THE YOUNG ECONOMISTS' SEMINAR to
17^{th} Dubrovnik Economic Conference

Organised by

Tomislav Ridzak

Are Some Banks More Lenient in Implementation of Placement Classification Rules?
An Application of Dichotomous Rasch Model to Classification of Credit Risk in Banking System

Hotel "Grand Villa Argentina",
Dubrovnik
June 29, 2011

Draft version

Please do not quote

Are some banks more lenient in implementation of placement classification rules?

An application of dichotomous Rasch model to classification of credit risk in banking system

Tomislav Ridzak

Introduction

This research aims to analyze differences in approach to the credit risk classification systems amongst the commercial banks in Croatia. Placement classification systems used by banks cannot be thoroughly inspected without a detailed knowledge of the actual quality of individual placements, and no regulator has the opportunity to gain such an insight into loan portfolios. This research presents a somewhat roundabout approach, based on a comparison of differences in placement classification of a common portfolio, to assess the relative strictness of banks.

Use of information on classification of multiple borrowers by different banks according to their credit risk has recently gained prominence in the literature, although applications still remain scarce due to extensive data requirements. However, even when such data is available, there is no straightforward way to translate them into measures of lenience / strictness for each bank. Direct comparison of common exposures for two banks yields solid bilateral measures of lenience / strictness in risk classification, but aggregation of those bilateral indicators across each of the banks may generate biased aggregate measures because distribution of bilateral exposures for individual bank may deviate from the system-wide thus distorting the aggregate measure. I propose application of a technique for construction of aggregate indicators on the basis of a Rasch model that allows the researcher to sort different types of evaluators by their strictness, from the most lenient to the strictest.

Evaluation of credit risk in the portfolio is a key issue in commercial bank management. The quality of credit approval and monitoring procedures in the bank is an important determinant of its financial performance, directly affecting bank stability. Loss on a given loan through increased loan provisions translates into the level of profit or loss of a given bank and affects its capitalization level. Therefore, the loan classification is important for bank management, depositors, owners, auditors and of course the regulators.

Structure of the paper is as follows. In the next section there is short survey of related literature. In the following one the Rasch model is explained. Then, the major characteristics of the data set are shown with a short overview of the Croatian regulation regarding loan classification, which is important in order to understand the problem at hand. In the fourth section, the results of the performed analysis are presented together with model diagnostics. Finally, after concluding, in the appendix correction the observed non performing loan ratios is used as an example for possible applications of the obtained measures.

Related literature

Although many regulators around the world have prescribed detailed rules for classification of bank credit risk, this process of classification per se is not straight forward. As Laurin and Majnoni (2003) in a Word Bank study put it, in most countries loan classification and provisioning involve substantial subjective judgment, requiring difficult assessments under considerable uncertainty. Moreover, such an assessment is performed with a view on incurred costs for the bank by classifying the loan as substandard since it increases the level of provisions and lowers the profit.

The literature related to bank credit risk classification is still evolving, with couple of major areas attracting most of the interest. A growing literature on causes and effects of loan restructuring brought some important insights into the dynamics of the process. The motivation for manipulation of provisioning levels and loan "evergreening" comes from income smoothing. Liu and Ryan (2003) show that US banks used lenient provisioning to smooth their income during the period of poor financial health and banking crisis. In the subsequent boom period the banks accelerated provisioning for loan losses and accelerated charge-offs in order to create cushions for any future shocks to loan losses and reduce their non-performing loan ratios to an acceptable level. It is important to note that income smoothing in not per se a bad idea and in fact many of the new reform proposals to the existing regulatory framework aim for introduction of income smoothing features. However, such regulatory proposals suggest that banks should build in advance sufficient capital buffers for this purpose rather than manipulate loan classification during the crises to achieve such goals.

Practice of restructuring a loan and keeping it in the books as a standard quality loan instead of accounting for potential losses may have important ramification beyond the banking sector. Such evergreening behaviour keeps provisioning levels artificially low while having a profound effect on the performance of real economy. As Caballero, Hoshi and Kashyap (2008) recently examined in detail, sham loan restructuring practices, to which they refer as evergreening or "zombie lending", where banks restructure their loans in order to keep otherwise insolvent borrowers alive, have adverse economic consequences as congestion created by zombie firms reduces profits for healthy firms and discourages entry and investment in sectors dominated by these firms. By avoiding recognition of the defaulted loans, especially if the loan is not adequately collateralized, the banks avoid depletion of their capital stock and possibly circumvent public scrutiny for exacerbating the recession.

The above surveyed literature brings together substantial evidence that banks might rate some of their clients as they see fit, in line with their needs and not based on some objective standards. From the perspective of a bank regulator, this issue is highly important. If bad loans are not accounted for in a truthful manner, in the limit, the stability of the bank is at stake, so, due to losses on bad loans, the bank might become insolvent. In the worst case if some banks continue to build-up loses, fiscal resources may have to be used in order to bail them out and turn them into major fiscal burden, which is especially problematic for large, systemically important banks. Consequently, the quality and objectiveness of the loan classification systems implying adherence to same objective standards is highly important from the financial stability perspective.

Although the aim of this paper is not to compare credit ratings but rather to assess relative strictness / leniency of placement classification systems between banks, the literature on credit ratings contains several important insights for such analysis. Carey (2001) presents one of the first attempts to tackle the issue of consistency of banks' ratings. He uses large dataset of commercial loans and compares the ratings assigned by different lenders to the same borrower. He first calculates frequencies of disagreements between different banks in assigned rating as well as resulting divergences in probability of default and capital allocation. Based on this information he also examines average difference in assigned grades for each lender relative to the pool of all other lenders. Findings show significant differences in loan ratings for some of the lenders, which are not related to available borrower characteristics.

Risk ratings used by banks are very important for banks operating under the Basel II accord as they directly determine the amount of capital needed. Jacobson et al (2005) use the sample of common borrowers rated by two different banks and show there are substantial differences in the implied riskiness between the banks. This implies that the required amount of capital for these two banks will differ only due to specifics of their internal rating systems.

Hornik et al (2007) use another approach to detect outliers amongst lenders. Rather than observe differences for each single lender in rating assignments against a pool of all other lenders, which may be skewed if two lenient banks are compared, they acknowledge limitations for extraction of aggregate measures for leniency or strictness of a bank and use information from all possible bilateral comparisons as input data to which they apply multidimensional scaling and then construct minimal spanning tree in order to detect outliers i.e., the banks that are least similar to other banks. Multi ratter information is also used in Hornik et al (2010) to assess the accuracy of estimated default probabilities and consensus probabilities of default. The authors also construct maps that help to detect biases the banks might have in specific industries.

Approach taken in this paper was to compare the loan classifications of multiple borrowers by different banks. Consequently, results should show relative positions of the banks within a sample for a given year. This will not give us objective measure of quality for each loan portfolio, but it is nevertheless a convenient method to detect banks differing from others in the way they apply loan classification system. In order to achieve this goal, the dichotomous Rasch model to the company × bank matrix is applied. The model allows us to extract relative leniency / strictness parameters for each bank, compared to other banks. This way we are able to compare bank's classification systems and perform what-if analysis, for example what would happen if any given bank switched to a different risk classification system or if all the banks shared the single risk classification system.

The model

The intuitive idea behind the Rasch model can best be explained in its original setting, in education research. As an example, imagine the situation where students are being tested by several teachers on the same set of question with more than one teacher assessing each of the students. In such circumstances, the model allows disentanglement of two measures: student ability and teacher leniency / strictness. At least in theory, the more able candidates should answer more questions correctly. Also, the stricter the teacher, he will give lower proportion of excellent marks to the same group of students. However, it is important to note, that the Rasch model is probabilistic one: it allows for the fact that some questions might be answered correctly by chance.

By using a Rasch model a researcher basically compares how the data at hand compares to a theoretical structure the data should fulfil in order to make the measurement theoretically valid. The misfitting items are detected and eliminated, modified or their behaviour is clarified. The ideal structure the data should exhibit is called the Gutmann structure, as explained in Alagumalai, et al. (2005). This structure stipulates that if a person succeeds on an item, she or he should also succeed on all items easier that that one. Similarly, if a person fails on an item, the person should also fail on all items that are more difficult than that one.

