory" risk profiles; both expected losses and the credit loss rates at a wide range of loss distribution percentiles vary considerably. Such variation is likely to translate into different levels of required economic capital. As a result, incentives could transpire for some banks to securitize part of their loan portfolio to reduce costs, as happened under the Basel I Accord, or to change the risk profile of their loan portfolio to generate higher returns.

Our results also confirm that not only the design of a rating system itself, but also a portfolio's rating grade composition, the size of a bank, the preferred level of insolvency risk for a bank and the forecast horizon are quantitatively important for the shape of credit loss distributions and thus for banks required capital structure. With common portfolio parameters credit risk can, for example, be reduced by up to 40 percent by doubling portfolio size. This make clear that the calibration of the Basel risk weight mappings and banks' internal borrower risk rating systems are not yet synchronized in a way that they result in consistent estimates of portfolio credit risk for regulators.

Key words: Internal ratings, credit risk, tails, Value-at-Risk, banks, Basel II.

JEL codes: C14, C15, G21, G28, G33, .

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1 Introduction

Although non-financial corporate debt (bond issues and privately issued debt) has become more common in the past 10-20 years, bank loans are still the prime source of business finance, especially for small and medium size enterprises (SME's). As a consequence, banks' ex-ante assessment of the riskiness of loan applicants and their resulting decision to grant credit or not, or to provide credit only at some risk-adjusted interest rate, is of great importance for businesses.

Bank regulators increasingly lean on the risk assessments made by banks: in the Basel Committee´s new capital adequacy rules, the so called Basel II Accord [11], internal risk ratings produced by banks have been given a prominent role. Unlike previous regulation, the rules of Basel II will make the size of the required buffer capital contingent on banks' appraisal of ex-ante *individual* borrower risk. It will be up to the banks to characterize the riskiness of the borrowers and loans in their portfolios by means of a relatively small number of risk categories or 'rating classes'.[1] Although the new supervisory rules will generate better incentives for banks to efficiently allocate resources with a socially acceptable level of risk, inconsistencies in ratings will also become a source of adverse selection and new business risk for banks.

Assessing borrower risk is generally considered one of the banking industry´s core activities. Economic theory explains banks' role as an intermediary by their supposedly superior ability to collect and assess information with respect to borrower risk. Research has been extensive in this area, since Diamond [23] formalized the concept of delegated monitors and Fama [26] put forth the hypothesis that banks were special relative to alternative lenders. Lummer and McConnell [38] and Mester, Nakamura and Renault [39], for example, describe the details of bank monitoring – based on bank access to borrowers' transaction accounts – that may make banks superior monitors of loans.

Banks' internal credit ratings summarize the risk properties of the bank loan portfolio and are used by banks to manage their risk. One usually thinks these ratings as monotonic transforms of the probability of default, although Loffler [37] and Altman and Rijken [8] have argued that credit ratings may have more complex functions. Internal ratings can also be considered to contain evidence of the private information that banks possess, and distinguishes them from public ratings of credit bureaus and bond rating agencies. These organizations also provide

[1] Altman and Saunders [10] have criticized the Basel proposal extensively because of its implications. They found, among other things, that relying on traditional agency ratings may produce cyclically lagging rather than leading capital requirements and that the risk based bucketing proposal lacks a sufficient degree of granularity. Among other things, they advise to use a risk weighting system that more closely resembles the actual loss experience on loans. Criticism like this has spurred subsequent research by authors like Carling, Jacobson, Lindé and Roszbach [22], Dietsch and Petey [24], Estrella [25], Calem and LaCour-Little [14], and Hamerle, Liebig, and Rösch [30], who have made an effort to apply credit risk models to the ultimate goal of calculating capital requirements under a variety of alternative systems.

credit ratings for businesses, but base them on public information that should be integrated into the internal ratings of banks.

However, despite their importance, still relatively little is known about the functioning and consistency of banks' internal ratings and the implied ex-ante risk in bank loan portfolios. The workings and effects of *external* ratings have been studied extensively. Altman [5] develops and calculates different measures of default for Standard & Poor's (S&P) rated bonds and studies [6] the determinants and implications of external rating changes. Moon and Stotsky [40] and Cantor and Packer [15] model the determinants of differences between Moody´s and S&P´s ratings and between Moody's/S&P's and third party external ratings for municipal and corporate bonds, while Poon [43] compares solicited and unsolicited ratings and finds that the latter are biased downwards. Nickell, Perraudin and Varotto [42] model Moody's rating class transition probabilities with a number of micro-variables and a business cycle index. Blume, Lim and Mackinlay [13] investigate what has been driving the decline in average credit rating for U.S. corporate bonds and conclude that the standards applied by external rating agencies became more stringent in the 1990s.

With respect to internal ratings and their implications for the ex-ante credit risk in bank loan portfolios, most research done so far has focused on examining the *general design* of banks' internal ratings systems and suggesting how specific design choices are likely to affect the eventual functioning of Basel II. Crouhy, Galai and Mark [21] suggest how a prototype internal rating system could be organized analogous to the systems used by Moody´s and S&P´s. Treacy and Carey [46] provide a broad and qualitative description of how ratings systems at large U.S. banks are constructed and present some descriptive statistics on, among other things, the distribution of loans over rating classes. Gordy [29] shows that ratings-based bucket models of credit can be reconciled with the general class of credit Value-at-Risk (VaR) models. From a simulated bank loan data set, Carey [17] concludes that the success of the internal ratings based (IRB) approach will depend on the extent to which it will take into account differences in assets and portfolio characteristics, such as granularity, risk properties and remaining maturities. Jacobson, Lindé and Roszbach [33] find that IRB parameters such as the target forecasting horizon, the method to estimate average probabilities of default (PD's) and banks´ business cycle sensitivity will also affect the way in which the IRB system can function. Carey and Hrycay [19] study the effect of internal risk rating systems on estimated portfolio credit risk and find that some of the commonly used methods to estimate average probabilities of default (PD's) by rating class are potentially subject to bias, instability and gaming. Carling, Jacobson, Lindé and Roszbach [22] study one bank's internal rating system, its risk properties, business cycle sensitiveness and workings under the proposed Basel rules.

About the actual functioning of internal rating systems and their influence on the measurement of the ex-ante riskiness of bank loan portfolios relatively little is still known. To our knowledge, the only work until now that has *compared* risk rating systems between banks is Carey [18].[2] Carey studies the consistency of rating assignments in a sample from 20 U.S. banks loan portfolios and finds that firms are rated identically across banks in 45 percent of all cases; 95 percent is rated within two grades. He also shows that the implied capital allocations differ by less than a percentage point for half of the borrowers, but up to 10 percentage points at the 95th percentile. Unfortunately, Carey's data set is rather small and the information available on each borrower is limited. As a result, many important issues like the consequences that the formal organization and actual implementation of an internal rating system can have for a bank's portfolio credit loss distribution (i.e. its risk profile) could not be looked into. Other questions that remain be uninvestigated hitherto relate to the match between the economic and regulatory capital requirements, the sources of rating differences between banks and the sensitivity of credit loss distributions to both changes in the riskiness of lending policies (intrabank) and risk profiles (interbank) when risk is defined in terms of portfolio shares of internal rating grades.

This paper attempts to fill part of this gap by comparing the internal rating systems and implicit credit loss distributions for two Swedish banks'. For this purpose we use the loan performance data and corresponding internal ratings from their complete business loan portfolios over the period 1997Q1 - 2000Q1 to derive the implied portfolio loss distributions. By exploiting the considerable size of the dataset and applying Carey's [16] non-parametric Monte Carlo resampling method we can avoid imposing any unneccessary assumptions about the correlation structure between loans.[3] Another attractive feature of our approach is that we have access to a subsample of 2,880 firms (17,476 observations) that simultaneously held loans in both banks. This enables us to identify the risk profile of a portfolio that can be considered equally risky in both banks, despite the fact that the banks had rating systems with an unequal number of rating grades.[4]

The main purpose of this paper is to study if and to what extent credit loss distributions of banks, that are required by their regulator(s) to report about the riskiness of their loan portfolios in terms of a distribution of credit over internal rating classes, can vary despite the fact that they have equal regulatory "risk profiles" at first sight.[5] We find that default risk is most likely

[2] Carey also refers to a study done under the auspices of the Risk Management Association and published in the RMA Journal (2000) Vol.83 No.3, pp 54- 61, *EDF Estimation : A Test-Deck Exercise.* However, this study only reports differences in probabilities of default and no informattion on internal ratings or capital allocations. The Basel Committee's latest quantitative impact study, QIS3 [12], only contains information on capital requirements.

[3] For the bank fewer but bigger loans in the portfolio we have approximately 180,000 observations, while the other bank provided us with just over 300,000 loan observations. During the sample period, the two banks accounted for approximately 40% of the Swedish business loan market.

[4] Their default definition was identical though.

[5] Under the new Basel II regulatory framework, major international banks will implement internal rating systems. Regulatory capital will then be set by the regulator by applying a rating grade specific or loan specific risk weight function to all credit. Basel II also entitles regulators to approve the models by means of which banks

not homogeneous within rating classes, as regulators would expect it to be. Our findings suggest that the banks in our dataset have not implemented internal borrower risk rating systems in such a way that they result in consistent estimates of portfolio credit losses. We reveal significant differences in the implied riskiness of a loan portfolio with an equal risk profiles between the two banks: both expected losses and the credit loss rates at a wide range of loss distribution percentiles vary considerably between banks. In normal banking practice, such variation would likely to translate into different levels of the required economic capital the banks will need to support their risk taking activities. If this wedge between the regulatory and economic cost of credit becomes sufficiently big, incentives could transpire for some banks to securitize part of their loan portfolio to reduce costs, as happened under the Basel I Accord. Another possibility is that banks will change the risk profile of their loan portfolio to generate higher returns. It also suggests that some elements of an internal rating system, such as the number of grades and the dispersion of credit over rating classes may constitute strategic choice parameters for a bank. Banks could thus adjust their rating systems to reduce regulatory costs. With common portfolio parameters credit risk can, for example, be reduced by up to 40 percent by doubling portfolio size.

