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

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Abstract

Counterpart risk rating is at the heart of the banking business. In the new Basel II regulation, internal ratings have been given a central role. Although much research has been done on external ratings, much less is known about banks´ internal ratings. This paper presents new quantitative evidence on the consistency of internal ratings based on panel data from the complete business loan portfolios of two Swedish banks and a credit bureau over the period 1997-2000. We study rating class distributions, - transitions and default behavior and compute the credit loss distributions that each rating system implies by means of a semi-parametric Monte Carlo re-sampling method following Carey [15].

Our results reveal, for a portfolio with identical counterparts, substantial differences in the implied riskiness between banks. Such differences could translate into different amounts of required economic capital and create (new) incentives to securitize part of their loan portfolios or increase the riskiness of loans in certain rating classes. We also shed light on the quantitative importance of portfolio composition, portfolio size and the forecast horizon for loss distributions. For example, with common portfolio parameters, credit risk can be reduced by up to 40 percent by doubling the loan portfolio size. We also discuss the relation between loss distributions and the desirable level of insolvency risk.

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

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

[*]We are grateful for comments from Malin Adolfson, Harry Garretsen, Bill Lang, Loretta Mester, Leonard Nakamura and seminar participants at Sveriges Riksbank, De Nederlandsche Bank and the Federal Reserve Bank of Philadelphia.

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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. In economic theory banks' role as an intermediary is commonly justified by their supposed superior ability to collect and assess information with respect to counterpart risk. Assessing counterparty risk is thus one of the banking industry´s core activities.

Bank regulators increasingly lean on the risk assessments made by banks: in the Basel Committee´s proposal for new capital adequacy rules, the so called Basel II Accord [10], internal risk ratings produced by banks have been given a prominent role.[1] 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* counterpart risk. It will be up to the banks to characterize the riskiness of the counterparts and loans in their portfolios by means of a relatively small number of risk categories or 'rating classes'.[2,3] Although the new supervisory rules will generate

[1] This committee works, although not hierarchically, under the Bank for International Settlements (BIS). Basel II is organized around three so-called pillars, with the first pillar describing the rules for determination of banks' required buffer capital, intended to cover for, among other things, incurred credit losses. The second, revised, proposal of the committee can be found on the homepage of Bank for International Settlements at: www.bis.org/publ/bcbsca.htm. Jackson et al.[28] provide an overview of the extensive empirical literature on the impact of the 1988 Accord on banks' behaviour.

[2] Each rating class will be associated with a specific risk weight such that the product of the relative risk weight, the exposure and the eight percent absolute capital requirement, summed over all loans will yield the bank's required minimum buffer capital. Risk weights can be determined along two routes under the new rules. Firstly, following a "standardized approach" designed to be implementable for all banks, a portfolio of bank loans is characterized by (a relatively small number of) risk categories and the risk weight associated with each category is based on an external rating institution's evaluation of counterpart risk. Secondly, there is a more elaborate so-called Internal Ratings Based (IRB) approach, that makes further use of the information collected and processed in the bank's internal counterpart risk rating operations. The empirical loss given default rates (LGD´s) for all rating classes constitute an important input in the risk weight formula in this approach. The underlying idea of the IRB approach is that banks are specialists in evaluating risks and that their evaluations should thus be a reasonable basis for risk-contingent capital adequacy determination. The current proposal allows banks to apply the IRB-approach at either of two levels of sophistication. The "foundation" only requires the bank to provide estimates of probability of default, while the "advanced" approach also requires internally generated inputs on loss given default and exposure at default.

[3] Altman and Saunders [9] 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

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.

Despite their importance, still relatively little is known about the actual 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 [34] and Cantor and Packer [14] 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 [36] compares solicited and unsolicited ratings and finds that the latter are biased downwards. Nickell, Perraudin and Varotto [35] model Moody's rating class transition probabilities with a number of micro-variables and a business cycle index. Blume, Lim and Mackinlay [12] 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 [20] 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 [39] 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 [26] 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 [16] 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 [30] 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 [18] 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

and Roszbach [21], Dietsch and Petey [22], Estrella [23], Calem and LaCour-Little [13], and Hamerle, Liebig, and Rösch [27], who have made an effort to apply credit risk models to the ultimate goal of calculating capital requirements under a variety of alternative systems. Overall, these papers have made clear how the proposed IRB approach relates to general Value-at-Risk (VaR) models of credit risk, what the current state of the art in risk rating is and how the technical specification of the final IRB design will affect banks' policies .

are potentially subject to bias, instability and gaming. Carling, Jacobson, Lindé and Roszbach [21] 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 [17].[4] Carey studies the consistency of rating assignments in a sample from 20 U.S. banks loan portfolios and finds that companies 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 counterpart is limited. As a result, important issues like the credit risk distribution (risk profile) implied by a bank's rating system, the match with the required capital allocation, the sources of rating differences and sensitivity to changes in lending policies cannot be investigated.

This paper attempts to fill this gap by presenting empirical evidence on internal ratings from two major Swedish banks´ complete business loan portfolios over the period 1997Q1 - 2000Q1. Both banks' loan data have been augmented with detailed information on the characteristics of the counterpart firms from a leading credit bureau. For the bank with the smaller portfolio we have approximately 180,000 observations at our disposal, while the bank with the larger portfolio has provided us with just over 300,000 loan spells. During the sample period, the two banks represent approximately 40% of the Swedish market for business loans. These data allow us to address a range of issues that are of interest for our understanding of the actual workings of internal rating systems, but have remained uninvestigated hitherto. In particular, we will study the consistency of the rating allocations between banks and over time for a sub-sample of 2,880 companies (17,476 spells) that simultaneously had loans in both banks. For this purpose, we compare their rating class distributions and - transitions and default behavior. We also examine the credit risk distributions that each rating system implies and perform some robustness tests by checking how changes in a number of portfolio characteristics influence the distributions' tails.