The Rasch model was primarily used in psychometrics, especially education measurement, where acquired skills were tested, in test calibration (Alagumalai et al. (2005)) and in design of computer adaptive tests (Stahl, Bergstrom, and Gershon (2000)). However, the model has also been applied to other areas such as health research and aptitude tests in marketing (Alagumalai et al (2005), Carriquiry and Fienberg (2005)).

The Rasch model was developed by Georg Rasch in order to separate measures of person ability and item difficulty which were (and are) often tangled together in the education research. The probability of a person answering correctly to an item is positively related to the difference between person ability (B_n) and item (question) difficulty (D_i). The more difficult an item is the probability of getting it wrong is higher. In the same vein, the more able the person is, the higher is the probability of getting the answer right. Expressed as a term:

$$P_n(x=1) = f(B_n - D_i) \qquad (1)$$

First, the raw scores (number of correct answers, or as it will be seen in this case, number of defaulted loans) from the observed responses are calculated, and they represent the crude measure of person ability and item difficulty. *Table 1* gives an example matrix where 5 persons answer 5 questions (items). The marginal row and column present raw scores.

Table 1 An example of person × item matrix

	item A	item B	item C	item D	item E	raw person score
person 1	1	0	0	0	0	**1**
person 2	1	0	1	1	1	**4**
person 3	1	0	0	0	1	**2**
person 4	1	0	0	1	1	**3**
person 5	1	1	1	1	0	**4**
raw item score	**5**	**1**	**2**	**3**	**3**	

In the analysis, the raw scores are then transformed to log odds scale, which transforms ordinal scale to interval scale and avoids the problem of bias towards medium scores. The procedure is to convert the raw score (i.e. 90 per cent correct answers) to logit, by using the log odds i.e. to natural logarithm of 90 over 10. Expanding the Equation (1) gives us the following equation for probability of success on an item, given the person's ability and item difficulty:

$$P_{ni}(x_{ni} = 1 \mid B_n, D_i) = \frac{e^{(B_n - D_i)}}{1 - e^{(B_n - D_i)}} \qquad (2)$$

In order to achieve parameter separation, which is a special feature of the Rasch model, we can divide the probability of success on an item (Equation (2)) by probability of failure, which equals 1 - probability of success, as shown in Bond and Fox (2001), to obtain the following interesting result:

$$\ln\left(\frac{\dfrac{e^{(B_n - D_i)}}{1 - e^{(B_n - D_i)}}}{1 - \dfrac{e^{(B_n - D_i)}}{1 - e^{(B_n - D_i)}}} \right) = B_n - D_i \qquad (3)$$

Equation (3) implies that the estimates of Di can be obtained without estimation of person parameters, Bn, by conditioning on them. This approach was initially suggested by Rasch who observed that the conditional distribution of responses (the left hand side of equation (3)) depends only on Di, if we use raw score as a conditioning variable (marginal column in *Table*

1). The estimation can then be performed by conditioning the likelihood on the Bn, person scores (or in our case company scores) which then vanish from the likelihood equation. To make such system identified, additional restrictions are imposed by setting some parameters to zero, which then represents baseline difficulty. Here I use the estimation routine for the R environment provided by Mair et al. (2010).

The data and the background on Croatian legislative regarding credit risk

The data for this research come from the database on credit risk classification obtained from Supervisory Department of Croatian National Bank. According to regulations[1], the banks should classify all their credit risk in excess of 200.000, 300.000, 400.000 500.000 or 700.000 kuna, depending on the bank size, individually, and the credit risk of amount smaller than that, bundled in a portfolios. There are three major risk groups for credit risk classification: A, B and C. The placements in group A are those extended to a reputable borrower with solid current and future cash flows or placements that are secured with adequate collateral. The placements in group B are the placements that probably will not be recovered fully, and placements in group C are the ones where no recovery in expected at all. More precisely, the regulations[2] stipulate that the credit risk should be classified by:

1. debtor's credit profile, which is assessed on the basis of project quality, capital, assets, liquidity and profitability,
2. debtor's payment regularity or the ability to pay back the loan instalments in due time
3. quality of instruments given as collateral

In this analysis I compare the placements given to same enterprises by multiple banks. Unlike credit rating that is related specifically to the company in question, the classification of loan placement depends on the company, but on the loan properties as well. This means that it is possible for the two banks to rate loan given to the same company in different way because of loan properties such as the collateral, or even for the single bank to rate differently two loans to the same company. The role that the collateral plays in this analysis is further elaborated in following section while here I give only a short introduction.

[1] Odluka o klasifikaciji plasmana i izvanbilančnih obveza banaka (Official Gazette no. 1/2009., 75/2009. and 2/2010)
[2] ibid

Classification criterion 1) should give the same rating to a borrower in different banks, as it deals mostly with debtor's attributes, which can be read from the balance sheet and income statement in case of a company or from a regular income and assets for individuals. The criterion 2) deals with solvency of the company, but again it should be assessed in a same way by multiple lenders: it is pretty much same obvious when a firm or an individual is insolvent. The criterion 3) might cause same differences in loan classification by various banks: maybe some loans are heavily collateralized and some are not. If a loan is sufficiently well collateralized and the bank initiates procedure to seize the assets, the bank may continue to classify it as fully recoverable for some period. However, bank should take note that non-payment has taken place[3]. In order to minimize the possible impact of collateral on loan classification, the loan is designated as defaulted whenever non-payment has taken place regardless of the size and type of collateral. The collateral may play another role at a more subtle level related to a previous point - it may influence the debtor's payment behaviour. A debtor may choose to strategically default on a less collateralized loan thereby preventing seizure of more valuable collateral. Therefore, differences in relative leniency / stringency may in part be driven by banks' policies on collateral. There is no straightforward way to control for such effects as information on collateral for each individual loan is not available. However, possibility that these effects drive the results will be indirectly examined by looking whether relative leniency / stringency measures for banks are correlated with the aggregate coverage of the loan portfolio by collateral.

Important question in this investigation is whether the classifications actually awarded by banks are more tied to the placement or to the company? The legislation is not straightforward in that respect, as the criteria include company financial standing, the quality of projects, but also specific directions for downgrading in case of non payment. Additionally, the line between relative roles of the company and loan specific features in the loan classification is blurred by the fact that not only placements, but also other types of exposures such as guarantees, are included in the database. Two notions emerge from previous analysis: first, the company and bank will not have relationship at all if the company fails to meet minimum standards set by the bank and second, when the relationship is established, further downgrading, if any, will depend on the bank's incentive structure and might be different for

[3] Non payment is defined as a loan that is more than 90 days overdue

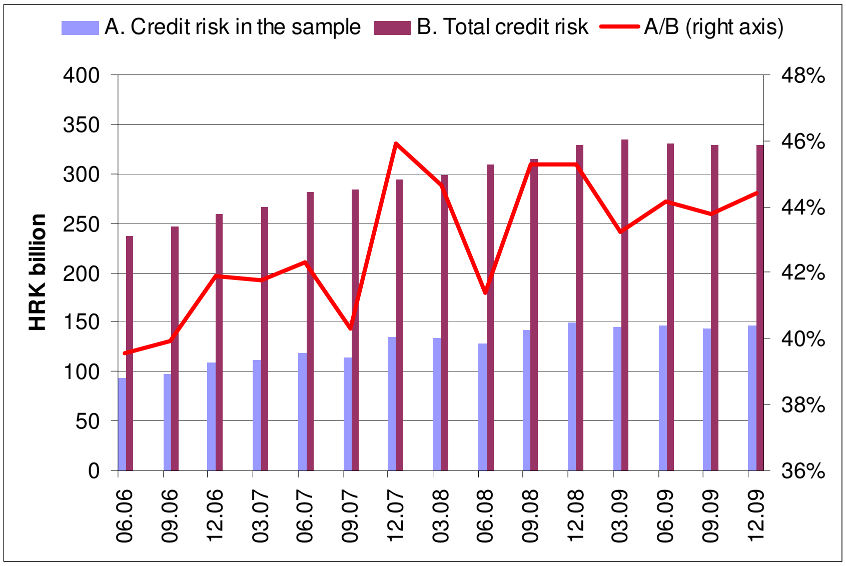
two banks. So, to conclude, the presence of classification is by itself a proof that a bank in at least at some point of time believed in the good financial standing of the company and it's promising future.