The organization of the remainder of this paper is as follows. First, in Section 2, we begin with a characterization of the two banks' business loan portfolios. Section 3 describes and examine the banks' internal rating systems. Section 4 describes our methodology and presents our Monte-Carlo simulation results. Here we also display both banks´ IRB capital requirements. Section 5 concludes the paper.

2 Data

This section provides a detailed description of the data that we use in Sections 3 and 4. The primary sources of our data are two of the four major Swedish commercial banks. Both banks are general commercial banks, with a nationwide branch network serving both households and businesses; neither of them has any clear specialization profile within these groups. For bank A, the data set is a panel consisting of 338,118 observations, covering 13 quarters of data on all 39,521 Swedish *aktiebolag* firms that had one or several loans outstanding at the bank on the last day of at least one quarter between January 1, 1997, and March 31, 2000. For bank B we have 183,392 observations on 20,966 *aktiebolag* between January 1, 1997, and June 30, 2000. *Aktiebolag* are by approximation the Swedish equivalent of US corporations and UK limited businesses. Swedish law requires every *aktiebolag* to have at least SEK 100.000 (approximately US \$ 10,000) of equity, to be eligible for registration at the Swedish Patent and Registration Office (PRV). However, a large part of the sample consists of small enterprises: respectively 65%

estimate loss distributions and credit risk measures such as VaR.

and 53% of the banks' observations concern businesses with 5 or fewer employees. During the overlapping sample period, from January 1, 1997 until March 31, 2000, 2,880 of these businesses simultaneously have one or more loans in both banks for at least one quarter. This results in 17,476 'overlapping´ observations, making the average overlap duration just over six quarters.

Both banks have supplied a full history of internal credit related data for all debtors, including the unique, government provided, firm identification number, the internal risk rating, the risk rating of the firm by the main Swedish credit bureau (Upplysningscentralen), the credit type, the amount of credit granted per type, actual exposure, (an estimate of the available) payment status and a 5 digit industry code. We converted the various types of credit into three broader groups, also used by the banks for certain analytical purposes: short term (less than one year), medium term (between one and three years) and long term lending. Of all borrowers at bank A (B) 69 (71) percent have short term loans and 72 (68) percent have a long term or some other type of loan.[6] Having multiple loans is quite common too: about 30 percent of A's and B's borrowers have both a short term loan and at least one other loan. The average (in-sample) duration of a firm's presence in the bank portfolio is 8.6 (8.7) quarters. On average, bank A's and B's portfolio have a size of SEK 168.4 bn. and 143.7 bn. and contain 24,895 and 12,642 firms respectively; B thus typically grants its borrowers over 50% larger loans than A does: 11.37 mn. kronor on average compared with 6.76 mn. for A.

Table 1: Profile of firms in bank loan portfolios: debtors split up according to employee number, credit line size and total sales (in percentage shares), N_A=323,671, N_B=176,985.

No. employees	A	B	Granted credit (SEK)	A	B	Total sales (SEK mn.)	A	B
0	11.07	14.32	0-50k	13.65	2.37	<.5	12.36	8.10
1	16.72	9.38	50k-100k	13.27	2.24	.5-1	11.00	6.67
2-5	37.67	29.79	100k-250k	19.85	6.53	1-2	15.67	10.56
6-25	24.42	32.46	250k-500k	15.71	12.17	2-3	9.52	8.10
26-50	4.27	6.65	0.5mn-1mn	11.20	20.52	3-4	6.36	6.63
51-100	2.54	3.86	1mn-2,5mn	10.76	23.80	4-5	4.74	5.43
101-250	1.83	2.26	2,5mn-5mn	5.75	12.68	5-7.5	8.08	9.80
250-1000	1.07	0.90	5mn-10mn	3.82	7.97	7.5-10	4.83	6.40
>1000	0.41	0.38	10mn-1bn	5.91	11.59	10-25	12.04	17.17
	100.00	100.00	1bn-	0.08	0.13	25-50	5.63	8.12
				100.00	100.00	50-100	3.76	5.57
						100-250	2.97	4.44
						250-1000	2.07	2.12
						>1000	0.97	0.89
							100.00	100.00

[6] Due to different ways of categorizing loans (according to duration and type) we cannot make detailed comparisons of subsets of the loan portfolios between the banks.

Table 1 offers some perspective on the banks' borrowers: to a great extent both grant loans to small and medium sized enterprises. Of all firms, 65 percent at A and 55 percent at B have 5 or fewer employees; A is somewhat better represented among businesses with 1-5 employees.[7] Only 6-7 percent of all firms at both A and B have more than 25 employees. The third column of Table 1 shows that A is slightly more specialized in small businesses: approximately 40 percent of its firms have sales under SEK 2 mn. and 25 percent even stay below SEK 1 mn., compared to 25 and 15 percent at B. Obviously, B has a larger presence among firms with higher sales; close to 40 percent have revenues over SEK 10 mn. whereas only 25 percent at A do so.

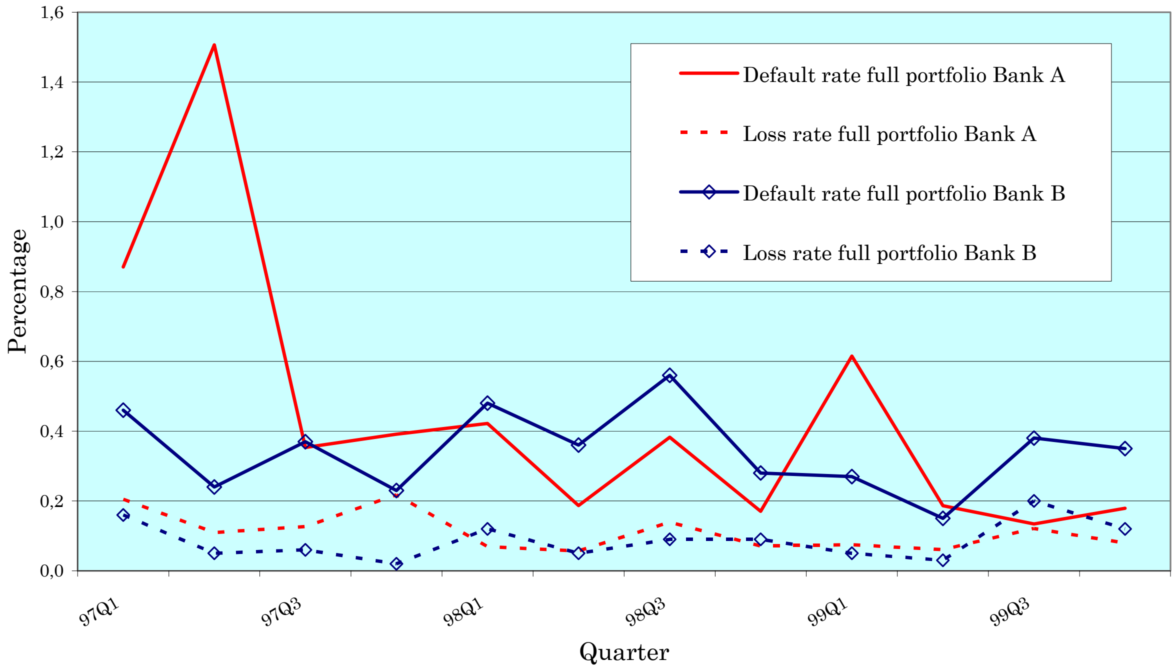
Table 1 also reveals that not only the average but also the median size of credit lines varies between banks, implying that differences not only occur at the tails of the distribution. In bank A the median credit line has a size between SEK 250k and SEK 500k, quite a bit below its average of SEK 6.76 mn., while bank B has a median credit facility between SEK 1 mn. and SEK 2.5 mn., somewhat closer to its average of SEK 11.37 mn. Although it is difficult to identify a single explanation, one can point out some differences. Bank A is strongly represented in the exposure segment up to SEK 1mn. Only about 25 percent of its credits exceed 1 mn. kronor, while over 45 percent of all loans are smaller than SEK 250,000. In bank B, on the other hand, more than 50 percent surpass SEK 1 mn. and only about 10 percent of all loans stay under than 250,000 kronor. About 12 percent of all bank B firms receive more than SEK 10 mn. compared with 6 percent in bank A. In general, B has a bigger share of its borrowers in industries with bigger credit lines, such as real estate, energy & water, and forestry & paper, and in addition lends more to some businesses than A does, for example in telecom and other services.

Figure 1 displays the average default rate and credit loss rate in the complete portfolios of both banks. Both default rates and loss rates reflect the percentage of all loans or credit originating in the specified quarter that default the quarter after. One can make at least three notable observations. First, default rates vary more and are on average somewhat higher in bank A than in bank B. Second, the loss rate is also higher in bank A, but only slightly. And third, loss rates are substantially lower than default rates. The latter phenomenon is a result of two effects. Firstly, both banks extend more credit to firms that have their loans rated in the grades that experience fewer defaults. The major part of all credit is therefore located in better rating grades, which reduces loss rates relative to default rates. Secondly, loans that default are typically substantially smaller than the average loan. The overall effect of these two things is that loss rates are approximately a factor five smaller than the default rates.[8]

[7] Firms without any employees are either owner-run businesses or holding/finance units within a larger concern. Adding them to the category 1-5 employees may therefore blur the picture somewhat when we are interested in the banks' involvement in SME's.

[8] Observe that the default and loss rates displayed here deviate from the corresponding rates in the respective banks overlapping portfolios because of the specific profile of the subsample.

Figure 1: Average quarterly default rates and loss rates in full portfolios of banks A and B.