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 contains the results from a set of Monte Carlo simulations (following Carey [15]) on the implied risk distributions and their sensitivity to

[4] 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 [11], only contains information on capital requirements.

changes in portfolio characteristics. 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 and the leading credit bureau in Sweden, Upplysningscentralen AB (UC). For bank A, the data set is a panel consisting of 338,118 observations on bank counterparts, covering 13 quarters of data on all 39,521 Swedish *aktiebolag* companies 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). Although we have annual report data on small firms such as general partnerships, limited partnerships and sole proprietors, these will be disregarded because we could not dispose of the relevant credit histories. Observe, however, that a large part of the sample still consists of relatively small enterprises: respectively 65% 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´ spells, 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, company identification number. By means of the latter, we have been able to match the banks' data with UC's database, that contains quarterly updated official annual report data and payment remarks information on all Swedish companies. The annual accounting data is collected by UC from PRV, to which firms are required to submit their annual report, and includes all typical balance sheet and income statement data, such as inventories, short and long term debt, total assets and a whole range of earnings variables. Payment remarks data are reported by banks and other businesses and stored by UC and comprise information on the events related to the remarks and payment behavior for both the company and its principals. The data provided by UC was available at different frequencies, varying from daily for payment remarks to annually for accounting data. We will discuss the specifics of both data sources in greater detail below. Appendix A contains a full list of the

Table 1: Profile of companies in bank loan portfolios: average credit line per industry and their relative importance in terms of counterparts and total credit outstanding, N_A=323,671, N_B=176,985.

Industry	C´parts (%)		Total credit (%)		Av. credit line (SEK mn.)	
	A	B	A	B	A	B
Agriculure & fishing	3.08	3.06	0.6	0.6	1.427	2.188
Forestry & paper	1.20	2.34	2.6	4.3	14.900	20.800
Electro	1.16	1.10	2.3	0.6	13.400	6.368
Chemical	0.54	0.48	2.6	0.7	32.800	17.400
Energy & water	0.34	0.78	3.6	5.0	71.000	73.000
Construction	9.80	8.21	3.5	3.6	2.423	4.956
Other manufacturing	13.55	15.54	20.2	8.8	10.079	6.473
Wholesale trade	17.73	19.61	10.1	9.9	3.848	5.717
Retail trade	9.64	9.23	3.1	2.4	2.143	2.903
Hotel & restaurant	2.51	2.49	0.8	0.8	2.229	3.870
Transport	6.95	7.52	4.8	4.4	4.653	6.591
Telecom	0.11	0.12	0.2	1.1	14.600	105.000
Finance	1.48	1.20	10.8	8.6	49.200	81.600
Real estate	6.62	13.79	26.33	33.1	26.900	27.300
Other services	22.35	13.18	7.94	15.8	2.401	13.623
Government & health	2.94	1.34	0.4	0.3	1.019	2.288

variables provided to us by the bank. Some of the more interesting variables are: the internal risk rating, credit type, the amount of credit granted per type, actual exposure, (an estimate of the available) collateral, payment status and a 5 digit industry code.

Both banks are general commercial banks, with a nationwide branch network serving both private and business customers; neither of them has any widely known specialization profile within these groups. We converted the various types of credit into three broader groups, also used by the banks for certain analytical purposes: short term, medium term and long term lending. Of all counterparts 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.[5] Having multiple loans is quite common too: about 30 percent of A's and B's counterparts have both a short term loan and at least one other loan. The average censored 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 counterparts respectively; B thus typically grants its counterparts over 50% larger loans than A does: 11.37 mn. kronor on average compared with 6.76 mn. for A. Still, despite this apparent difference, Table 1 shows that the banks are quite similar in many respects. Agriculture, forestry, electrochemical industries, energy and water, construction, wholesale, retail, hotel and restaurants, and transport, for example, have very similar shares

[5] Due to different granularities in the banks' classification systems, it is difficult to make detailed comparisons beyond short term loans.

Table 2: Profile of companies 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			Granted credit (SEK)			Total sales (SEK mn.)		
	A	B		A	B		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

in the banks' portfolios, both in terms of counterparts and most of them also in terms of total exposure. In terms of client numbers, other services, wholesale trade and other manufacturing are the three largest customer groups in bank A. In bank B it is real estate, wholesale trade and other manufacturing.[6,7] Together, they account for about 50 percent of all customers. Other industries with large groups of counterparts are other services (13,2% of all counterparts in B), construction (9.8 and 8.2% respectively), retail trade (9.6 and 9.2%) and transport (7.0% for A). For each bank, approximately three out of four counterparts come from one of these six industries. Despite the apparent similarities between bank A and B, there are also a number of differences to speak of, mainly related to the variation in the size of average credit lines between industries, both within each bank and between banks. The most significant differences between the banks occur in telecom, finance, the chemical industry and other services. In telecom, bank A grants on average a little less than SEK 15 mn. while bank B has an average exposure of SEK 105 mn. To financial and other services companies, bank A furnishes on average SEK 49.2 and 2.4 mn respectively, compared with 81.6 and 13.6 mn. by B. In the chemical industry, A is a

[6] Real estate business includes, among other things, the exploitation of land, trade in real estate, intermediation, rental and management of both commercial and private real estate and tenant-owners associations.

[7] Broadly, other services is composed of three main groups: business, publicly and personally oriented service companies. The first consists mainly of computer and software consultancy, R&D and all other remaining business service companies, including law firms, accountants and (non-computer) consultants. The second comprises cleaning, waste management and special interest organizations. The last group includes, apart from any other services that most people regularly purchase, artistic professions, radio, tv, museums and leisure activities.

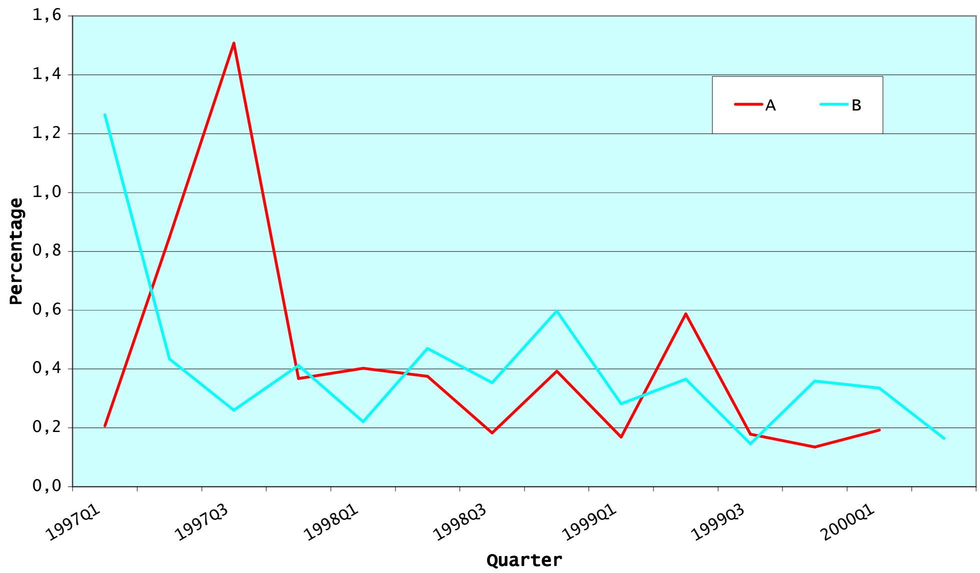
provider of larger loans, with on average SEK 32,8 mn. (17,4 mn. at B). Industries that have big loans in both banks are energy & water businesses and real estate services. The former category of debtors receives on average SEK 71 mn. at bank A (SEK 73 mn. at B) to while the latter gets SEK 27 mn at both banks. The banks have in common that the least significant debtors come from agriculture & fishing, government & health, retail trade and hotel and restaurants, with average loans ranging between SEK 1.0 and 3.9 mn.