This analysis uses only data on non-financial companies, so all exposures to individuals and government entities are removed from the database. The data refer to the end of each year during the observed period, from 2006 to 2009. For the purpose of the analysis, the placements are recoded as follows. The A placements are coded as 0 (non-defaulted). The A placements, where there is more than 90 days delay in obligatory payments are coded as 1 (defaulted), irrespective of the collateral, and placements B and C are coded as 1 as well. In principle, it is possible for a bank to have different exposures towards the same company classified in different risk categories. There are only a few such examples in the sample, but in those cases a "majority rule" was applied and rating was awarded according to the category of the prevailing size. Finally, a matrix where columns represent banks and rows represent companies was constructed.

The Sample

Figure 1 compares aggregate bank exposures towards companies in the sample with the totals for the banking system. The database with detailed exposures recorded on a company basis for each reporting bank contains a significant share of total credit risk in the banking system, ranging from 40 to 45 per cent of the total credit risk. Cleaning of the sample for debtors classified in public administration and defence, those classified as foreign entities and financial intermediaries as well as any duplicate entries reduces the sample size a bit further. Natural persons were also excluded from the analysis, while the sole proprietors were maintained in the sample.

Figure 1 Credit risk covered by the sample and total credit risk of the banking system



Source: CNB

In order to make results more robust and representative, banks with less than 2 defaults recorded in any of the periods were also excluded from the sample. Although the Rasch model theoretically allows estimation with only one default episode per bank, due to robustness only banks that had at least two defaulted companies were included, which reduced number of banks represented in the analysis (number of excluded banks is shown in *Table 3*). All the applied adjustments did not significantly affect the credit risk covered in the analysis as *Table 2* shows that the final sub-sample still accounts for more than 90 per cent of our original sample, except in 2007, where it is slightly below that level (87.5 per cent).

Table 2 Credit risk of the banking system, number of companies and shares in total sample classified by number of banks per firm

Credit risk in firms sorted by number of banks per firm	**31.12.2009**			**31.12.2008**			**31.12.2007**			**31.12.2006**		
	Number of companies in sub sample	Credit risk in sub sample (HRK 000)	Share in total sub sample	Number of companies in sub sample	Credit risk in sub sample (HRK 000)	Share in total sub sample	Number of companies in sub sample	Credit risk in sub sample (HRK 000)	Share in total sub sample	Number of companies in sub sample	Credit risk in sub sample (HRK 000)	Share in total sub sample
5 and more (banks with too few defaults excluded)	128	39.597.940	27,6%	85	36.207.466	26,6%	82	25.027.448	21,2%	67	16.961.416	16,4%
4 and more (banks with too few defaults excluded)	257	50.474.556	35,2%	187	45.245.584	33,2%	174	34.413.042	29,1%	146	29.578.468	28,6%
3 and more (banks with too few defaults excluded)	641	68.437.096	47,7%	514	60.625.207	44,5%	444	47.989.052	40,6%	421	43.103.946	41,7%
2 and more (banks with too few defaults excluded)	2.125	93.154.256	65,0%	1.821	86.285.779	63,3%	1.662	70.982.096	60,1%	1.549	63.794.361	61,7%
1 and more (banks with too few defaults excluded)	13.042	143.349.581	100,0%	12.000	136.252.638	100,0%	11.401	118.123.654	100,0%	10.404	103.472.125	100,0%
All firms and all banks		146.059.500	101,9%		148.704.568	109,1%		134.954.420	114,2%		108.624.662	105,0%
Memorandum items:												
Firms with 3 and more banks / Total credit risk in the banking sector			*20,8%*			*18,5%*			*16,3%*			*16,6%*
All firms and all banks / Total credit risk in the banking sector			*44,4%*			*45,3%*			*45,9%*			*41,9%*

Source: CNB

Table 2 showing the sample structure allows to tackle the trade off between the size of the sub sample and the selected minimum number of banking links. The methodology applied to the problem theoretically allows estimation by use of the two different banks per one company. The choice was made to use only companies that have relations with at least 3 banks. This increases robustness and minimises the probability that the company's credit risk will be assessed by two similar, lenient or strict banks. Companies with 3 and more banks represent more than 40 per cent of our total sample and from 16.6 in 2006 to 20.8 in 2009 per cent of total credit risk of the banking system, which should be representative for most banks.

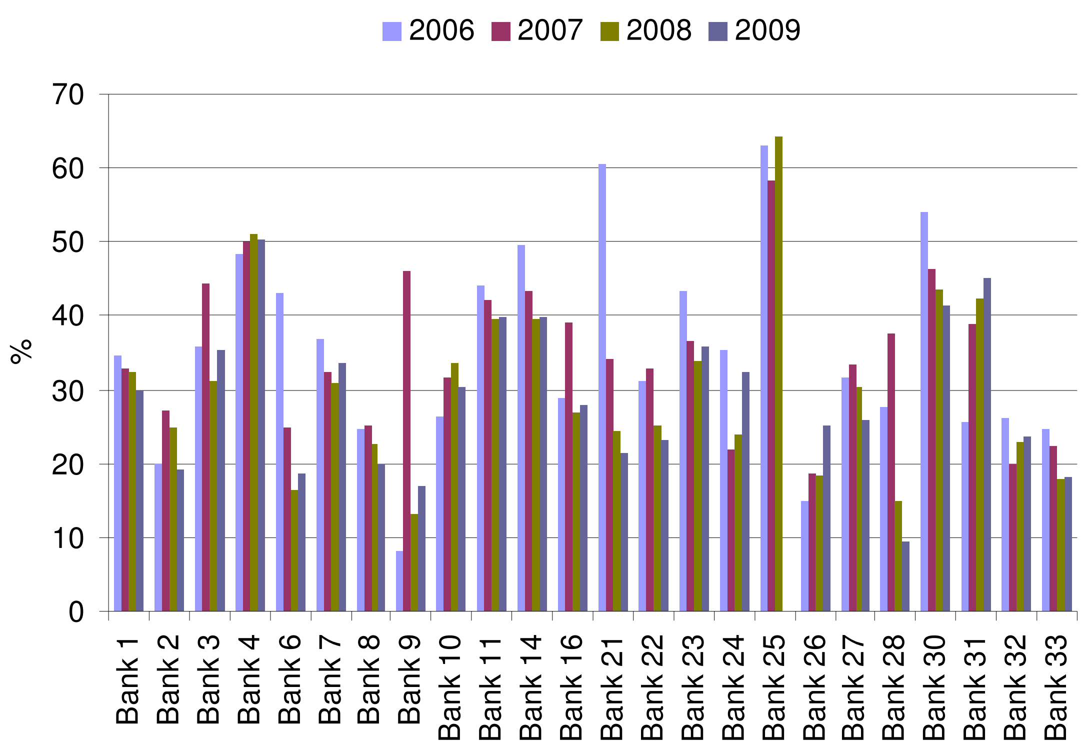
Table 2 also indicates that exposures of the banking system towards multiple borrowers have increased more than the total credit risk, indicating perhaps increased competition that enables companies to pick between banks as the number of companies with multiple bank relations from the end of 2006 to the end of 2009 increasing more than the total number of companies in the sample. This is particularly relevant for companies with four or more links, increasing the number of average links with the banks.

Bank leniency and the application of the Rasch model

The bank has several options when a company defaults on its contractual loan payments. First option is to seize the assets given as collateral, liquidate it and close the loan. The bank will be more willing to embrace this option if the loan is well collateralized and the enforcement of the liquidation is fast and straightforward. In addition to this, the bank has to think about the reputation risk. If the bank forecloses on a company that faces temporary difficulties, it might loose future income from this company and get a bad name in the business community. So, if the collateral in not adequate, enforcement is slow or the bank cares about its reputation, it might delay the process of downgrading the loan and initiating legal proceedings. Additionally, downgrading a loan exerts negative influence on net income as it increases loan loss provisions, or may even bite into the banks capitalization if a significant portion of the loan portfolio is affected by downgrades. An attractive alternative to the loan downgrading might be a loan renewal, where a new loan is issued instead of the old one or a loan is placed under a moratorium.