3 The internal rating systems

Both institutions use internal credit rating systems to rank their borrowers. They follow similar processes to generate the ratings and have comparable risk control mechanisms at their head offices. At least partially these resemblances were due to the fact that they actively exchanged knowledge about their credit risk modeling efforts and experiences during the sample period. For this reason, we will in our description of the ratings systems concentrate our attention to one of them, bank A, and refer to bank B only where we are aware of any differences.[9] Bank A requires each business customer to be assigned to one of 15 credit rating classes, while B uses 7 classes. At A rating class 1 represents the highest credit quality and class 15 is used exclusively for defaulted firms, with the intermediate grades intended to imply a monotonically increasing risk profile. Bank B has the most creditworthy firms in rating class 1 and the defaults are collected in class 7.[10] In both banks, the internal ratings are explicitly meant to reflect borrower default risk, not facility risk, nor the expected loss rate. They operate with quite similar default definitions implying that two conditions must be satisfied for a borrower to be assigned to the default category. First, payments on the principal or interest must be at least 60 days overdue.

[9]Bank A provided us with more detailed information about the internal rating grades' description.

[10]The original system of bank B had the best borrowers in class 7 and the defaults in 1. For the sake of consistency and simplicity, we transformed these ratings so that both banks have the best loans in grade 1, with creditworthiness falling as the rating class increases.

Secondly, a bank official needs to make a judgement and conclude that any such payment is unlikely to occur in the future.[11] A comparison with data from the leading Swedish credit bureau Upplysningscentralen AB (not reported here), shows that ratings A15 and B7 are both highly correlated with (the officially registered) bankruptcy. In general, a rating class default event occurs one or more quarters earlier than a bankruptcy default event. This is most likely due to the length of legal procedures that have to be completed before bankruptcy is officially invoked. In the remainder of this paper, when talking about a default, we will refer to the above definition by the banks: a borrower that is assigned to rating class 15 in bank A or class 7 in B.

Internal ratings at both banks are the outcomes of a judgmental process that, depending on the type of firm (quoted or not) and the size of the exposure, was supported by quantitative tools. Typically, a loan officer manually entered a firm's annual report information and - if there was any - its credit history at the bank into a simple decision tree, which then produced an internal rating as outcome. For small business clients this rating was then compared with the credit rating from the credit bureau (UC). The latter sells firm risk ratings that reflect its estimate of bankruptcy risk over the next 8 quarters. The UC rating is calculated with a logistic regression model that uses information available from the tax authorities, PRV and payment remarks that are reported to UC by the banks and other organizations, such as the tax authorities, as inputs.[12] . For the biggest clients (with exposures over approximately SEK 10 mn) even scores from other models, like Altman's [1] Z-score model, the Zeta model of Altman, Haldeman and Narayanan [7] or the KMV model.[13]. If the internal rating deviated too much, then the manager in charge of this particular loan proposal would enter a discussion with the loan officer about the merits of the client and the reasons why the internal rating deviated so much from other default risk measures. What constituted a substantial deviation was an imprecise qualification, to be interpreted at the discretion of the manager in charge for the particular loan size. Internal ratings were thus always the outcome of a judgmental process in a credit committee, the exact composition of which depended on the size of the loan to be granted (or the existing exposure).

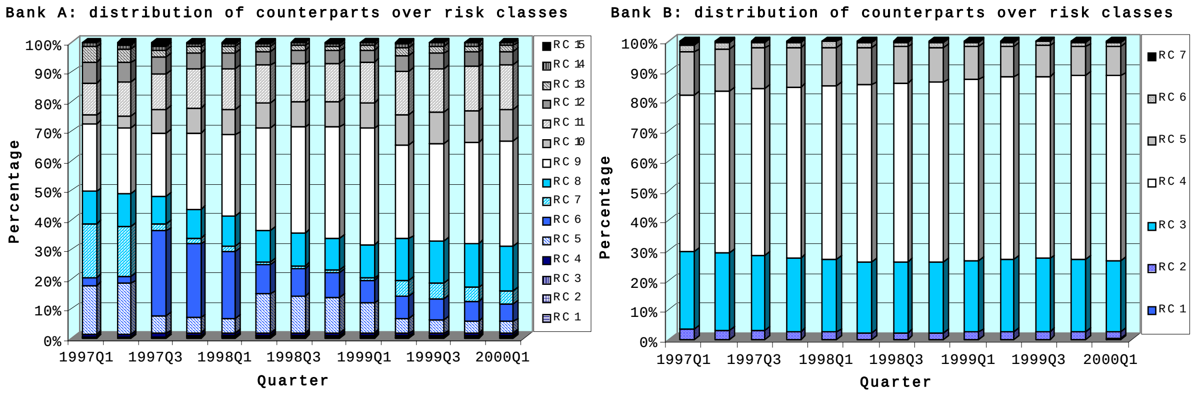
Credit ratings had to be updated at least once every 12 months or whenever a change in the bank's commitment was to take place. This policy was enforced by letting the risk control department at the head office run its own models, usually once a year around August (so that the latest annual report data was available), for all borrowers in the whole loan portfolio. They used credit bureau data to estimate their models and as input to make default risk predictions. The ratings they obtained were then compared with the ratings produced by the loan officers (or the responsible credit committee if there was a large deviation from the credit bureau rating at the time when the rating was created). If they differed much or the rating had not been updated

[11] This definition does not coincide with the 90 days default definition in Basel II.

[12] For details and an evaluation of their model based approach, see Jacobson and Lindé [32].

[13] See www.moodyskmv.com/products/default.html for a description of the KMV model.

Figure 2: Distribution of debtors over risk classes in the complete portfolios of banks A and B.



during the past 12 months, the responsible loan officer was notified and asked to explain what was going on, and potentially requested to update the rating.

Bank A maps these probabilities of default into a rating class scheme such that the classes should mimic the ratings of Moody's and Standard & Poor's. The qualitative criteria are summarized in a borrower rating classification handbook. The handbook provides so called verbal definitions (descriptions) of the properties of firms in a given rating class along a number of dimensions. The banks strive for assigning "through the cycle" ratings, but have also mentioned that they realize that some "surfing" through the cycle is unavoidable. Figure 2 shows how the borrowers in the complete portfolios were distributed over all rating grades. A number of characteristics are worth mentioning. First, both banks allocate a large share of debtors to one risk class. Over the sample period, bank A has between 20

Table 2: Corresponding internal rating in banks A and B.
Table shows, for each rating class, how counterparts in bank A are simultaneously rated in bank B. The distribution over rating class is expressed in percent. Rows sum to 100 percent.

	Bank B							
Bank A	1	2	3	4	5	6	7	Obs.
1	3.90	61.04	29.87	5.19				77
2	0.62	42.77	40.00	16.62				325
3	1.63	40.11	33.39	19.96	4.90			551
4	1.37	42.27	39.75	13.52	3.09			873
5		6.01	42.28	43.95	7.53	0.15	0.08	1315
6	0.20	12.80	57.03	26.66	2.96	0.35		1992
7		23.31	50.92	23.68	1.47	0.61		815
8		1.11	21.65	67.18	8.83	1.00	0.22	1801
9	0.02	3.19	32.76	56.56	6.70	0.50	0.26	5387
10		5.04	53.78	37.43	3.50	0.25		1627
11		2.50	15.27	64.13	17.08	0.85	0.17	1762
12		0.66	11.44	59.20	18.57	5.97	4.15	603
13			1.48	54.07	37.41	5.56	1.48	270
14			2.40	20.36	50.90	20.36	5.99	167
15			5.45	34.55	36.36	1.82	21.82	110
								17675

and 40 percent of all firms in class 9, while bank B has 50-60 percent in rating class 4. To a large extent, this phenomenon reflects the fact that new loans generally enter the system in these two classes. Given the inertia in internal ratings, this automatically creates a concentration in the "entrance" class. At any point in time, bank A has between 95 and 99 percent of all firms in 9 out of its 15 risk classes. Similarly B has about the same share in only 3 rating classes. In bank A, the relative importance of each class within this group of nine varies quite a bit. Grades 5 and 7, for example, almost disappear for a couple of quarters, due to a massive transition into rating class 6. Over time, risk classes 8-12 are gaining ground at the expense of ratings 1-7: the share of the latter in the total portfolio falls from close to 50 percent at the start of the sample period to approximately 30 percent at the end. The main source of this shift lies in the (relative) migration of borrowers from the more creditworthy rating class 5 into 6 and 7 and from 7 into 8 and 9. Also, borrowers move out from the three riskiest categories, 13-15, to safer grades. In bank B, the pattern is simpler and clearer, due to the smaller number of classes: the share of ratings 5 and 6 drops over the sample period, while that of class 4 rises from 50 percent to 60 percent. At the same time, however, the share of rating grade 3 also falls somewhat. The aggregated effect of these composition changes on the riskiness of the portfolios is, however, difficult to determine without a scheme to weigh the loans in each rating class.[14]