Because other industries with comparable or larger average loan sizes contain relatively few counterparts, both banks have the largest exposure in real estate, with portfolio shares of 26 and 33 percent. Otherwise bank A has relatively more exposure in manufacturing, 20.2 percent (8.8 percent for B). Wholesale trade, finance and 'other services' are other important debtor groups for both banks, with loan portfolio shares of close to 10 percent. B has a somewhat bigger involvement in 'other services': 15,8 percent. Table 2 offers some more perspective on the banks' counterparts: to a great extent both grant loans to small and medium sized enterprises. Of all counterparts, 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.[8] Only 6-7 percent of all counterparts at both A and B have more than 25 employees. The third column of Table 2 supports our first impression of A being slightly more specialized in small businesses: approximately 40 percent of all its counterparts 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 2 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 loan size 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 counterparts even receive more than SEK 10 mn. compared with 6 percent in bank A. As we saw in Table 1, B generally has a bigger share of its counterparts 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.

[8]Companies 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.

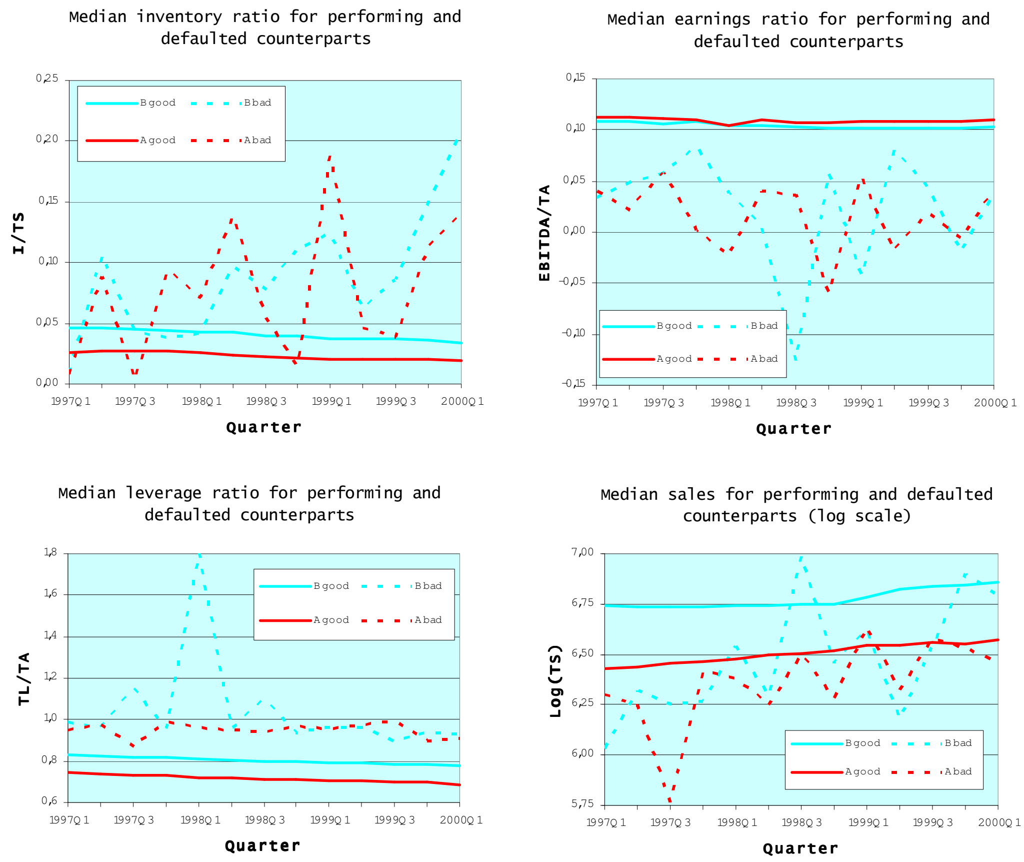
Figure 1: Quarterly default rates for counterparts in complete portfolios of banks A and B.



Figures 1 and 2 provide us with some further insight into the counterparts of both banks. Figure 1 summarizes the available information on default behavior among counterparts in each bank's business loan portfolio. Although the sample period is rather short, the default rates display quite some fluctuation over time. In Bank A defaults reach their maximum rate in the third quarter of 1997 at a level of 1.51%. In bank B the sample peak is reached two quarters earlier, at 1.26%. It should be noted though that a likely cause of the severity of both peaks, beside the general slump in business that occurred in 1997, can be found in the aftermath of the Swedish real estate crisis in the early 1990's. The ensuing recession struck the Swedish economy during the first half and middle of the 1990's, but its overall peak came off in 1991-92 and was accompanied by a full banking crisis. In 1992 the Swedish government granted a non-bankruptcy guarantee to all banks and founded a national banking emergency authority. Bad loan portfolios of banks that were in risk of collapse were taken over and managed by this authority. It is not unlikely that the short 1997 recession lead to the default of a number of businesses that had been in trouble since the early 1990's but not at immediate risk of collapse. The difference in timing of the peaks could then be a mere result of the individual banks' timing of write-downs. From 1998 onwards the quarterly default rates of both banks move up and down more or less synchronously, at levels between 0.6 and 0.1 percent. Differentials of about 0.2% occur, though, during nearly half of the remaining sample period.

The data set from the credit bureau contains information on balance sheet and income statement variables. Some examples of balance sheet entries are cash, accounts receivable and payable, current assets and liabilities, fixed and total assets, total liabilities and total equity.

Figure 2: Financial ratios for performing and defaulted counterparts in banks A and B.