As mentioned above, possible effects of collateral on loan classification pose the biggest problem for the analysis. On the one hand, borrowers may be less inclined to perform a strategic default on a well collateralized loan. On the other hand, bank holding a well collateralised loan might be more willing to acknowledge a default and initiate a workout than a bank that has a loan with no collateral. Our dataset unfortunately doesn't include collateral information for each individual exposure so it is not possible to directly control for effects arising from different loan collateralization. This might skew the results of our analysis and tilt them towards measuring how well collateralised are loans instead of measuring bank leniency or strictness, with the unknown possible direction of the effect. This issue is in part tackled by using a strict definition of default: as mentioned above, as soon as non-payment in excess of 90 days occurs, we designate the loan defaulted regardless of the expected loss. Statistics presented in *Figure 2*, which shows bank level data on share of collateralized placements in total placements, provides additional assurance. Most banks have fairly similar aggregate coverage ratios, with only a few of them drastically diverging from the rest of the system.

Figure 2 Share of loans covered by the collateral, end of year data



Source: CNB

Furthermore, if collateral plays an important role in the loan classification, leniency / strictness estimates shuld be correlated with the share of collateralised credits in credit portfolio, i.e. the banks with significantly better collateralisation of portfolio will be rated significantly stricter. This issue will be further examined bellow, in the results section.

From the literature presented in the introduction and the banks' incentive structure explained above, it is obvious that the process of loan classification is far from being a well established program with minimal human interaction. Just to the opposite, two banks might tend to classify the same loan differently, according to their incentive structure.

The Rasch model enables ranking of the banks according to their strictness. The idea is to treat banks as examiners and the companies as examinees. The company × bank matrix described in the data section with a sample of loans to the same firms by multiple banks is a starting point for the analysis that should give us the relative strictness / leniency estimate. For example, if multiple banks have the loan to the same company in their books and all but one bank designate the company defaulted, the conclusion is that the remaining bank is less strict that the rest of the banks. The model enables us to do such comparison on a whole dataset and extract the strictness / leniency estimate for each bank.

Estimation results are given in *Table 3*, where banks that are stricter from the average of the system have estimates lower than 0 and banks that are more lenient than the average on the system have estimates larger than 0. Changes in the score between years are not comparable, because the estimation is performed on the data for every given year and the mean strictness / leniency of the system which is a base for comparison can drift with time.

Table 3 Estimation results

	2006				2007				2008				2009			
	est.	sig.	low. CI	upp. CI	est.	sig.	low. CI	upp. CI	est.	sig.	low. CI	upp. CI	est.	sig.	low. CI	upp. CI
Bank 1	**1.14**	**	**0.20**	**2.08**	**1.15**	**	**0.30**	**2.01**	**1.29**	**	**0.36**	**2.22**	0.53		-0.11	1.17
Bank 2	0.37		-0.87	1.60	-0.71		-1.76	0.34	**1.27**	*	**0.13**	**2.41**	0.88		-0.47	2.23
Bank 3					0.98		-0.78	2.73	0.12		-0.95	1.18	-0.28		-1.32	0.76
Bank 4					0.42		-1.46	2.29					-0.73		-2.12	0.67
Bank 5																
Bank 6									0.24		-0.88	1.37	0.04		-0.80	0.88
Bank 7					**-3.47**	**	**-5.98**	**-0.97**	-0.37		-2.58	1.84	**-2.14**	*	**-4.05**	**-0.22**
Bank 8	**-0.97**	**	**-1.67**	**-0.27**	0.02		-0.80	0.83	0.30		-0.43	1.03	-0.40		-0.96	0.17
Bank 9	**-2.54**	**	**-3.91**	**-1.17**	-0.74		-2.84	1.37	0.07		-1.23	1.37	0.06		-0.97	1.08
Bank 10	-0.50		-1.17	0.17	0.14		-0.53	0.81	-0.42		-1.10	0.25	**-1.58**	**	**-2.12**	**-1.05**
Bank 11					1.34		-0.06	2.75	0.84		-0.86	2.55	0.08		-1.43	1.59
Bank 12									-0.65		-1.97	0.67				
Bank 13																
Bank 14	**-5.07**	**	**-6.76**	**-3.38**	**-4.38**	**	**-6.15**	**-2.62**	**-2.57**	**	**-3.50**	**-1.63**	**-1.41**	**	**-2.41**	**-0.40**
Bank 15	**1.92**	*	**0.11**	**3.73**									**1.10**	*	**0.05**	**2.16**
Bank 16	-1.03		-2.45	0.38	-0.95		-2.74	0.84					0.64		-0.52	1.80
Bank 17																
Bank 18																
Bank 19																
Bank 20																
Bank 21	1.97		-0.38	4.31									**1.05**	*	**0.01**	**2.08**
Bank 22	0.32		-0.63	1.28	0.19		-0.62	1.01	-0.18		-0.95	0.60	-0.09		-0.78	0.61
Bank 23	0.91		-0.37	2.19	0.82		-0.58	2.22					-0.82		-1.77	0.12
Bank 24	-0.53		-1.39	0.33	0.51		-0.46	1.47	-0.67		-1.47	0.13	**-1.11**	**	**-1.75**	**-0.47**
Bank 25	0.45		-0.72	1.62	0.75		-0.47	1.96	0.02		-1.04	1.08				
Bank 26	**1.47**	**	**0.44**	**2.50**	**1.41**	**	**0.42**	**2.40**	0.59		-0.18	1.37	**-1.34**	**	**-1.98**	**-0.70**
Bank 27	-0.71		-2.32	0.91	0.34		-1.70	2.38					**2.19**	**	**0.75**	**3.62**
Bank 28	0.90		-0.87	2.66	-0.53		-2.77	1.71					-0.84		-2.11	0.44
Bank 29																
Bank 30	2.13		-0.05	4.31									**1.29**	**	**0.24**	**2.33**
Bank 31	-0.80		-2.37	0.78					-0.89		-2.44	0.66	0.64		-1.48	2.77
Bank 32													1.33		-0.47	3.13
Bank 33	0.57		-0.56	1.70	**2.72**	**	**1.03**	**4.41**	1.00		-0.34	2.34	0.91		-0.19	2.01
no. of banks assessed		19				19				17				24		
total. no. of banks		33				33				33				32		
no. of sig. <> 0		6				5				3				9		
proportion		31.6%				26.3%				17.6%				37.5%		
no. of strict		3				2				1				5		
proportion		15.8%				10.5%				5.9%				20.8%		
no. of lenient		3				3				2				4		
proportion		15.8%				15.8%				11.8%				16.7%		

* significant at 10 per cent

** significant at 5 per cent

Results indicate a number of banks in each year that behave significantly different from the rest of the system, which is normalised to sum to 0 in this research. Proportion of such banks goes from circa 18 per cent in 2008 to circa 38 per cent in 2009. In terms of strictness and leniency, as shown in the *Table 3*, these outlying banks are divided between these two camps and there is no tendency for grouping in any of these extremes.

Although the results are not directly comparable from year to year, i.e. we can not say that the Bank 26 is significantly stricter in 2009 than 2008, we can compare the relative position of that bank. For example, this bank has migrated from being more lenient than average to being stricter than average of the banking system. On a year to year basis, the results are generally stable as there are no major jumps from severe strictness to extreme leniency which indicates that the majority of the banks change their loan assessment and risk management practices slowly or in line with the rest of the system. This also gives indication of the robustness of the model.

Results for the 2009 are particularly interesting. In the year when the economic activity contracted significantly, and share of bad loans in the books of the banks expectedly increased, the dispersion of strictness / leniency scores of the banks increased, with proportion of strict banks increasing to historical high, reversing the trend observed in the data since 2006. This indicates that the banks pursued two different strategies after the crises broke out. The first one was to acknowledge the rise in proportion of bad loans and initiate downgrades, which is reflected in the increase in the number of strict banks. The other was to keep to business as usual and try to keep loans in the highest category for as long as possible.