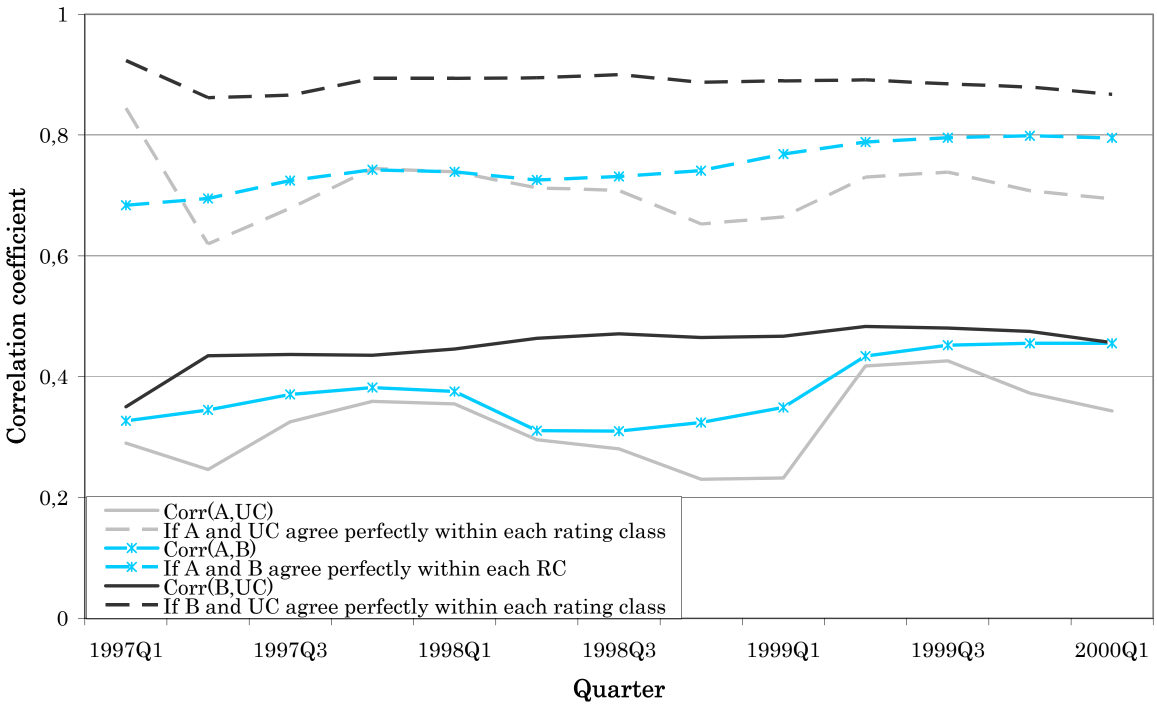
[14] Carling et al. [22] do evaluate the effect of borrower migrations on aggregate risk, by calculating VaR with a credit risk model.

Table 3: Corresponding internal rating in banks B and A.
Table shows, for each rating class, how counterparts in bank B are simultaneously rated in bank A. The distribution over rating class is expressed in percent. Columns sum to 100 percent.

	Bank B							
Bank A	1	2	3	4	5	6	7	Obs.
1	9.68	2.90	0.37	0.05				
2	6.45	8.57	2.11	0.66				
3	29.03	13.63	2.98	1.35	1.88			
4	38.71	22.75	5.62	1.45	1.88			
5		4.87	9.01	7.08	6.88	1.21	1.18	
6	12.90	15.72	18.40	6.51	4.10	4.24		
7		11.71	6.72	2.37	0.83	3.03		
8		1.23	6.32	14.83	11.04	10.91	4.71	
9	3.23	10.60	28.59	37.35	25.07	16.36	16.47	
10		5.06	14.17	7.46	3.96	2.42		
11		2.71	4.36	13.85	20.90	9.09	3.53	
12		0.25	1.12	4.38	7.78	21.82	29.41	
13			0.06	1.79	7.01	9.09	4.71	
14			0.06	0.42	5.90	20.61	11.76	
15			0.10	0.47	2.78	1.21	28.24	
Obs.	31	1622	6173	8159	1440	165	85	17675

To be able to make a closer comparison of the two rating systems, we have taken the subset of overlapping firms and mapped the ratings of all firms in one bank into those of the other, as displayed in Tables 2 and 3. Given the amount of idiosyncratic noise normally found in panel data and the additional fact that the banks have different numbers of rating classes, we should not expect perfectly correlated ratings. A closer look reveals the that a substantial part of the overlapping firms are rated ratings quite differently by the two banks. Most interestingly, only 21.8 percent of the firms that were in default at bank A simultaneously defaulted at B. This need not necessarily suggest that the two banks operate with differing default definitions; it is perfectly conceivable that a given firm may perform with one bank and simultaneously non-perform with the other. Four out of ten defaults in A actually have a grade 3 or 4 at B. Of bank B's defaults, only 28,2 percent was rated correspondingly at A. Most of them are, however, rated between 11 and 15 by A. Some additional anomalies appear to exist. For example, bank B has only about 1 percent of all borrowers in grades 1 and 6, implying that its already limited possibilities to differentiate are further restricted. We also see that not all of the best rated borrowers in bank A are classified as 1 or even 2 in bank B, despite the fact that one would expect the safest grade in A to be contained in a much smaller interval of default probabilities than in B, given the larger number of rating grades. Even borrowers allotted to class 2 in bank A display this property in bank B.

Figure 3: Spearman rank correlations between ratings of the banks and the credit bureau.



To get a more exact measure of the correlation between firms' rating in banks A and B, we calculated their Spearman rank correlation for each quarter of our sample period. In Figure 3 the unbroken dark grey line shows that the correlation between the ratings of A and B varies between .31 and .45, with a tendency to be higher at the end of the sample period. Unfortunately, the discrete nature of the ratings in combination with the particular distribution over the 7 and 15 rating grades tends to push down the size of the Spearman correlation.[15] By assuming that the ratings of bank A are a reasonable measure of the relative riskiness of borrowers *within* each of bank B's rating classes, we can obtain another estimate of the correlation between ratings in A and B that compensates for the information that is lost when credit scores are aggregated into credit ratings.[16] Because banks A and B rating systems have a different number of grades, the discreteness of ratings could potentially affect the estimates of the correlation between the A and B ratings one the one hand and the UC ratings on the other in different ways.[17] Sorting

[15] To arrive at the above correlations, exposures with equal ratings were all given the same, average, rank value. As a result, the 50-60 percent of all observations with grade B4 all received the same rank value. When calculating the rank correlation with A's risk sorted ratings, this obviously increases the likelihood of "mismatches" as grade B4 spans all 15 ratings of bank A. Unfortunately, we have no information available from bank B that allows us to rank counterparts *within* its rating classes.

[16] Furthermore, within each rating class of B, we sort observations that have identical ratings in bank A according to their firm number.

[17] The credit bureau makes use of a rating scale with five grades to describe the likelihood of a firm going

exposures within one banks' rating classes according to the rating they have in the other bank, weakens this effect. However, both correlation measures provide us with the same picture, that bank B's ratings are more correlated with the ratings of UC than A's ratings are.

Table 4: Ratings of defaulted counterparts in bank A prior to default

Distribution of defaulted counterparts over all rating classes for range of time periods prior to the default, S = 1, 2, …. , 12 quarters. The share of all defaults that was not yet in the bank's portfolio *S* quarters earlier is reported separately as "exits". Rating class shares thus represent the distribution of "already present" counterparts.

Rating			Lag length										
Class	*T*	*T-1*	*T-2*	*T-3*	*T-4*	*T-5*	*T-6*	*T-7*	*T-8*	*T-9*	*T-10*	*T-11*	*T-12*
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.04	0.06	0.02	0.02	0.03	0.04	0.04	0.04	0.05	0.06	0.07	0.04
6	0.00	0.01	0.01	0.02	0.02	0.04	0.05	0.04	0.02	0.02	0.01	0.00	0.00
7	0.00	0.03	0.04	0.01	0.01	0.01	0,00	0.02	0.04	0.03	0.00	0.00	0.04
8	0.00	0.13	0.13	0.10	0.13	0.11	0.10	0.10	0.10	0.10	0.07	0.07	0.04
9	0.00	0.11	0.12	0.11	0.13	0.13	0.14	0.16	0.16	0.13	0.18	0.18	0.10
10	0.00	0.00	0.01	0.02	0.02	0.03	0.03	0.02	0.02	0.04	0.07	0.08	0.10
11	0.00	0.13	0.17	0.23	0.24	0.25	0.24	0.26	0.26	0.23	0.26	0.29	0.25
12	0.00	0.17	0.18	0.20	0.20	0.20	0.19	0.20	0.19	0.20	0.18	0.21	0.35
13	0.00	0.19	0.17	0.15	0.11	0.10	0.09	0.08	0.08	0.13	0.08	0.05	0.00
14	0.00	0.19	0.11	0.15	0.11	0.10	0.12	0.08	0.08	0.08	0.09	0.05	0.04
15	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Exits	*0.00*	*0.07*	*0.11*	*0.15*	*0.17*	*0.20*	*0.21*	*0.27*	*0.32*	*0.36*	*0.25*	*0.24*	*0.31*
Nobs	879	879	743	470	406	340	280	251	191	158	82	51	29

bankrupt in the coming 24 months. For more details, see Jacobson and Linde [32].

Table 5: Ratings of defaulted counterparts in bank B prior to default

Distribution of defaulted counterparts over all rating classes for range of time periods prior to the default, S = 1, 2, ... , 12 quarters. The share of all defaults that was not yet in the bank's portfolio *S* quarters earlier is reported separately as "exits". Rating class shares thus represent the distribution of "already present" counterparts.

Rating	Lag length												
Class	*T*	*T-1*	*T-2*	*T-3*	*T-4*	*T-5*	*T-6*	*T-7*	*T-8*	*T-9*	*T-10*	*T-11*	*T-12*
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.02	0.03	0.02	0.03	0.03	0.04	0.07	0.11	0.13	0.17	0.19	0.18
4	0.00	0.35	0.42	0.45	0.49	0.53	0.54	0.59	0.64	0.64	0.57	0.55	0.53
5	0.00	0.46	0.42	0.40	0.38	0.34	0.33	0.25	0.19	0.19	0.18	0.18	0.18
6	0.00	0.16	0.14	0.13	0.10	0.10	0.10	0.09	0.05	0.00	0.03	0.02	0.04
7	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.05	0.04
Exits	*0.00*	*0.12*	*0.14*	*0.15*	*0.18*	*0.21*	*0.26*	*0.31*	*0.36*	*0.42*	*0.40*	*0.43*	*0.51*
Nobs	570	570	518	486	429	398	332	280	197	158	109	89	43

To get a better understanding of each bank's ability to identify future problem loans, we display in Tables 4 and 5 the ratings of defaulted borrowers in the quarters prior to their default . Being able to identify problem loans is important for several reasons, the obvious ones being that it allows a bank to adjust its monitoring behavior and pricing. Another reason is that the risk weight functions in the new Basel regulation are concave in default risk, thereby creating a reward on grouping future bad loans. Furthermore, a limited identification ability would indicate a need to improve credit management routines. Table 4 shows that bank A does reasonably well in locating future defaults. One quarter before their default, 19 percent of all borrowers is rated A14; Grades A11 to A14 account for about 15 percent of the loan portfolio but for 68 percent of all defaults. This share is surprisingly stable for any horizon up to 12 quarters. In bank B the picture is quite different due to the smaller number of risk classes. Here grades 5 and 6, that contain 10 percent of all credit, account for about 60 percent of all defaults one quarter before their occurrence. However, this share drops steadily to just over 20 percent at a 12 quarter horizon. Grade B4, the rating of close to 50 percent of all firms, stands for 35 to 64 percent of all defaults. Classes B3 and B4, that stand for 30-40 percent of all credit, produce merely 2-18 percent of the defaults.