From the income statement entries like total turnover, earnings before interest, depreciation, amortization, financial income, extraordinary income and taxes are available. Appendix B contains a complete list of all variables available from the credit bureau, including annual report data. In addition to the annual report data collected by PRV, we have information on the firms' track records regarding payment behavior, recorded by means of remarks for 61 various credit and tax related events. Broadly, remarks belong to one of two categories: non-payment remarks or bank remarks. Storage and usage of the first group are regulated by the Credit Information Act, the Personal Data Act and overseen by the Swedish Data Inspection Board. Examples of events that are registered are: delays in tax payments, the repossession of delivered goods, seizure of property, resettlement of loans and actual bankruptcy. In practice, with a record of non-payment remarks individuals will not be granted any new loans and small businesses will find it very difficult to open new lines of credit. The second type of remarks provide information on firms' payment behavior at banks. All Swedish banks participate in this scheme and report any abuse of a bank account or a credit card and slow loans (repayment is considered questionable) to the credit bureau, that maintains these records. Storage and usage of these remarks is regulated merely by the Personal Data Act. Whereas a bank remark may have the same consequences as having a non-payment remark, this is not the case in general. Their effect on individual applications for credit presumably works mainly through the accumulation of negative indicators. Appendix C contains the complete list of non-payment and bank remarks.

In Figure 2 we characterize the businesses in the bank portfolios over time by means of four financial ratios, that are commonly used to study bankruptcy risk.[9] Counterparts of banks A and B are quite similar in terms of their accounting ratios. In both banks healthy businesses display stable or steadily improving ratios over the sample period. Although the small size of the subsamples of defaulting counterparts may be responsible for the degree of variation in the ratios, the median defaulting firm is persistently worse off than a performing business when measured by the earnings ratio and the leverage ratio. Inventory turnover is, mostly but not always, lower for defaulting firms, although there is quite some variation over time. Total sales are also generally, but not always, lower for defaulting firms. Broadly, these data confirm the impression we obtained in Table 1 and 2: counterparts in both banks are quite similar, even though some differences exist. For example, performing counterparts in bank B are slightly bigger in terms of their sales, are marginally more indebted and have somewhat higher inventory ratios.

3 The internal rating systems

Both institutions maintain an internal credit rating scheme. 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 stands for the lowest credit quality (factual default) with the intermediate grades intended to imply a monotonically increasing risk profile. Bank B has the most creditworthy counterparts in rating class 1 and the least creditworthy ones in class 7.[10] Two conditions must be satisfied for a counterpart to be assigned to the default category. First, payments on the principal or interest must be at least 60 days overdue. Secondly, a bank official needs to make a judgement and conclude that any such payment is unlikely to occur in the future. A comparison with data from the credit bureau (not shown here) shows that ratings A15 and B7 are both highly correlated with (the officially registered) bankruptcy. Generally the rating class leads the latter by one or more quarters, 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

[9] Altman [2], [3], and [4], Frydman, Altman and Kao [24], Li [33], and Shumway [38] are examples of authors that employ financial ratios . Carling, Jacobson, Lindé and Roszbach [21] follow a similar approach, controlling for macroeconomic variables using a panel data set from one of the banks in this paper.

[10] The original system of bank B had the best counterparts in class 7 and the worst 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.

Table 3a: Characterization of a selection of rating classes.

Risk rating	Ownership	Industry	Management
1	listed shares, easy access to additional capital	industry leader, recession resistant counter-cyclical industry	highly respected and experienced
6	acceptable structure, may have difficulty to raise new capital	well-established in cyclical industry, small market shares	adequate to above average
9	structure just adequate, doubts whether new capital can be raised	in cyclical industry recovering from recession, or newly established	adequate
14	weak owners, cannot access new capital, shares trading suspended	negligible market shares in a troubled industry, small chances of continued operation	little experience in tough decision-making, significant management turnover, no plan for financial crisis

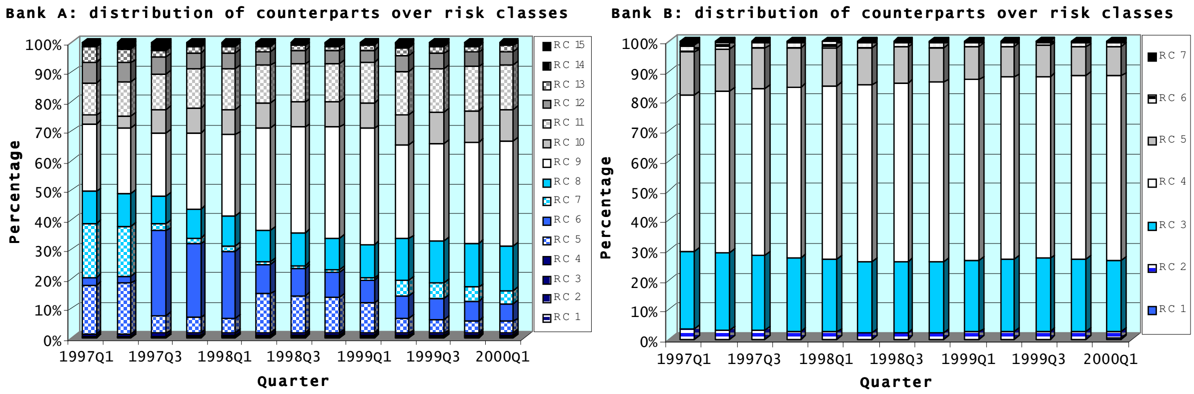
Table 3b: Characterization of a selection of rating classes.

Risk rating	Financial status	General
1	steady sales growth, very conservative balance sheet ratios, very solid cash flow, excellent debt service capacity	only a handful of large firms make it to this class
6	moderate potential growth in sales, adequate balance sheet ratios, volatile cash flow, at times thin debt service coverage	unlikely that well established firms in solid markets fall beyond this class
9	little or no potential to change mediocre sales growth, possible over-capacity problems, great volatility in cash flow	–
14	negative sales growth outlook, balance sheet ratios give rise to serious concern, cash flow shows extreme volatility, may be in process of distressed selling of critical assets	marked increase or unacceptable level of delinquency in payment to trade creditors

to the above definition by the banks: a loan that is assigned to rating class 15 in bank A or class 7 in B.

The assignment of an internal rating class to a new loan, or the re-evaluation of a counterparty rating is performed according to a set of quantitative and qualitative criteria. There are two

Figure 3: Distribution of debtors over risk classes in the complete portfolios of banks A and B.



quantitative measures. First, the credit bureau UC provides an external rating that reflects the assessment of counterparty bankruptcy risk over the next 8 quarters. This rating is calculated using information available from the tax authorities, PRV and credit remark data.[11] Second, the banks estimate the probability of default by means of models that use both the information available from UC internal information as inputs. Our understanding is that these models have been inspired by the Z-score model of Altman [1], the Zeta model of Altman, Haldeman and Narayanan [7] and the KMV model.[12] 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 counterparty rating classification handbooks. The handbook provides so called verbal definitions (descriptions) of the properties of firms in a given rating class along a number of dimensions. In Table 3a and 3b we have attempted to capture the essentials of bank A's handbook characterization of the rating classes. It should be noted that the criteria are not weighted according to some *formal* scoring procedure in the rating decision. Ultimately, a so called credit committee aggregates all information and decides to what class a counterpart is assigned. Credit ratings are updated at least once every 12 months.