As a matter of comparison it is possible to select any bank as a baseline. In that case the results will show how other banks in the system compare to that bank. Picking a bank whose rating system is deemed adequate and contrast it with other banks might be a useful exercise. *Table 4* shows how the comparison with Bank 10 looks in 2009. Results show that circa 54 per cent of the banks is more lenient than Bank 10. If we have had chosen Bank 10 as optimal good practice example, many banks in the system require tougher standards.

Table 4 Estimation results with Bank 10 as a benchmark

	est.	sig.	low. CI	upp. CI
Bank 1	**2.11**	**	**1.16**	**3.06**
Bank 2	**2.46**	**	**0.72**	**4.21**
Bank 3	1.31		-0.04	2.65
Bank 4	0.86		-0.96	2.68
Bank 5				
Bank 6	**1.62**	**	**0.50**	**2.74**
Bank 7	-0.55		-2.97	1.87
Bank 8	**1.18**	**	**0.34**	**2.03**
Bank 9	**1.64**	**	**0.28**	**3.00**
Bank 10	0.00			
Bank 11	1.66		-0.31	3.63
Bank 12				
Bank 13				
Bank 14	0.18		-1.17	1.52
Bank 15	**2.69**	**	**1.23**	**4.14**
Bank 16	**2.23**	**	**0.68**	**3.77**
Bank 17				
Bank 18				
Bank 19				
Bank 20				
Bank 21	**2.63**	**	**1.22**	**4.04**
Bank 22	**1.50**	**	**0.53**	**2.46**
Bank 23	0.76		-0.52	2.04
Bank 24	0.47		-0.36	1.30
Bank 25				
Bank 26	0.24		-0.66	1.15
Bank 27	**3.77**	**	**1.88**	**5.66**
Bank 28	0.75		-0.91	2.41
Bank 29				
Bank 30	**2.87**	**	**1.45**	**4.29**
Bank 31	2.23		-0.46	4.91
Bank 32	**2.91**	**	**0.60**	**5.22**
Bank 33	**2.50**	**	**1.01**	**3.98**
no. of banks assessed		24		
total. no. of banks		32		
no. of sig. <> 0		13		
proportion		54.2%		
no. of strict		0		
proportion		0.0%		
no. of lenient		13		
proportion		54.2%		

** significant at 5 per cent

The Model Robustness

There are several factors that could potentially affect the interpretation of the results. First, data structure may not be appropriate for application of the Rasch model. Popular way to test the applicability of the Rasch model to the data at hand is by constructing so called maps, where the vertical axis shows strictness / leniency estimate and horizontal axis measures misfit. The misfit is defined as a sum of squared differences between the observed and expected pattern if the bank rated all the companies in line with its relative leniency / strictness estimate. In that respect, the misfit can be in two directions, i.e. recorded data can be too random for Rasch model or too deterministic (too close to Guttman response pattern). In both cases the test statistic will indicate a misfit, in the first case, the fit statistic will be negative, indicating too deterministic response pattern ("overfit" of the data to the model) and in other case the statistic will be positive, indicating pattern that is more random than the Rasch model expects, basically unpredictable ("underfit"). As it is explained in Bond and Fox (2001) the fit statistics can be transformed to approximately normalized t distribution, where $t>2$ indicates an underfit of the model and $t<-2$ overfit of the model at 5 per cent significance level.

Figures 4 to 7 in the Appendix show how the Rasch model fits our dataset. In all four periods only a few banks lie outside of the 95% confidence interval proposed by the Rasch model. Having said that, it is important to note that most of the misfitting banks are in the overfit region, indicating that they closely follow the Guttman structure, meaning that if they are strict they rate majority of their loans defaulted (significantly more than Rasch model would predict) and if they are lenient, they rate majority of their clients as standard loans (again, significantly more than the Rasch model predicts). Another way to interpret misfitting banks it to treat over fitting banks as completely coherent with the rest of the banking system and their measured leniency / strictness in an almost deterministic (i.e. they are always more lenient than some stricter bank and vice versa) and to treat underfitting banks as giving marks randomly, completely different than all other banks in the system.

End 2009 (*Figure 7*) is particularly interesting period for close examination. In that period we see the largest number of misfitting banks (5). Most of them (4) are in the region of overfit, indicating they are close to the Guttman structure, i.e. their behaviour is non random, and the categorization of the loans is coherent with the rest of the banking system. One bank is in the region of underfit, indicating that categorization of the loans in its portfolio resembles a random process, which is a case for Bank 31. Possible interpretation is that as a result of the crisis and increases in the share of non-performing loans in their portfolios these banks started re-rating larger proportions of their portfolios and they did that in line with their relative strictness. In the data this was observed as a move from the middle ground, where some loans were rated randomly (compared to the Guttman structure) to rating greater proportion of the loans as their strictness / leniency rating suggests. If the banks were strict before (comparing to other banks), on a smaller portion of their portfolio, now they are stricter on a larger proportion of their portfolio, so the difference between idealistic Guttman structure and real data is smaller. Similarly, if the banks were more lenient than other banks, as the proportion of the overall portfolio that is being re-rated by the banks increases, and some banks kept their lenient approach, they move closer to the idealistic Guttman pattern. The banks that are in this region of overfit in 2009 are Bank 30, Bank 15, Bank 11 and Bank 8.

The issue arising from the impact of collateral on loan classification was already discussed earlier. Correlations between the loan coverage ratio and strictness / leniency estimate for the complete sample should give some indication on the relevance of that issue (*Figure 3*).

Figure 3 ***Correlation between loan coverage ratio and strictness / leniency estimate***