These stylized facts allow us to draw some preliminary conclusions about the design and implementation of internal ratings systems. Firstly, the possibility to choose the number of rating grades may be a non-trivial feature of a rating system design. For example, both the degree of concentration in and the distribution of borrowers over classes differ clearly between the banks in this study. Secondly, the large concentrations of borrowers in a small number of rating classes make it quite likely that default risk will not be homogeneous within a single grade. Therefore applying a single probability of default may not be as appropriate as one, for example, envisions in Basel II.

4 Method and results

In this section, we investigate the properties of both banks' credit loss distributions, as calculated with a Monte Carlo resampling method. Our objective is twofold. Firstly, we want to get a better understanding of the characteristics of the loss distributions for banks business loan portfolios. We hope that the insights from the exercises below can help us understand if the implementation of internal risk rating systems by large banking corporations, as envisioned by the Basel Committee, will provide regulators with a consistent picture of banks' loan portfolio credit risk.

Secondly, we aim to investigate whether and, if so, to what extent, credit loss distributions of banks, that are required by their regulator(s) to report about the riskiness of their loan portfolios in terms of a distribution of credit over internal rating classes, can vary despite the fact that they have equal regulatory "risk profiles".

We consider the experiments below as an illustration of the way in which banks and their regulators will interact under Basel II. Under the new regulation, many bigger banks will report to their regulators about the riskiness of their loan portfolios in terms of a distribution of credit over internal rating classes. At the same time, however, they will use statistical models to derive either a full credit loss distribution or at least a number of moments or percentiles of this distribution. When the outcomes of these models indicate that regulatory capital is too large relative to economic capital, banks are likely to engage in a discussion with their regulators about adjustments of the regulatory buffer.[18]

In normal banking practice differences between the loss distributions, given equal "regulatory risk profiles", are likely to translate into different levels of economic capital that banks will need to support their risk taking activities.[19] If this wedge between the regulatory and economic cost of credit becomes sufficiently big, incentives could transpire for some banks to securitize part of their loan portfolio to reduce costs, as happened under the Basel I Accord. Another possibility is that banks will change the risk profile of their loan portfolio to generate higher returns. It also suggests that some elements of an internal rating system, such as the number of grades

[18] Choosing a certain credit risk model and estimating or calibrating essential risk parameters are therefore likely to be important activities for banks. Basel II offers national regulators quite some leeway in the application of the risk weight mappings. Basel II also contains references to regulatory approval of credit risk models that are used by banks. Understanding these models is therefore obviously of importance for regulators.

[19] The estimated amount of capital needed by a bank to support its risk taking activities is generally termed required or allocated "economic capital". The economic capital is in theory chosen such that the probability of unexpected credit losses exceeding economic capital, or "insolvency", stays below some desired level. The probability of insolvency is typically selected in a way that gives a bank the credit rating it desires. Expected losses are commonly thought to be provided for by a bank's loan loss reserves, not by economic capital.

and the dispersion of credit over rating classes may constitute strategic choice parameters for a bank. Banks could thus adjust their rating systems to reduce regulatory costs. Any evidence that loan portfolios with equal "regulatory risk profiles" have different risk properties, i.e. loss distributions, should therefore be seen as indicative of future complications in applying and implementing the Basel II rules.

To examine if our findings are robust, we also analyze to what extent the loss distributions - and especially their tails - are affected by changes in a number of ex-ante portfolio characteristics and other simulation parameters, such as the forecast horizon, portfolio size, risk profile and macroeconomic conditions. This also allows us to infer how banks' required economic capital ought to vary with changes in these portfolio parameters.

4.1 Methodology

The sampling method that we use to estimate the portfolio loss distributions is a non-parametric Monte Carlo method that closely follows Carey [16]. An advantage of this method is that it avoids any assumptions about parametric forms. Many currently and frequently used risk management systems/models need to impose a correlation structure. A very common solution is to employ a common factor model to capture default correlations between assets. Due to a lack of data, many of the (parametric) loss correlation assumptions that are incorporated in these models remain untested. Due to the size of the dataset and the non-parametric estimation method, this paper keeps clear of such conjectures.

The selection of the data is done as follows. First, we store, for each borrower in each bank, the firm number, the date (quarter t) of the observation, the loan size at t and the risk rating at t.

Next, we determine for each observation present at date t if it is still present in the portfolio at quarter t+h, where h is the forecast horizon that we want to apply. If it is still present and has not defaulted, we store the rating class at t+h. If the firm is still present but has defaulted, we store the actual exposure and a default indicator. If the firm is not present anymore at t+h, we verify if it defaulted at any of the dates between t and t+h. If it did, we store the actual exposure at the date of default and a default indicator. For firms that were present at t+h, we also verify if they didn't exit from the portfolio or defaulted at any intermediate quarter. Loans that defaulted at an intermediate date but returned before or at date t+h are registered as a default - not with the rating with which they re-enter or have at t+h. We assume that the banks are likely to incur at least some losses on such defaulting borrowers and then continue the relationship, most likely at renegotiated terms.[20] Firms that exited at an intermediate date but returned before or at t+h are considered not to have transited and therefore disregarded. For

[20] This effect could have been captured by a loss given default (LGD) rate. Unfortunately, such data was not available to us.

our experiments, this implies that we ignore any possible selection effect that exiting behavior may have on credit risk. However, since we are unable to determine the causes of non-default exits (voluntary by a healthy firm or, for example, a forced exit of a potentially bad loan), we prefer to abstract from this effect. After repeating this for all quarters that are at least h quarters away from the last quarter of the sample period, T, we obtain T-h data matrices, one for each quarter 1, 2, ... T-h. Each such data matrix contains four variables for each borrower: the credit exposure and the corresponding risk rating at time t and at t+h. borrowers that were absent at one of these two points in time, or any intermediate quarter, receive only zero entries.

Finally, we identify a risk profile of a portfolio that can be considered equally risky in both banks by exploiting the occurrence of multiple-bank-borrowing. An attractive feature of this approach is that using these 2,880 firms (17,476 observations) that simultaneously held loans in both banks enables us to identify the risk profile of a portfolio that can be considered equally risky in both banks, thereby allowing us to circumvent the fact that the firms' internal ratings at the two banks are not directly comparable as a results of the unequal number of internal rating grades they employed. We determine the average profile of each bank's "overlapping portfolio" in terms of the percentage share of all credit that is rated in each risk rating class. We will hereafter call these the "standard" portfolio profiles for bank A and bank B.

Once we have determined the size of the portfolio we want to generate and the number of portfolios we need to obtain a distribution that has converged, we can start drawing observations from the dataset. In our experiments, 50,000 portfolios turned out to be enough for convergence.[21] Resampling then occurs according to the following steps. Before anything else, we impose two conditions when sampling. First, to avoid that portfolio loss rates display "abnormal" outliers, we restrict any loan to make up a maximum of three percent of the total portfolio. Second, we do not to sample any observations from a rating class if it contains fewer than 15 observations at that specific date to make sure that small loans do not end up making up a big part of a portfolio because they are repeatedly drawn "to fill the class". Next we randomly draw a date. This determines from which quarter we will be sampling. By separating quarters, we avoid that good and bad times even out the estimated losses. Although our data only cover 13 quarters, Figure 1 shows that there is quite some variation in the default rate within this period. Still, our results should not be seen as representative for a full business cycle. Then we draw loans from the rating classes in the respective bank's full (not only the overlapping) credit portfolio according to the proportion of the "standard" portfolio, until the desired portfolio size is attained. Losses are then calculated as the sum of all exposures at *the date of default* to borrowers that defaulted between t and t+h. Since we do not know the actual losses given default, we need to assume a fixed loss rate. We chose a 100 percent LGD. This

[21] By converging, we mean here that the estimated percentiles do not change more than marginally when increasing the number of portfolios generated.

requires clearly a caveat when analyzing our results in case the actual loss-rates systematically differ between the two portfolios. The full loss distribution is obtained by sorting the percentage loss rates according to size. A percentile is obtained by picking out the (nobs*percentile/100)th observation from the loss distribution. For further details, we refer to Carey [16].

4.2 Results

In this section we present, for each bank, the one-quarter ahead credit loss distributions for the standard portfolio with the above described benchmark properties: a portfolio size of SEK 54.5 bn. (approximately USD 6.7 bn.), a maximum portfolio share of three per cent per loan and at least 15 observations per risk class to sample from.[22] Given that the loans in our sample sum up to a total of SEK 2,189 bn. for bank A and 1,868 bn. for bank B, any such simulated portfolio will constitute only a small fraction of the available data material.[23] Thereafter, we carry out five experiments to see if our findings are robust to changes in a set of portfolio characteristics. First, we will compute the loan loss distribution for the standard portfolios for a forecast horizon of four quarters. Second,

Table 6: Simulated portfolio loss rates for standard portfolios in banks A and B for two forecast horizons.
The table shows various percentiles of the loss distribution for bank A and B for forecast horizons of 1 and 4 quarters.