The banks strive for assigning "through the cycle" ratings, but have also mentioned that they realize that some "surfing" through the cycle is unavoidable. This mixture of objectives can be recognized by the criteria that are summed up in the third column of Table 3a. To some extent it also shows, for example, that the size of a company, and the resulting loan size, may directly affect its rating.

Figure 3 shows how the counterparts in the complete portfolios were distributed over all rating grades. A number of characteristics are worth mentioning. First, both banks appear to allocate a large share of debtors to one risk class. Over the sample period, A has between 20

[11] For details and an evaluation of their model based approach, see Jacobson and Lindé [29].

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

Table 4: Corresponding internal rating in banks A and B.
Table shows, for each rating class, how counterparts in bank A are rated in bank B at the same time. 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 counterparts in class 9, while 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 risk 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 counterparts 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 counterparts from the more creditworthy rating class 5 into 6 and 7 and from 7 into 8 and 9. Also, counterparts 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.[13]

[13] Carling et al. [21] do evaluate the effect of counterpart migrations on aggregate risk, by calculating VaR with a credit risk model.

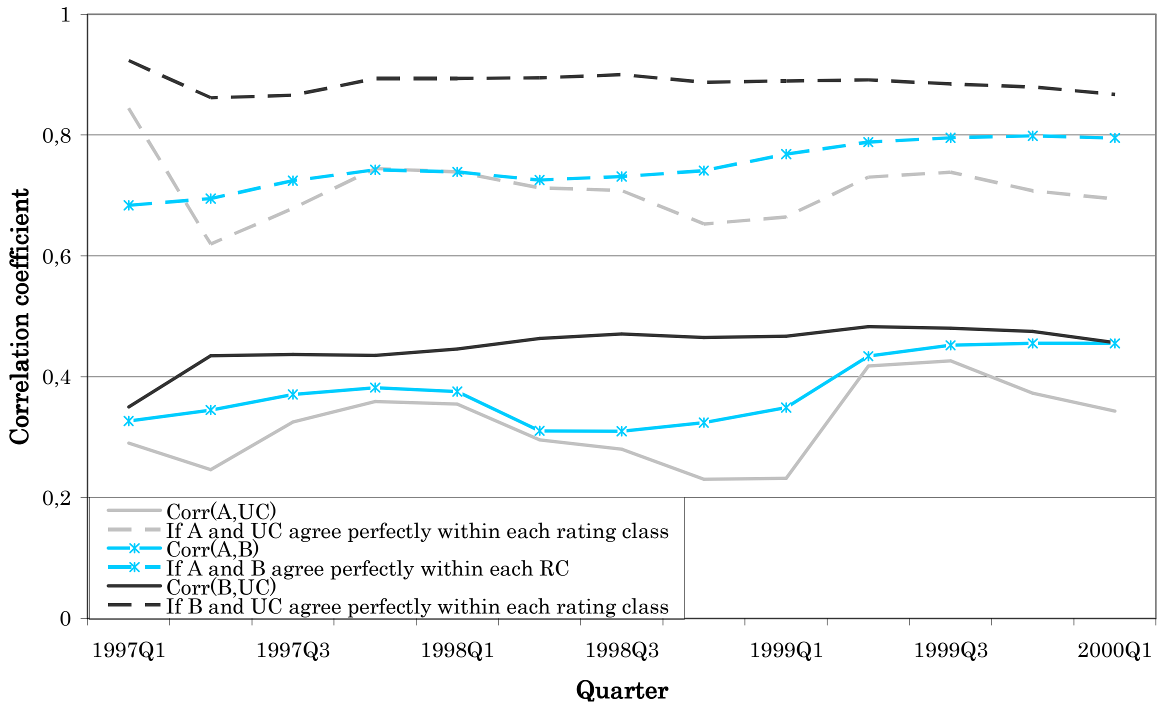
Table 5: Corresponding internal rating in banks B and A.
Table shows, for each rating class, how counterparts in bank B are rated in bank A at the same time. The distribution over rating class is expressed in percent. Columns sum to 100 percent.

	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 selected the subset of overlapping counterparts and mapped the ratings of all counterparts in one bank into those of the other in Tables 4 and 5. A quick glance at the tables shows that observations appear to be more or less clustered around the "diagonal" of the tables, as they ought to be. 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 both banks' ratings of identical counterparts indeed differ widely in quite some cases. Most interestingly, only 21.8 percent of the companies that were in default at bank A simultaneously defaulted at B. 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 counterparts 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 counterparts 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 counterparts allotted to class 2 in bank A display this property in bank B.

In Figure 4 we provide Spearman rank correlations as formal measures of the degree of

Figure 4: Spearman rank correlations between ratings of the banks and the credit bureau.



covariation between the two ratings. 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. This might seem somewhat low, given the observed clustering around the diagonal. The seemingly weak correlation may be a result of the discrete nature of the data in combination with a shortcoming of (one of) the (common) definition(s) of the Spearman correlation. To arrive at these correlations, observations with equal values 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. We can, however, use the information available from bank A, by assuming that the ratings by A are a reasonable risk measure according to which counterparts *within* bank B's rating classes can be ranked.[14] This way, we will obtain a measure of the maximum possible correlation between the ratings of banks A and B, as it

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

Table 6: Internal ratings' transition matrix for bank A, horizon= 4 quarters (in percent).