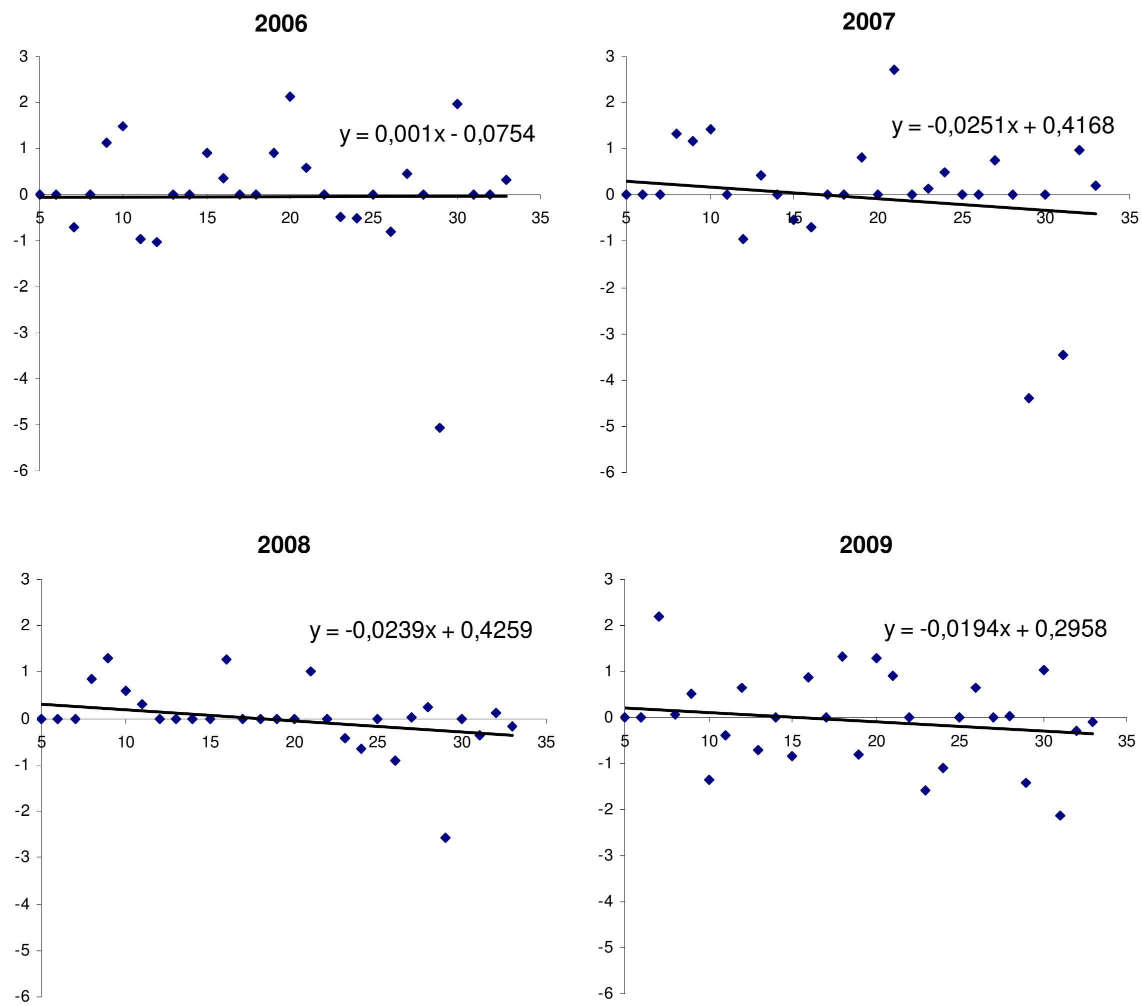


Figure 3 shows a combination of loan coverage ratio and strictness / leniency estimate for all the banks over the observed period. First, observations are spread widely around the regression line, indicating low significance of the relationship. Also, scatter plot shows that a possible impact of bank's collateral policy on the estimated level of leniency / strictness is rather weak, with the possible sign of the relationship being negative rather than positive. This means that high coverage by collateral is more likely to induce loan downgrade and initiation of the collection procedure than the opposite.

Only two banks that have above average collaterization levels have strictness / leniency estimates significantly different from the rest of the system, and among those banks, one bank is significantly more strict that the system and the other one is significantly more lenient than the rest of the system (Bank 14 and Bank 30). Among the banks with the loan portfolio substantially less collateralized than the rest of the system, only one bank (Bank 9) is significantly different from the rest of the system being stricter and that happens in the year when its coverage ratio is lowest in the sample.

Conclusion and potential application of results

Bad loans and provisions have been in the core of interest of both central bankers, commercial banks, governments and general public in many countries around the world for some time now. The model presented here should give additional information to central bank's prudential department and management on the reliability of risk classification systems used by most banks, but also to commercial bankers.

Analyzing the data and thinking about it in terms of Rasch model gives an excellent way to aggregate available information about banks' approaches to classification of credit risk. The sole process of preparing the data for the analysis is useful as it opens the new way to thinking as interrelations between banks are used. The results of the model, where the most lenient banks are singled out and all banks are ordered by their leniency give an excellent starting point for concentration of surveillance efforts so that supervision can focus on credit classification and risk management in the most lenient banks. Furthermore, the instances where the classification of specific companies differs can be explored in detail, within a single bank as well as between different banks. Also, if structure of the defaults for some banks deviates from the expected, although it does not necessarily have to be lenient, it may indicate potential problems with risk classification. Additionally, the sole fact that not all banks can enter the analysis because they have too few defaults in the sample that includes only firms rated by multiple banks is an obvious indication for further analysis of that bank loan portfolio and risk management and credit classification system.

In addition to providing valuable information for performing the supervisory function, the results can also aid the assessment of financial stability of the banking system as they allow quick assessment of the risk management practices in the banking system. Specific bank for which the risk management practices are regarded adequate can be used as an anchor and what-if analysis can be performed - what would happen with the bad loans of the banking system if the risk management practices of that bank were applied throughout the system? This would give an indication of the potential extent of manipulations with loan classification in the banks' books and allow the analyst to estimate "true" amount of bad loans. In the appendix I explore a possible way to achieve that.

The area with big future potential for methods based on the Rasch model is comparison of credit risk assessment systems. As literature surveyed in first section shows, the comparison of credit rating systems is a big and interesting topic for central and commercial banking. Basel accord stimulates banks to use internal ratings and rely on those in order to determine needed capital. Under such an approach to capital allocation, better internal credit risk system will be a comparative advantage for the bank as it will optimize the amount of capital. The Rasch model can be applied to that problem and rating systems between two banks can be compared quickly and efficiently, so banks whose rating system are considered sufficiently good may be benchmarked against other banks.

Literature

Alagumalai, S., Curtis, D. D., Hungi, N. (2005) Applied Rasch Measurement: A Book of Exemplars: Papers in Honour of John P. Keeves (Education in the Asia-Pacific Region: Issues, Concerns and Prospects), Springer

Bond, T. G., Fox C. M. (2001) Applying the Rasch Model : Fundamental Measurement in the Human Sciences, Lawrence Erlbaum Associates, Inc.

Caballero, R. J., Hoshi, T., Kashyap, A. K. (2008) Zombie Lending and Depressed Restructuring in Japan, American Economic Review, 98:5, 1943-1977

Cantor, R. and Packer F. (1997), Differences of Opinion and Selection Bias in the Credit Rating Industry, Journal of Banking and Finance 21, 1395-1417

Carey, M. (1998) Credit Risk in Private Debt Portfolios, Journal of Finance, Vol. LIII, 1363-1387

Carey, M. (2001) Some Evidence on the Consistency of Banks' Internal Credit Ratings, mimeo

Carriquiry, A. L., Fienberg, S. E., (2005) Rasch models in Armitage, P., Colton, T., Encyclopedia of Biostatistics, Wiley

Hornik, K., Jankowitsch, R., Leitner, C., Lingo, M., Pichler, S., Winkler, G. (2010) A latent variable approach to validate credit rating systems. In Daniel Rösch and Harald Scheule, editors, Model Risk in Financial Crises, pages 277-296. Risk Books, London

Hornik, K., Jankowitsch, R., Lingo, M., Pichler, S., Winkler, G. (2007) Validation of Credit Rating Systems Using Multi-Rater Information, Journal of Credit Risk, Volume 3, Number 4

Jacobson, T., Lindé, J., Roszbach, K. F. (2005) Internal Ratings Systems, Implied Credit Risk and the Consistency of Banks' Risk Classification Policies. Journal of Banking and Finance, Forthcoming; Riksbank Working Paper No. 155

Laurin A., and Majnoni G. (2003) Bank Loan Classification and Provisioning Practices in Selected Developed and Emerging Countries, World Bank working paper no. 1

Liu, C. C. and Ryan, S.G. (2003) Income Smoothing over the Business Cycle: Changes in Banks' Coordinated Management of Provisions for Loan Losses and Loan Charge-offs from the Pre-1990 Bust to the 1990s Boom, NYU Stern Working Paper Series S-CDM-03-15

Mair P., Hatzinger R., Maier, M. (2010) Extended Rasch Modeling: The R Package eRm

Mair, P., and Hatzinger, R. (2007) Extended Rasch modeling: The eRm package for the application of IRT models in R, Journal of Statistical Software, 20(9), 1-20.

Odluka o adekvatnosti jamstvenoga kapitala kreditnih institucija (Official Gazzete no. 1/09., 75/09. i 2/10.