Portfolio characteristics			Simulated portfolio loss rates at loss distribution percentiles							
Horizon	Bank	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
1	A	0.06	0.13	0.16	0.19	0.28	0.31	0.40	0.43	0.57
1	B	0.03	0.06	0.09	0.13	0.16	0.17	0.18	0.30	0.42
4	A	0.27	0.43	0.49	0.55	0.63	0.69	0.74	0.80	0.92
4	B	0.16	0.29	0.35	0.39	0.46	0.50	0.54	0.60	0.75

we expand this experiment and study how the loss distributions change when the portfolio size is varied. In the third experiment we vary the share of the portfolio that each bank holds in its riskiest classes. Fourth, we investigate the impact of aggregate fluctuations on the risk distribution. Finally, we study if both banks' loss distributions shift in the same way if the banks decide to invest half of their loan portfolio in the safest borrowers.

In the first two lines of Table 6, eight percentiles and the mean of the one-quarter-ahead simulated credit loss distributions of bank A and B are presented. An entry in the table should be interpreted as follows: the probability that a portfolio share of x percent, where $x \in [90; 99.99]$ will be lost within one quarter is less than 1-percentile/100. For example, the probability that

[22] We have chosen the average of A's and B's portfolio size as the benchmark, B's standard portfolio was 18 per cent larger than A's in terms of credit volume.

[23] Of all observations in banks A and B, .1 and .3 percent respectively, representing about 5 and 8 percent of total credit, violate the 3 percent portfolio share condition for the standard portfolio.

bank A's credit losses will exceed .13 percent of the total portfolio value within the next quarter is .1; however, the probability that they will exceed .57 percent is only a mere .01. Expected losses amount to .06 percent of the portfolio for A. The second line of Table 6 shows that bank B considers its portfolio with identical borrowers considerably less risky, regardless of the percentile we choose. B expects to loose only .03 percent of its portfolio within a quarter, half as much as A does. The further outward in the tails of the credit loss distribution we move , the more A and B come to resemble each other however. At the 90th percentile, for example, B still expects to incur only half the losses of A within the next quarter, but at the 97.5th percentile the margin has shrunk to a fraction of 1/3; at the 99.99th percentile B's losses are only 25% smaller than A's .57 percent.

Lines three and four of the table contain similar figures for both banks' four-quarter loss rates. As one would presuppose, the expected loss rates for a four quarter horizon are approximately four times as large as for a one quarter horizon: A expects to loose .27 percent of its exposure within a year and B .16 percent. Although there is a persistent difference between A and B at all loss percentiles, the factor between the four and one quarter losses becomes smaller as one moves out towards the tails of the distribution. For example, at the 90th percentile, credit losses at A (B) are a little more than three (four) times as large for the four quarter horizon, at the 99th percentile they are a factor 2.2 (3) larger, and at the 99.9th percentile these figures are less than or twice as large than at a one quarter horizon. The reason for this shrinking effect is that losses far out in the tail of the distribution are influenced by extreme events that occur seldom.

Table 7: Simulated portfolio loss rates for varying portfolio sizes (horizon = 1 quarter)
The table shows various percentiles of the loss distribution for bank A and bank B when portfolio size is varied, but the risk profile of the portfolio is maintained. The forecast horizon is 1 quarter.

Portfolio characteristics		Simulated portfolio loss rates									
Size			at loss distribution percentiles								
(bn SEK)	Bank	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
5	A	0.09	0.22	0.34	0.58	1.23	1.36	1.52	1.78	2.77
5	*B*	*0.04*	*0.10*	*0.17*	*0.25*	*0.43*	*0.53*	*1.02*	*1.41*	*1.61*
10	A	0.08	0.17	0.27	0.46	0.66	0.74	0.90	1.21	1.39
10	*B*	*0.04*	*0.08*	*0.13*	*0.18*	*0.28*	*0.40*	*0.70*	*0.76*	*0.81*
25	A	0.07	0.15	0.23	0.30	0.39	0.52	0.57	0.63	0.94
25	*B*	*0.03*	*0.07*	*0.11*	*0.14*	*0.26*	*0.32*	*0.34*	*0.36*	*0.65*
50	A	0.06	0.12	0.16	0.20	0.29	0.31	0.36	0.45	0.62
50	*B*	*0.03*	*0.06*	*0.09*	*0.13*	*0.18*	*0.19*	*0.20*	*0.34*	*0.38*
75	A	0.06	0.12	0.14	0.20	0.23	0.30	0.33	0.40	0.49
75	*B*	*0.03*	*0.06*	*0.09*	*0.12*	*0.13*	*0.14*	*0.23*	*0.24*	*0.34*
100	A	0.06	0.11	0.13	0.16	0.21	0.24	0.28	0.32	0.39
100	*B*	*0.03*	*0.06*	*0.09*	*0.10*	*0.11*	*0.17*	*0.18*	*0.19*	*0.27*
150	A	0.06	0.10	0.12	0.15	0.18	0.21	0.24	0.27	0.35
150	*B*	*0.03*	*0.06*	*0.07*	*0.08*	*0.12*	*0.13*	*0.14*	*0.18*	*0.23*

By construction, the 99.9th percentile consists of the 49,950th out of 50,000 simulated portfolios (sorted by loss rate). Out in the very end of the tail, increases in the number of defaults (and thus the loss rate) do not exhibit any near linear relationship, but slowly fade out.

These results show that if both banks would use their internal rating data in a nonparametric method, like the one we employ here, to estimate the credit loss distributions for a portfolio of identical borrowers, they would obtain rather different perceptions of their riskiness.

The differences between bank A and B are by and large driven by two conditions. First, despite a lower average annual default rate than bank B, bank A on average incurs bigger annual losses rate. This is not caused by a higher LGD, but by the fact that bad loans in A are relatively big when compared to performing loans in A (0,46% of a performing loan, compared with 0,22 at B). Second ,borrowers in the overlap portfolio were om average given better ratings in B than in A. As a result, the resampling exercise drew relatively more observations from risky rating classes for bank A than for B.

One conclusion we can draw from the above results is that these banks could be faced with different capital requirements for a portfolio with identical borrowers. If we translate the figures in Table 6 into loan loss provisions and capital requirements and assume it is appropriate to consider a one-year horizon, then bank A should hold loan loss provisions of .27 percent of its loan portfolio, more than 1.5 times B's provisions. In addition, it follows from the third and fourth row in Table 6 that if both banks were to obtain an (external agency) rating that corresponds to an insolvency risk of .1 percent - and maintained the above loan loss provisions - then A would require an economic capital equal to $(.80 - .27) = .53$ percent of its loan portfolio while B would need a capital of $(.60 - .16) = .44$ percent. For a bank with, for example, a loan portfolio worth approximately SEK 100bn, such differences in margins imply it could be required to hold an equity capital of either SEK 530 mn. or SEK 440 mn. Equivalently, bank A would have to realize a profit that is more than a quarter higher than bank B's, creating incentives to increase the riskiness of (some of its) rating classes.

Observe also that a regulators´ choice of a specific forecast horizon length, in combination with a specific loss percentile, may greatly affect his measurement of riskiness of a bank's loan portfolio and the level of capitalization it thus requires.[24] Had, for example, 1 percent been an acceptable level of insolvency risk, then A and B could have sufficed with a capital base of .36 and .30 percent respectively. Similarly, the choice for a specific "policy" horizon will also have an impact on the required capital base.

In Table 7, we report the one-quarter loss rates for portfolios with varying sizes. These portfolios are constructed with the rating class proportions of the standard portfolio and the aforementioned restrictions.[25] The table illustrates the importance of portfolio size for credit risk. For each bank, at every shown percentile, credit losses of a SEK 150 bn. portfolio are between 50 and 85 percent smaller than for a SEK 5 bn. portfolio. If one compares the SEK 100 bn. portfolio with that of SEK 50 bn., which is very close to the actual standard portfolio, one can observe that, for these portfolio sizes, losses only tend to fall significantly with increasing portfolio size in the tails of the distribution. Although an increase in portfolio size always reduces credit losses at all displayed percentiles, the "gain" is larger (i) the further out one moves in the tails, and (ii) the smaller the original portfolio is. For example, at the 99th and 99.5th percentiles, bank A can cut its unexpected losses in half by doubling its portfolio size from SEK 5 bn. to SEK 10 bn., thus diversifying away idiosyncratic risk. At the 90th and 95th percentile, the gain would only be 20-30 percent. For a portfolio size of SEK 25 bn., the effect of doubling portfolio size has shrunk to 30-40 percent at the 99th and 99.5th percentiles, and once at a portfolio size of SEK 50 bn. the benefit is further reduced to 25-35 percent. Note that expected losses do not, and should not, change significantly when varying the portfolio size.[26] It is also

[24] See also Calem and LaCour-Little [14] p.18, for further insights into the issue of jointly choosing horizon and loss percentile.

[25] Although it is more common to use a forecast horizon of one year for the purpose of credit risk analyses, we have chosen to use a quarterly horizon in order to maximize the number of available time periods and avoid smoothing of the data. This is especially important in the last experiment, presented in Table 15 below. Results for the one year horizon, displayed in Figures 5 and 6, in general resemble those of the one quarter horizon in the same way as in Table 10.

[26] Any changes that actually show up here stem from counterparts disappearing from or entering the set of

good to keep in mind that the uncertainty about loss percentile estimates falls when moving to the very extreme of the tails. Estimates with smaller numbers of simulated portfolios (10,000) indicated an increased sensitivity of higher end percentiles. Here, when considering for example the 99.9th and 99.99th percentiles of bank A's 5 bn. and 10 bn. portfolios, there appears to be some irregularity.

Table 8: Simulated portfolio loss rates in bank A for varying risk profiles

The table shows percentiles of the loss distribution for bank A when the share of the 6 riskiest classes is varied, and the relative share of the other risk classes in the remainder of the portfolio equals that in the standard portfolio. The forecast horizon is 1 quarter. Losses are expressed as a percentage share of the loan portfolio.