	To														
From	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	77.6	4.2	0.0	4.9	0.7	7.0	0.0	0.0	4.2	1.4	0.0	0.0	0.0	0.0	0.0
2	0.7	76.0	5.7	2.6	0.0	4.8	2.6	0.2	5.8	0.9	0.9	0.0	0.0	0.0	0.0
3	1.1	4.6	74.9	7.0	1.0	5.6	0.9	0.1	3.0	1.0	0.7	0.0	0.0	0.0	0.0
4	0.5	0.4	7.0	75.9	0.9	6.3	3.0	1.2	3.7	0.5	0.4	0.1	0.0	0.0	0.0
5	0.1	0.1	0.1	0.3	23.8	23.7	3.6	8.5	18.1	11.0	7.5	1.9	0.4	0.2	0.7
6	0.0	0.1	0.1	0.5	24.8	37.2	8.4	5.3	12.0	6.2	4.3	0.7	0.1	0.0	0.3
7	0.0	0.1	0.2	0.6	9.9	39.6	13.7	5.4	15.5	6.8	5.8	1.4	0.3	0.1	0.6
8	0.0	0.0	0.1	0.1	6.4	3.6	1.4	49.2	14.1	3.7	12.0	4.9	1.7	0.7	2.2
9	0.0	0.1	0.1	0.3	5.7	5.0	3.1	10.1	55.7	6.2	7.7	3.0	1.3	0.6	1.2
10	0.0	0.0	0.1	0.2	7.0	2.4	2.4	6.6	15.7	58.5	4.6	1.5	0.5	0.2	0.3
11	0.0	0.0	0.0	0.1	1.5	1.9	0.4	10.3	7.7	1.9	64.7	6.2	1.9	0.8	2.5
12	0.0	0.0	0.0	0.0	2.9	0.9	0.3	7.6	6.2	1.5	19.6	46.0	6.9	2.5	5.5
13	0.0	0.0	0.0	0.0	1.4	0.6	0.2	3.8	3.8	1.5	15.5	13.9	41.7	5.0	12.5
14	0.0	0.0	0.0	0.0	0.4	0.2	0.0	1.4	1.1	0.2	5.4	7.9	9.4	49.1	24.9

implicitly assumes that one bank agrees *perfectly* with the other on the ordering *within* a rating grade.[15] The dotted dark grey line shows that the maximum level of correlation between both banks' ratings was between 0.68 and 0.80. As a benchmark, we have also plotted the corresponding correlations between the ratings of each of the banks and the risk classification of UC, the credit bureau. Clearly, bank B's ratings are more correlated with the ratings of UC than A's ratings are. This finding is consistent with the (qualitative) information we received from the banks about the importance of the UC rating. B reported that greater weight is placed on the credit bureau's rating. Over the sample period the Spearman coefficient for B varied between .35 and .48, compared with .23-.43 for A. The maximum correlation between the bank rating and the credit bureau rating varies between .86 and .92 for bank B and .62-.84 for bank A.

Table 7: Internal ratings' transition matrix for bank B, horizon= 4 quarters (in percent).

	To						
From	1	2	3	4	5	6	7
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	1.4	77.6	18.8	2.0	0.3	0.0	0.0
3	0.0	1.1	82.6	15.0	0.9	0.1	0.2
4	0.0	0.0	3.6	87.8	5.7	0.6	2.2
5	0.0	0.0	0.2	18.5	67.9	2.5	10.9
6	0.0	0.0	0.2	6.2	11.2	56.8	25.6

[15] It seems unlikely, though, that this is the case given the differences the ratings of banks A and B (Tables 5a and 5b).

Table 8: 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

To get some feeling for the dynamics in the banks' internal rating systems, we have computed the empirical transition frequencies between the 15 respectively 7 rating classes at a 4 quarter horizon. These are displayed in Tables 6 and 7. By and large the transition matrices display properties that one would expect from a reasonably functioning rating system.[16] Zero elements occur mostly in the upper-right corners reflecting that initially high-rated counterparts are not downgraded very far or very often. Likewise, the transitions of poorly rated counterparts are not in the direction of the better grades. The diagonal elements reveal a high degree of persistence for the most creditworthy counterparts, 70-80 percent of these counterparts remain in their rating class from one year to another. The least creditworthy debtors migrate more often, with only 40-60 percent transiting, while the greatest fluctuations occur in the middle classes 5-7. From the columns under heading 15 we can also see which rating grades are the most important sources of defaulting firms. Out of those classified as A14, 24.9 percent defaults within four quarters, compared with 12.5, 5.5 and 2.5 percent for three adjacent grades. After another four quarters (not shown here) these frequencies rise to 40.7, 22.7, 10.9, and 6.0 percent respectively. Default risk is thus monotonically increasing in the grade for these four rating classes; for the remaining classes the picture is slightly blurred, with grades 5 and 8, for example, having (relatively) too high default frequencies.

[16] The transition matrices are computed in the following way: for any transition horizon h, we compared and counted the internal rating of each company that was included in the bank's portfolio at both time τ and $\tau + h$, for $\tau = 1,\ 2,\ \ldots,\ 24 - h$. Companies that defaulted, i.e., ended up in the absorbing state of rating class 15 between τ and $\tau + h$, were also taken into account.

Table 9: 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

For bank B, the share of all grade 6 counterparts that defaults within 4 quarters is .26, while respectively 10.9, 2.2 and 0.2 percent default from grades 5 to 3. As one would expect, the persistence in the ratings is higher than at bank A: between 75 and 90 percent of the businesses in grades 2-4 maintain their rating four quarters later. Lower grade companies migrate more often than the better ones, although less so than in bank A between 55 and 65 percent stay in the same grade.

To get a better understanding of each bank's ability to identify future problem loans, we display in Tables 8 and 9 the ratings of defaulted counterparts 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 8 shows that bank A does reasonably well at locating future defaults. One quarter before their default, 19 percent of all counterparts 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 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 that close to 50 percent of all credit is given, stands for 35 to 64 of all defaulting counterparts. Classes B3 and B4, that stand for 30-40 percent of all credit, produce merely 2-18 percent of the defaults.

In view of these stylized facts, we may already draw some preliminary conclusions about the design and application of the internal ratings systems. Firstly, the possibility to choose the number of rating classes, that will continue to exist under Basel II, may be a non-trivial feature of the rating system design that will lead banks to implement differing rating systems. For example, both the degree of concentration in and the distribution of counterparts over classes differ clearly between the banks in this study. Secondly, the large concentrations of counterparts 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 Loss distributions and tail events

In this section, we investigate the properties of both banks' credit loss distributions, as calculated with a Monte Carlo resampling method. Our main interest is to study how explicit differences, like the number of rating classes and implicit differences, like the use of different quantitative and qualitative methods to evaluate default risk, affect the implied credit loss distributions of the banks. These effects should be of interest for several reasons. At a very general level, it is important for both bank regulators and risk managers to understand if and how the choice of a specific internal rating systems affects the implied riskiness of their loan portfolios. As the banks under investigation here have implemented counterparty risk rating systems, we are inclined to expect that both have similar perceptions of the (overlapping) portfolio's credit risk. Should we, however, find that both banks have strongly diverging perceptions, then this will raise a number of questions about the sources of these differences. At a more specific level, we believe that the insights from this paper can help us to understand if the implementation of internal risk rating systems by large banking corporations, as envisioned by the Basel Committee, will provide regulators with a correct and/or consistent picture of banks' loan portfolio credit risk.