Odluka o klasifikaciji plasmana i izvanbilančnih obveza banaka (Official Gazette no. 1/2009., 75/2009. and 2/2010)

R Development Core Team (2010). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/

Song, I. (2002) Collateral in Loan Classification and Provisioning, IMF Working Paper WP/02/122

Stahl, J., Bergstrom, B., Gershon, R. (2000) CAT Administration of Language Placement Examinations Journal of Applied Measurement, 1(3), 292-302

Appendix

Figure 4 The Item fit map for 4Q of 2006

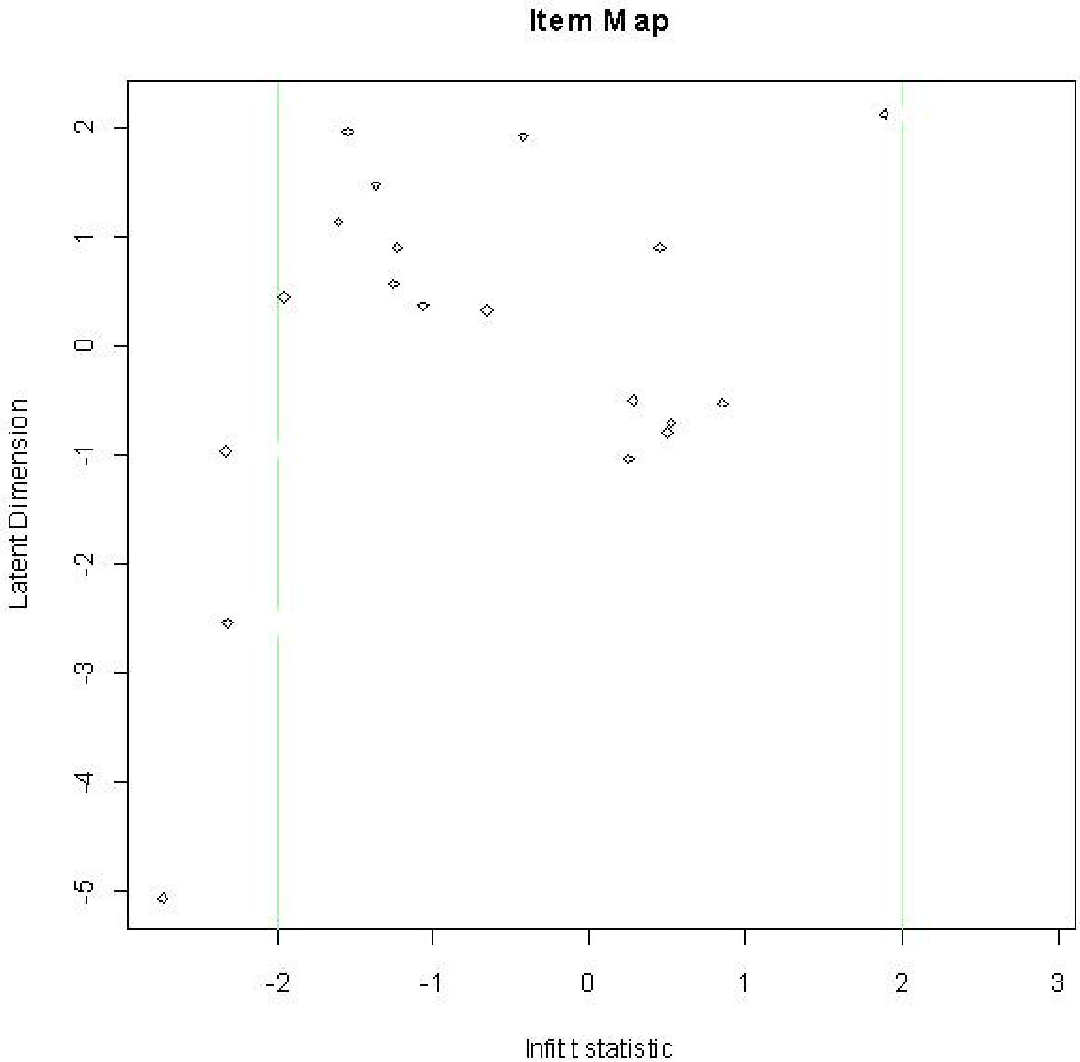


Figure 5 The Item fit map for 4Q of 2007

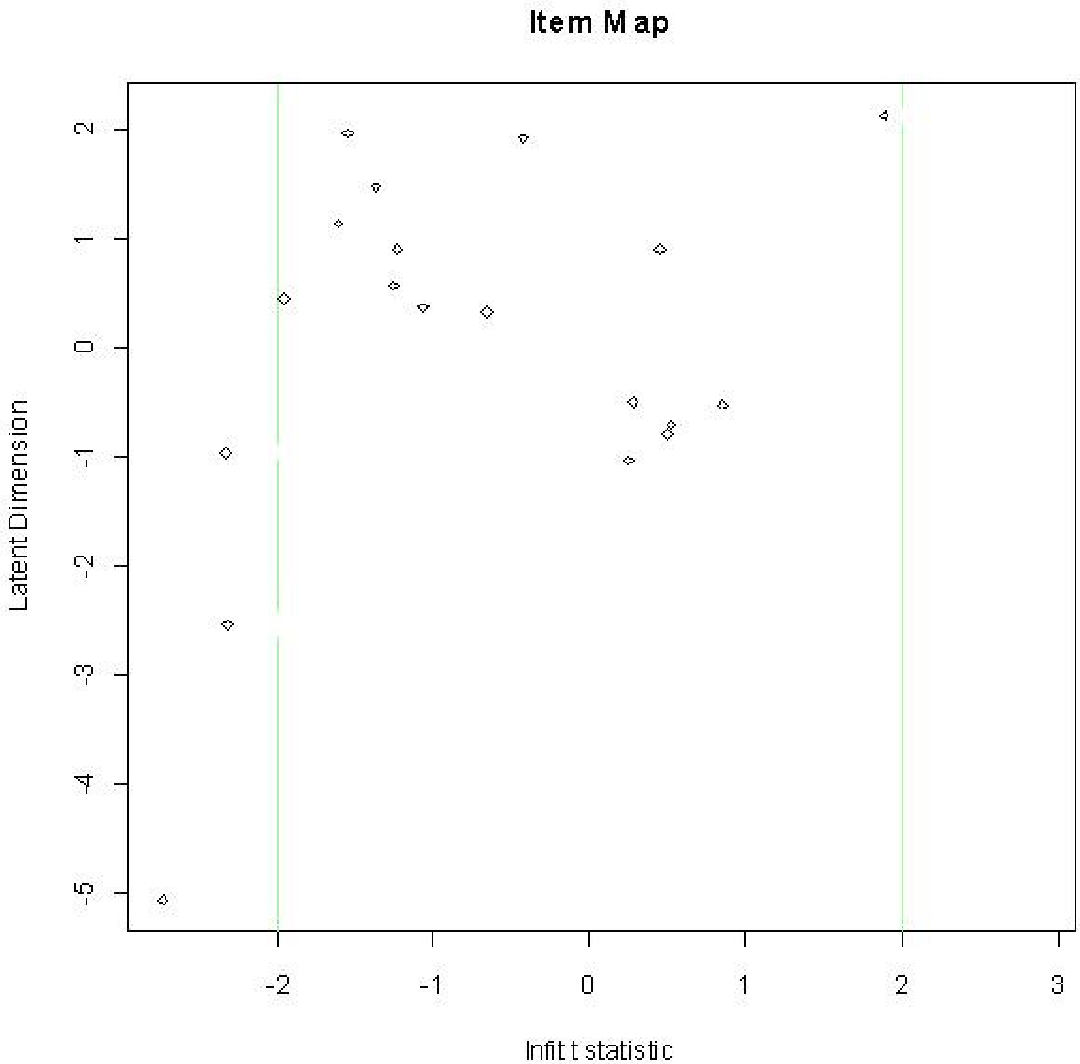


Figure 6 The Item fit map for 4Q of 2008

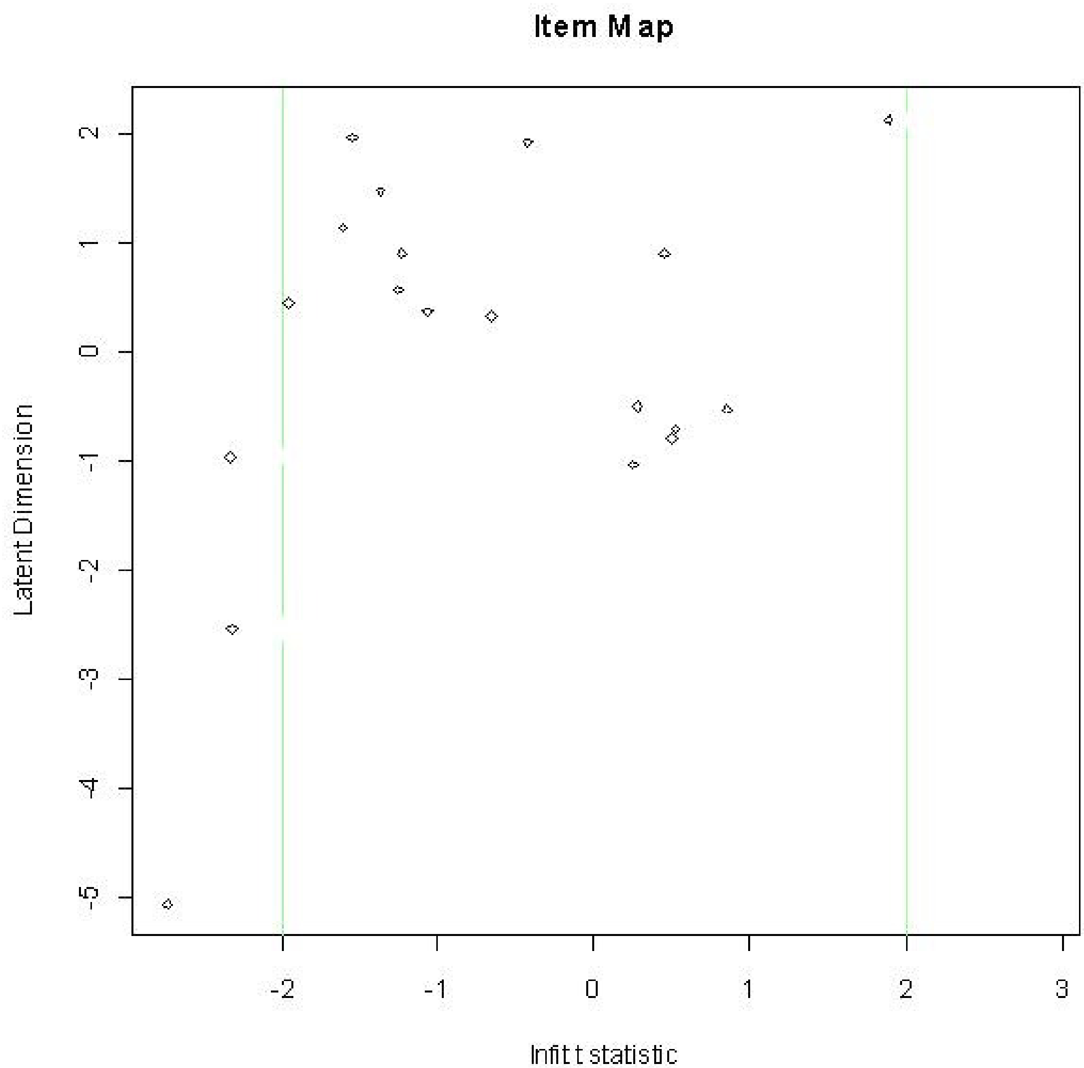
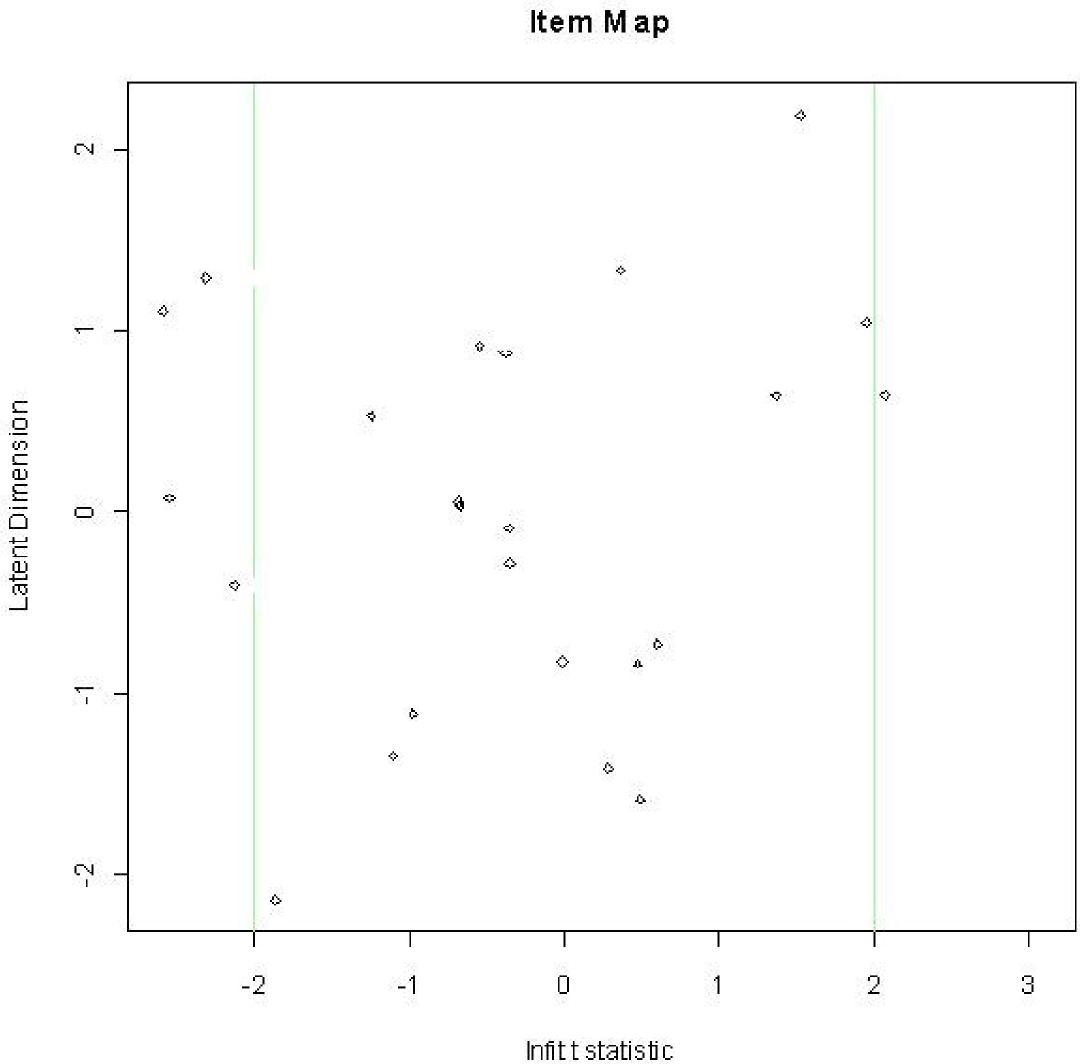


Figure 7 The Item fit map for 4Q of 2009



How to obtain corrected NPL ratios using strictness / leniency estimate?

One possible step forward is to use estimated strictness / leniency estimates in order to correct non performing loan ratios by using relative strictness / leniency estimate. The share of non-performing loans was revised up for banks less strict than the reference bank, while it was revised down for stricter banks. Reference bank can be picked on the basis of a priori knowledge of risk management quality.

As explained above, the scores from Rasch analysis are log odds, so we can obtain estimated probabilities from the Rasch estimate. For example, using log odds calculation Rasch score of 2.20 transforms roughly to a probability of 90 per