Portfolio characteristics		Simulated portfolio loss rates								
	Percentage		at loss distribution percentiles							
Bank	rated > 8	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
A	10	0.04	0.08	0.13	0.17	0.27	0.34	0.40	0.48	0.58
A	20	0.05	0.11	0.15	0.19	0.27	0.31	0.39	0.43	0.57
A	30	0.07	0.14	0.17	0.20	0.28	0.30	0.39	0.42	0.57
A	40	0.08	0.16	0.19	0.23	0.29	0.32	0.39	0.42	0.57
A	50	0.10	0.18	0.21	0.26	0.31	0.36	0.39	0.44	0.55
A	60	0.11	0.20	0.24	0.28	0.33	0.38	0.42	0.47	0.59
A	70	0.12	0.22	0.26	0.31	0.37	0.40	0.45	0.51	0.63
A	80	0.14	0.24	0.29	0.34	0.39	0.44	0.48	0.53	0.63
A	90	0.15	0.27	0.32	0.37	0.42	0.47	0.52	0.58	0.74
A	100	0.17	0.30	0.36	0.41	0.47	0.52	0.57	0.62	0.80

Finally, Table 7 demonstrates that bank A and B differ not only in their perceptions of the riskiness of their standard portfolio, but - depending on their current portfolio size and the chosen risk of insolvency - also in the extent to which they could benefit from increasing portfolio size and diversifying away idiosyncratic risk. For example, with a portfolio of SEK 50 bn. and a preferred risk of insolvency in a range between 1 and .1 percent, B can lower its credit losses by 10-40 percent when doubling its portfolio size, while A steadily achieves a 25 percent saving. At the 99.9th percentile, a type A bank that is twice as big can suffice with a 33 percent smaller economic capital. A type B bank could nearly cut its economic capital in half; were both to triple their portfolio sizes, then even B would realize such a reduction. Differences between internal ratings systems are thus likely to create incentives for expansion or securitization that may well come to vary widely between banks, thereby continuing the possibilities for so called regulatory capital arbitrage.

Tables 12, 13 and 14 offer a view on how changes in the rating composition of the banks' loan portfolio impact on their loss distributions. In Tables 12 and 13 we start by varying the share the banks' riskiest rating classes, choosing for practical reasons the bottom classes that

feasible observations due to the three percent portfolio share restriction.

together account for approximately 20 percent of the total portfolio, while keeping the portfolio size equal to that of the benchmark standard portfolio.[27] In Table 8 we increase the share of A's six riskiest classes, that stand for 24,7 percent in the standard portfolio from 10 to 100 percent; within the remainder of the portfolio the proportions between the other eight rating

Table 9: Simulated portfolio loss rates in bank B for varying risk profiles

The table shows percentiles of the loss distribution for bank B when the share of the 3 riskiest classes is varied, and the relative share of the other risk classes in the remainder of the portfolio equals that in the standard portfolio. The forecast horizon is 1 quarter. Losses are expressed as a percentage share of the loan portfolio.

Portfolio characteristics		Simulated portfolio loss rates								
	Percentage		at loss distribution percentiles							
Bank	rated > 3	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
B	10	0.02	0.05	0.07	0.12	0.16	0.17	0.19	0.24	0.32
B	20	0.04	0.09	0.14	0.17	0.22	0.26	0.31	0.34	0.46
B	30	0.06	0.13	0.18	0.23	0.30	0.34	0.37	0.43	0.51
B	40	0.08	0.17	0.22	0.29	0.35	0.39	0.45	0.49	0.57
B	50	0.09	0.20	0.27	0.35	0.42	0.49	0.53	0.60	0.72
B	60	0.11	0.23	0.33	0.39	0.49	0.54	0.59	0.65	0.81
B	70	0.13	0.26	0.37	0.46	0.54	0.61	0.67	0.73	0.85
B	80	0.15	0.30	0.41	0.52	0.61	0.68	0.74	0.80	0.95
B	90	0.17	0.33	0.45	0.56	0.68	0.75	0.82	0.88	1.08
B	100	0.19	0.38	0.52	0.62	0.74	0.81	0.88	0.95	1.10

classes are kept unchanged from the standard portfolio. In Table 9, we do the same with B's three most risky rating classes - that have a share of 19.7 percent in B's standard portfolio. For both banks losses are monotonically increasing in the share of low quality loans. The only exceptions are bank A's upper four percentiles for portfolios with 10 and 20 percent low quality loans. Most likely, these deviations are not significant and an artifact of the low default frequency combined with the bigger firm size in grades A1-A8. For bank B, however, the loss rate increases much faster with the share of bad grade borrowers than for bank A. At low grade portfolio shares of 40 percent and more, B's portfolios turn more risky than A's. Although we cannot draw any categorical conclusions because of the different portfolio shares of grades A9-A14 and B4-B6, a comparison of Tables 12 and 13 strongly suggests that worse rated borrowers contribute substantially more to expected and unexpected losses in bank B than they do in A. For example, in bank B a 100 percent bad grade portfolio exhibits expected losses that are nearly ten times as high as those of the 10 percent bad grade portfolio, compared with four times in bank A. The

[27] Ideally, we would have increased the share of those rating classes that are equivalent to external rating agencies "below investment grade" ratings. Unfortunately, it is difficult to map both banks' ratings into Moody's and S&P's rating classes. To keep some match between the quality of the borrower segments chosen for each bank, while simultaneously avoiding too big a reduction in the number of observations available for the Monte Carlo sampling and keeping clear from including borrowers with top or next-to-top ratings, we selected the bottom classes with a portfolio share of approximately 20 percent.

mirror image of this difference in rating borrowers is that bank A has riskier and/or more risky borrowers in its high quality grades than bank B does. Because such business make up over three quarters of the overlap portfolio, bank A will consider the overlap portfolio more risky than bank B.

In Table 10 we show simulation outcomes for four additional standard sized portfolios that instead have a larger share of *better* rated loans. For bank A, we generate two portfolio with either 50 or 100 percent of the exposure in rating classes 1-4 and another two that have either half or all exposure rated between 5 and 8. As before, the remainders of these portfolios

Table 10: Simulated loss rates in bank A and B for portfolios with low risk profiles.
The table shows various percentiles of the loss distribution for banks A and B when the share of loans in (groups of) safer risk classes is increased and the relative share of the other risk classes in the remainder of the portfolio equals that in the standard portfolio. The forecast horizon is 1 quarter. Loss rates are expressed as a percentage share of the loan portfolio.

Portfolio characteristics			Simulated portfolio loss rates at loss distribution percentiles							
Bank	Share of portfolio picked from RC#	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
A	Standard	0.06	0.13	0.16	0.19	0.28	0.31	0.40	0.43	0.57
A	50% in 1-4	0.05	0.11	0.15	0.18	0.26	0.29	0.33	0.41	0.54
A	100% in 1-4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A	50% in 5-8	0.06	0.12	0.16	0.24	0.29	0.39	0.42	0.53	0.68
A	100% in 5-8	0.04	0.08	0.24	0.36	0.50	0.58	0.65	0.75	0.98
B	Standard	0.03	0.06	0.09	0.13	0.16	0.17	0.18	0.29	0.42
B	50% in 2	0.03	0.07	0.10	0.15	0.18	0.20	0.23	0.28	0.34
B	100% in 2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B	50% in 3	0.04	0.08	0.13	0.17	0.21	0.25	0.30	0.34	0.44
B	100% in 3	0.00	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.04

Table 11: Simulated portfolio loss rates in good and bad quarters
The table shows various percentiles of the loss distribution for bank A and bank B when counterparts are drawn from either good or bad quarters. Standard outcomes for the overlap portfolio are provided as a benchmark. The forecast horizon is 1 quarter.
Loss rates are expressed as a percentage share of the total loan portfolio.

Portfolio characteristics			Simulated portfolio loss rates at loss distribution percentiles							
Years	Bank	mean	90	95	97.5	99	99.5	99.75	99.9	99.99
Standard	A	0.06	0.13	0.16	0.19	0.28	0.31	0.40	0.43	0.57
	B	*0.03*	*0.06*	*0.09*	*0.13*	*0.16*	*0.17*	*0.18*	*0.29*	*0.42*
Good	A	0.06	0.11	0.13	0.15	0.18	0.20	0.22	0.25	0.30
	B	*0.03*	*0.05*	*0.08*	*0.10*	*0.15*	*0.17*	*0.19*	*0.22*	*0.27*
Bad	A	0.06	0.14	0.18	0.25	0.30	0.37	0.41	0.49	0.61
	B	*0.05*	*0.12*	*0.17*	*0.20*	*0.25*	*0.30*	*0.32*	*0.36*	*0.46*

consist of loans rated with grades that are left over in the same proportion as in the standard case. For B, we do correspondingly and construct two portfolio pairs, of which one consists completely of either class 2 or class 3 loans and the other has equal shares in either class 2 or 3 and the remaining rating classes.[28] The results in Table 10 are less straightforward than in the two preceding tables. Except for the one in row five, none of the portfolios displays losses that are significantly higher than the standard portfolio. Increasing the share of high grade loans to fifty percent reduces loan losses, both on average and at all percentiles for bank A. For bank B the effect is ambiguous, however. The changes are very small, though, and may be a consequence of having to leave out class 1 loans. For A (B) credit risk, and thus the required

Table 12: Required regulatory capital for banks A and B
The table shows what percentage of the loan portfolio each bank should hold as a regulatory capital base. Regulatory capital is calculated by means of the latest version of the Basel II Accord. All firms are assumed to belong to the corporate category. Probabilities of default are calculated (cumulatively) over the last four-quarters. Economic capital is calculated as the differential between a specific loss percentile and expected losses. These figures have been derived from Table 10.