To verify 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.[17] Since high credit risk levels in the tails imply a need for more economic capital, and equity is a relatively expensive means of business finance, banks should have an incentive to (attempt to) diversify away such risk when possible. This is another reason for being interested in the outcomes of the robustness tests. Moreover, because we have both banks' internal ratings and loan data for all counterparts at our disposal, these experiments will help us to understand if changes in the portfolio characteristics and other risk parameters are likely to affect the credit loss distributions and their tails in a

[17] 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.

uniform way for rating systems that satisfy the general terms of Basel II but are implemented in different ways.

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 the approach of Carey [15]. An advantage of this method is that it avoids any assumptions about parametric forms. Many currently and frequently used risk management systems/models use some type of common factor model to estimate loss correlations between assets. Due to a lack of data, many of the (parametric) loss correlation assumptions that are incorporated in these models remain untested. The approach used here keeps clear of such conjectures.

The selection of the data is done as follows. First, we store, for each counterpart in each bank, the company 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 company is still present but has defaulted, we store the actual exposure and a default indicator. If the company 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 companies 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 counterparts and then continue the relationship, most likely at renegotiated terms.[18] Firms that exited at an intermediate date but returned before or at t+h are considered not to have transited and therefore disregarded. For our experiments, this implies that we ignore any possible effect that exiting behavior may have on credit risk. However, since we are unable to determine the causes of the exit (voluntary exit by a healthy company 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 counterpart: the credit exposure and the corresponding risk rating, if any, at time t and, if any, at t+h; counterparts that were absent at one of these two points in time, or any intermediate quarter, have zero entries. Third, 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

[18] Had we disposed of data on actual losses, then this effect would have been captured by the loss given default (LGD) rate.

rating class. We will call this the "standard" portfolio profile.

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.[19] 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 at 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 counterparts that defaulted between t and t+h. 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 [15].

4.2 Results

In this section we present, for each bank, the 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.[20] 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.[21] 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 another forecast horizon. Second,

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

[20] 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.

[21] 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.

Table 10: 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 counterparts.

In the first two lines of Table 10, 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 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 8 shows that bank B considers its portfolio with identical counterparts 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 main explanation for this shrinking factor lies in the fact that loss rates further out in the tails are steered by extreme events that

Table 11: 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*

occur seldom. 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 the two banks have rather different perceptions of credit risk. However, given that both have reported to assign internal risk ratings to companies based on counterparty risk and not loan specific risk or collateral adjusted credit risk, no structural differences in either average default rates or loss rates ought to be expected.[22]

One conclusion from the above results is that these banks could be faced with different capital requirements for a portfolio with identical counterparts. If we translate the figures in Table 10 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 10 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

[22] Sizable counterparty specific differences in loan size between banks could generate differences in loss rate distributions.

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.[23] 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 11, 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.[24] 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. This tendency is easier to observe in Figures 5 and 6: 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.[25] It is also 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.

[23] See also Calem and LaCour-Little [13] p.18, for further insights into the issue of jointly choosing horizon and loss percentile.

[24] 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.

[25] Any changes that actually show up here stem from counterparts disappearing from or entering the set of feasible observations due to the three percent portfolio share restriction.

Figure 5: Loss rate distributions for varying portfolio sizes in bank A (horizon = 1 quarter).

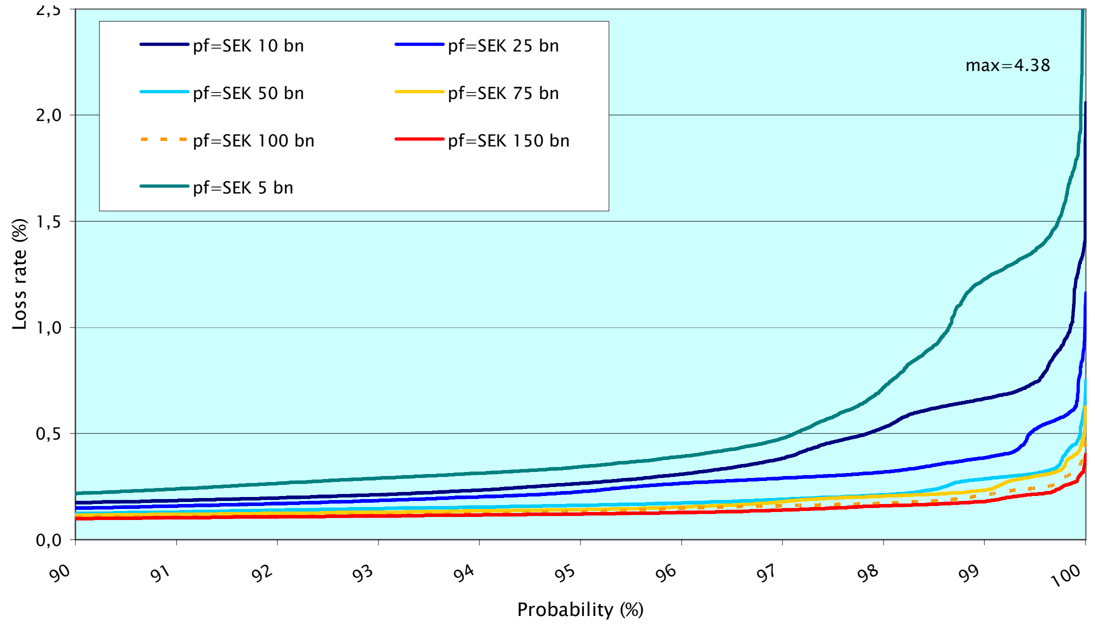


Figure 6: Loss rate distributions for varying portfolio sizes in bank B (horizon = 1 quarter).