cent of being rated defaulted (the natural logarithm of 0.9/0.1=2.20) which should be compared to the default probability of 50 per cent for the average bank in the system (the natural logarithm of 0.5/0.5=0). If the same transformation is applied to a reference bank and any other banks, we can use their odds ratio to correct the non-performing loan ratio, where we can put the reference bank in the numerator and the bank to which we are applying correction in the denominator. If the odds ratio is 1 this implies similar probability of being sorted as non performing in both banks, if this ratio is higher than 1, the probability of being sorted as non-performing in the reference bank is higher and vice versa in case where the ratio is less than 1. For example we would interpret the odds ratio of 2, as that the placement is 2 times more likely to be classified as bad in the reference bank that in the bank being assessed. We can use that line of reasoning to obtain the correction, for non performing loans ratio (NPLR), and new, corrected NPLR for the bank being would be 2 × original NPLR. *Table 5* gives an example correction of NPLR based on a Rasch leniency / strictness estimate.

Table 5 An example of NPLR correction using Rasch score

INPUTS	Rasch score	Probability being sorterd as defaulted
Reference bank	1,25	0,78
Bank being assesed	0,35	0,59
Assesed bank NPLR		5,32
OUTPUTS		
Odds ratio (refrence / assesed bank)	0,78 / 0,59 =	1,33
Corrected NPLR for assesed banl	**5,32 × 1,33 =**	**7,05**