		Quarter								
Bank		1998Q1	1998Q2	1998Q3	1998Q4	1999Q1	1999Q2	1999Q3	1999Q4	2000Q1
A	Regulatory	9.76	9.42	7.56	7.76	7.80	7.58	8.23	8.02	7.55
B	Regulatory	8.16	7.63	6.35	6.36	6.86	6.38	7.24	7.15	8.10
			Default risk percentiles							
			90	95	97.5	99	99.5	99.75	99.9	99.99
A	Economic		0.16	0.22	0.28	0.36	0.42	0.47	0.53	0.65
B	Economic		0.13	0.19	0.23	0.30	0.34	0.38	0.44	0.59

economic capital, more or less evaporates due to the (near) absence of defaults in these grades (see Tables 6 and 7), for portfolios with all exposure rated in the top four (two) grades. Although banks with such portfolios may seem unrealistic at first, it is good to keep in mind that bank A has more than 30 percent of its *entire* loan portfolio rated A4 or better and B has close to 70 (25) percent rated B3 (B2) or better.[29] Just as the results in Table 7, these figures indicate that banks are likely to continue to be spurred to engage in some form of securitization.

Despite the substantial advantage that our resampling method has over parametric methods in terms of producing robust results, it also shares a weakness For our computation of the unconditional loss distributions controls for systematic factors, i.e. macroeconomic fluctuations, only to the extent they are represented in the sample data. Although our data contain quite some fluctuation in the "aggregate" default rates (see Figure 1), our panel is relatively short

[28] In the standard portfolio, internal rating classes A1-A4 have a share of 40.6 percent while A5-A8 fill up the remaining 34.7 percent. In the other bank, class B2 and B3 have shares of 32.3 and 47.4 percent respectively. Because B1 has no or very few observations in a number of quarters, we cannot use this class in this experiment.

[29] For A this stems from 1.6 percent of all A's borrowers. At B, 27.5 (2.6) percent of all counterparts are rated B3 (B2) or better.

(three years) and mostly covers a period with relatively strong GDP growth.[30] It is therefore not impossible that actual default rates and loss percentiles have been underestimated and would have been higher if a complete(r) set of possible macro outcomes had been represented in the data set. To test the extent of any such underestimation, we ran an experiment in which we split up the data set into "bad" and "good" quarters and loans were drawn from only one of these sample parts. Because we have data over a relatively short sample period, but with a higher, quarterly, frequency, we have chosen not to create "closed" intervals, but instead to simply allot individual quarters based on their one quarter default rate. This basically represents a worst-case scenario, that generates the maximum possible difference between the two groups.[31] However, one should avoid interpreting the results of this scenario as an "economic downturn" case.

The outcomes in Table 11 indicate that "aggregate" fluctuations, and thus an extension of the sample period, are likely to have an important impact on our estimates of credit losses. For bank A expected losses and losses in the lower percentiles are only modestly higher during bad quarters, but in the upper percentiles losses increase by a factor two relative to good quarters. At bank B, however, the effect is different: losses more than double at the 90th and 95th percentile, but rise only by about 50 percent at the top percentiles. Bank B thus appears to be less sensitive to aggregate fluctuations. Our main result - that using internal rating systems data to calculate expected loss rates can lead to widely estimates of risk for a portfolio of identical borrowers - is however unaffected by this fact.

Finally, we compare the economic capital with the regulatory capital that each bank would be required to hold. To obtain the regulatory capital requirements, shown in the first two lines of Table 12, we use the risk weight functions provided in the latest version of the Basel II Accord.[32] Economic capital, in the last two lines, is derived from the loss distributions presented in Table 6 and computed as the difference between the portfolio loss at a chosen risk level of insolvency risk. The regulatory capital requirement captures the relative riskiness of bank A's portfolio, reflected by the bigger economic capital of bank A. Only in the last quarter would A need to hold a less regulatory capital than B. Most striking for both banks, however, is the big difference between the economic and the regulatory capital requirement: the former is exceeded by the latter by between six and nine percent points, despite the fact that regulatory capital

[30] See Carling et al. [22] and Jacobson and Lindé [32] for longer series of aggregate default rates, GDP growth and the output gap.

[31] The six quarters with the highest default rates in bank A are, in order of falling rates, 2, 1, 9, 4, 7, and 5. The ones with the smallest rates of default are 11, 8, 10, 6, 12, and 3. For B the worst quarters are 7, 5, 1, 3, 9, and 11, and the best 10, 4, 2, 8, 12, and 6.

[32] See the risk weights in The New Basel Accord [11]. We do not differentiate between SME credit, retail credit and corporate loans, and assume simply that all loans in the banks' portfolios belong to the category "corporate exposure". See Jacobson, Lindé and Roszbach [34] for a study of the differences between retail, SME and corporate credit in the Basel II proposal.

is based on past-year probabilities of default. Although the figures in Table 11 do suggest that the required economic capital would be likely to rise if a full business cycle had been included in the sample period, it is unlikely that economic and regulatory capital would approach each other. According to these figures, regulatory capital requirement would thus impose a binding constraint on both banks.

The size of and the large differences between economic and regulatory capital requirements are driven by two main factors. First, economic capital requirements should be relatively low in our experiments because the default and loss rates of borrowers in the standard portfolio are lower than for the average borrower in the banks' complete portfolios. This is a result of the fact that the overlap portfolio consists to a greater extent of relatively big and hence more creditworthy firms. That default rates among these bigger firms are smaller than among the average firm in the full portfolio can easily be seen by comparing column 3 of Tables 10 and 11 with the default rates in Figure 1. However, this circumstance has a downward effect on both economic and regulatory capital. Second, as Table 6 shows, varying portfolio size greatly affects credit losses in the outer tails of the distribution. At the portfolio size that we chose for our standard portfolio, SEK 54 bn, much of the idiosyncratic risk has already been diversified away. For smaller portfolio sizes, economic capital would not have attained the level of regulatory capital ,but at least been above 2 percent. Hence, in periods with only smaller aggregate fluctuations, successful diversification of all idiosyncratic risk means that one ends up with a nearly riskfree portfolio. This is exactly what we observe in Table 12. Since Basel II rules do not adjust capital buffers to the size of portfolios or their degree of diversification, full application of the new framework is likely to lead to unnecessary large regulatory capital requirements in certain cases (especially for loan portfolios with large numbers of borrowers or high quality borrowers). Therefore, we believe that the new Basel regulation is a potential source of regulatory arbitrage attempts. This tendency will be strengthened by two circumstances. First, the new Basel rules for international capital requirements contain a lot of room for regulatory discretion by national supervisory authorities. Many articles in the new Accord allow national authorities to deviate from the framework if they deem this justified. Banks will be allowed and able to use internal models to argue why lower capital requirements may be appropriate. Given the fact that many supervisors will have an informational disadvantage in their relation with banks, internal models are likely to become instrumental in banks search for the lowest possible capital buffers (that is, buffers that meet the banks economic requirement).

5 Summary and conclusions

In contrast with the broad body of knowledge about external credit ratings, relatively little is known about banks' internal rating systems and their relation to portfolio credit risk. The only three studies comparing rating systems known to us, are by Carey and Treacy [20] and Carey [18], that studies the qualitative properties of rating systems [20] and the analysis of rating differences [18]. Nakamura and Roszbach [41] investigate the contribution of banks' internal information from monitoring their clients when assigning ratings.

This paper aims at improving our understanding of internal risk rating systems at large banking corporations and the way in which they are implemented, to verify if they will provide regulators with a consistent picture of banks' loan portfolio credit risk, as is envisioned in the Basel II Accord. We study two banks' internal rating systems and the properties of their implied credit loss distributions and investigate to what extent the loss distributions of banks, that are required by their regulator to report about the riskiness of their loan portfolios in terms of a distribution of credit over internal rating classes, can vary despite the fact that they have equal "regulatory " risk profiles.

The experiments in this paper can be seen as an illustration of the way in which banks and their regulators will interact under Basel II. Under the new regulation, many bigger banks will report to their regulators about the riskiness of their loan portfolios in terms of a distribution of credit over internal rating classes. At the same time, however, they will use statistical models to derive either a full credit loss distribution or at least a number of moments or percentiles of this distribution. When the outcomes of these models indicate that regulatory capital is too large relative to economic capital, banks are likely to engage in a discussion with their regulators about adjustments of the regulatory buffer. In normal banking practice differences between the loss distributions, given equal "regulatory risk profiles", are likely to translate into different levels of economic capital that banks will need to support their risk taking activities.

The data set we use consists of the credit histories and internal borrower risk ratings for two Swedish banks' complete business loan portfolios over the period 1997Q1 - 2000Q1, including data on a group of firms that simultaneously borrowed from both institutions. The size of the data set allows us to apply Carey's [16] non-parametric Monte Carlo re-sampling method. As a result of this we can derive the implied loss distributions for each of the banks without making any assumptions about correlations between assets.

We show that there are substantial differences in the riskiness of both low and high grade borrowers *between* banks and also that the degree of concentration in and the distribution of borrowers over classes differs widely between them. The presence of large concentrations of borrowers in a small number of rating classes, as we observe, makes it likely that default risk will not be homogeneous within all rating classes, as it ought to be from a regulator's perspective. Our results also reveal substantial differences between the implied loss distributions of the two banks with equal "regulatory" risk profiles. Both expected losses and the credit loss rates at a wide range of loss distribution percentiles vary considerably between the banks. Such variation translates into different levels of the economic capital the banks will need to support their risk taking activities.

If the concomitant wedge between the regulatory and economic cost of credit becomes sufficiently big, incentives could transpire for some banks to securitize part of their loan portfolio to reduce costs, as happened under the Basel I Accord. Another possibility is that banks will change the risk profile of their loan portfolio to generate higher returns. It also suggests that some elements of an internal rating system, such as the number of grades and the dispersion of credit over rating classes may constitute strategic choice parameters for a bank. Banks could thus adjust their rating systems to reduce regulatory costs.

Our findings make clear that the calibration of the Basel risk weight mappings and banks' internal borrower risk rating systems are not yet synchronized in a way that they result in consistent estimates of portfolio credit risk for regulators. They also confirm that not only the design of a rating system itself, but also a portfolio's rating grade composition, the size of a bank, the preferred level of insolvency risk for a bank and the forecast horizon are of great importance for the shape of credit loss distributions and thus for banks required capital structure.

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