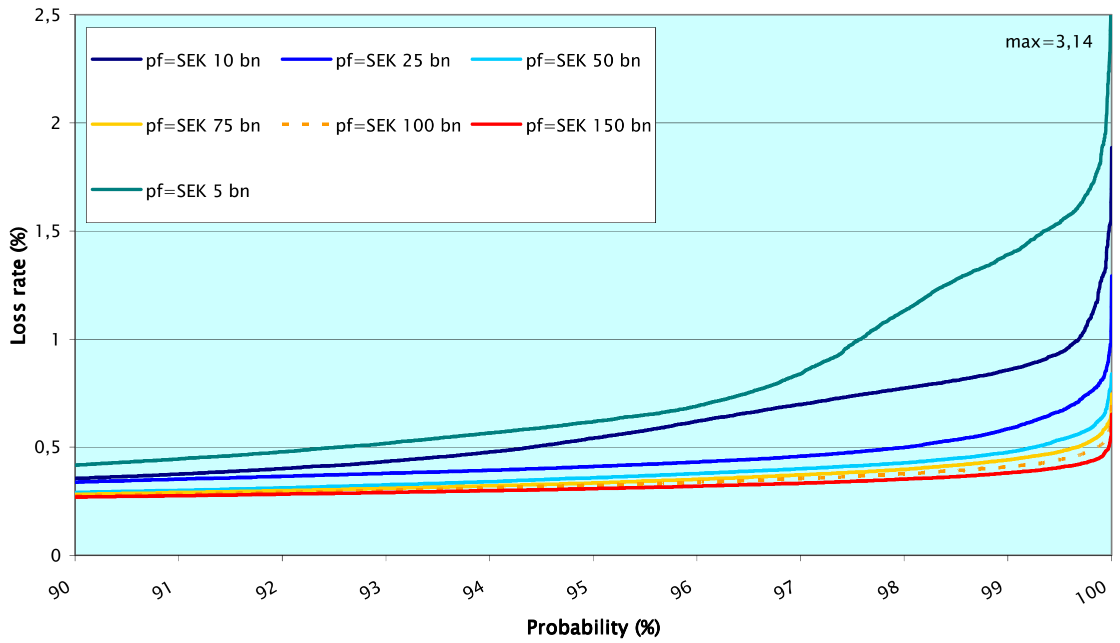


Table 12: Simulated portfolio loss rates in bank A for varying risk profiles

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 11 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 together account for approximately 20 percent of the total portfolio, while keeping the portfolio size equal to that of the benchmark standard portfolio.[26] In Table 12 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

[26] 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 counterpart 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 counterparts with top or next-to-top ratings, we selected the bottom classes with a portfolio share of approximately 20 percent.

Table 13: 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 at loss distribution percentiles							
Bank	Percentage 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 13, 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 counterparts 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 counterparts 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 mirror image of this difference in rating counterparts is that bank A has riskier and/or more risky counterparts 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 14 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 14: 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 15: 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.[27] The results in Table 14 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

[27] 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.

Table 16: 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 are taken from Table 10.

	Type of	Quarter								
Bank	capital requirement	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
			Levels of default risk							
			90	95	97.5	99	99.5	99.75	99.9	99.99
A	Economic		0.16	0.23	0.30	0.38	0.44	0.49	0.57	0.72
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.[28] Just as the results in Table 11, these figures indicate that banks are likely to continue to be spurred to engage in some form of securitization.

A flaw of the resampling method we apply, is that 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 (three years) and mostly covers a period with relatively strong GDP growth.[29] 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 mitigate the effect of any possible underestimation, we also report the results from two experiments in which we split up the data set into "bad" and "good" quarters and loans are drawn separately from these sample parts. Because we have a relatively short sample period, but data with a quarterly frequency, we have chosen not to create "closed" intervals, but instead to simply allot individual quarters based on their one quarter default rate in order to generate the maximum possible difference between the two groups.[30] The outcomes in Table 15 indicate that "aggregate" fluctuations are likely to have an important impact on credit losses. For bank A

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

[29] See Carlin et al. [21] and Jacobson and Lindé [29] for longer series of aggregate default rates, GDP growth and the output gap.

[30] 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.

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 appears to be the reverse: 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.

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 16, we use the risk weight functions provided in the latest version of the Basel II Accord.[31] Economic capital, in the last two lines, is derived from the loss distributions presented in Table 10 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 is based on past-year probabilities of default. Although the figures in Table 15 do suggest that the required economic capital would be likely to rise if a full business cycle had been included in the sample period, and the regulatory risk weights are concave in default risk, it is unlikely that we will see economic and regulatory capital approach each other. It is thus likely that the regulatory capital requirement will impose a binding constraint on both banks.[32]

5 Summary and conclusions

In this paper we advance new quantitative evidence on how internal rating systems affect banks' perception of credit risk. The only two studies comparing rating systems known to us, are by Carey and Treacy [19] and Carey [17] and focus either on the qualitative properties of rating systems [19] or on the analysis of rating differences [17]. In this study we use panel data from two banks' complete business loan portfolios including a group of companies that simultaneously borrowed from both institutions. By using the banks' loan and internal counterparty risk rating data and applying a non-parametric Monte Carlo re-sampling method we are able to derive

[31] See the risk weights in The New Basel Accord [10], pp. 50-53. The proposal is currently being adjusted. In the latest version, loans to businesses with total sales below EUR 50 mn. can be given special treatment according. Retail exposure, defined as loans with a maximum size that are treated as retail credit, can also be given a more favourable treatment. Because our loan portfolios are only characterized in terms of a risk profile, 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 [31] for a treatment of the differences between retail, SME and corporate credit in the Basel II proposal.

[32] The new Basel proposal is currently being redrafted. In the upcoming version risk weights are expected to be constructed such that regulatory capital will cover for unexpected losses only.

the implied loss distributions for each of the banks without making any assumptions about correlations between assets.

Our findings suggest that banks do not implement internal counterparty risk rating systems, as envisioned by the new Basel II Accord, in such a way that they result in consistent estimates of portfolio credit losses. In this study, the degree of concentration in and the distribution of counterparts over classes differs widely between banks; the presence of large concentrations of counterparts in a small number of rating classes make it quite likely that default risk will not be homogeneous within all rating classes. Moreover, there are substantial differences in the riskiness of low and high grade counterparts between banks.

The experiments in this paper reveal significant differences in the perceived riskiness of the overlapping portfolio between the two banks: both expected losses and the credit loss rates at a wide range of loss distribution percentiles vary considerably between banks. Such variation could also translate into differences in the economic capital that banks require to support their risk taking activities. This in turn could (continue to) create incentives for some banks to securitize part of their loan portfolio or to increase the riskiness of loans/counterparts in certain rating classes in order to generate higher returns. Furthermore, the results suggest that some optional properties of an internal rating system, such as the number of grades and the dispersion over classes may constitute strategic choice parameters for a bank, since risk measures may turn out not be invariant to parameter changes.

Simulation outcomes also demonstrate that not only the design of the rating systems but also the rating composition and, especially, the size of the banks (or their portfolios) are of great importance for credit loss distributions and thus for banks required capital structure. For some portfolio sizes, depending on the loss percentiles chosen, credit risk can be reduced by up to 40 percent by doubling loan portfolio size. This report also confirms the importance of appropriately choosing a forecast horizon and a desirable level of insolvency for banks.

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