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DISCRETIONARY CREDIT RATING AND BANK STABILITY IN A FINANCIAL CRISIS

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DISCRETIONARY CREDIT RATING AND BANK STABILITY IN A FINANCIAL CRISIS*

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ABSTRACT

In this paper we study the incentives for discretionary credit risk assessment under current banking regulation. We use the Slovenian data on credit ratings of non-financial enterprises and analyse their reliability as predictors of corporate default to test whether banks in financial distress systematically underestimate credit risk. Our results show that predictive accuracy of credit ratings deteriorated during the Great recession both in absolute terms and relative to the benchmark econometric model that uses publicly available data only. Moreover, we show that predictive accuracy was lowest for domestically owned banks and, within this group, for small banks. These results can be linked to incentives to underestimate credit risk due to exposure to non-performing loans and limitations to raise additional capital. Given that credit ratings are closely related to loan-loss provisions, our analysis indicates that under-estimation of credit risk served to inflate banks' books. These findings can rationalise the results of the comprehensive review of the Slovenian banking system in 2013, which revealed significant capital shortfalls on average, but also significant differences in capital shortfalls across groups of banks with different incentives to under-estimate risk. Robustness checks confirm the validity of our conclusions. Our findings provide a plausible explanation for the results of a similar comprehensive review in the Euro area prior to the launch of the Single Supervisory Mechanism in 2014.

POVZETEK

V članku analiziramo spodbude za diskrecijsko ocenjevanje kreditnega tveganja v okviru obstoječe bančne regulative. S proučevanjem sposobnosti bonitetnih ocen za napovedovanje neplačila je na primeru slovenskega bančnega sistema pokazano, da banke v času finančne krize težijo k podcenjevanju kreditnega tveganja. Rezultati kažejo na poslabšano natančnost napovedi bonitetnih ocen v času krize, tako absolutno, kakor tudi relativno glede na primerjalni logit model. Poleg tega je v članku pokazano, da je natančnost napovedi najnižja pri bankah v domači lasti ter, znotraj te skupine, pri majhnih bankah. Te banke so imele največje spodbude za podcenjevanje tveganja, saj so bili njihovi portfelji bolj izpostavljeni slabim posojilom, poleg tega pa so bile tudi bolj omejene pri pridobivanju dodatnega kapitala. Ker so bonitetne ocene tesno povezane s stopnjami oslabitev, naša analiza kaže, da je podcenjevanje kreditnega tveganja služilo izboljševanju bilanc bank. Rezultati prikazani v članku so v skladu z rezultati skrbnega pregleda slovenskega bančnega sistema, ki je bil izveden v letu 2013 in je pokazal občutne razlike v potrebni dokapitalizaciji med skupinami bank, ki so imele različne spodbude za podcenjevanje tveganja. Številni testi robustnosti potrjujejo veljavnost rezultatov. Naše ugotovitve ponujajo verjetno razlago za podobne ugotovitve skrbnega pregleda, ki je bil izveden pred uveljavitvijo enotnega nadzornega mehanizma (SSM) v 2014.

JEL-Codes: G01, G21, G28, G32, G33

Keywords: discretionary credit ratings, Great recession, probability of default, underestimation of credit risk

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Non-technical summary

This paper analyses the discretion in credit risk assessment. We study the case of Slovenian banking system in the financial crisis that began in 2008. Discretion is in this paper understood as the bank-specific choice of standards in the assessment of creditworthiness of borrowers. We use Credit Registry data of the Bank of Slovenia that contains the information on credit contracts at bank-client level over the period 2006-2012 and credit ratings assigned by banks to their non-financial corporate clients. Our test of the extent of discretion in credit risk assessment is based on a test of the ability of ratings to predict financial distress of banks' clients. Starting from a base year 2006 before the crisis we measure how the predictive ability of credit ratings evolves through time and across groups of banks. The predictive capacity of credit ratings is measured against the predictive capacity of a conventional econometric (logit) model that uses only information available to banks through regular reporting, such as various financial ratios of banks' clients.

Our results indicate that the precision of bank ratings in predicting financial distress deteriorated during the crisis, both in absolute terms and, more importantly, against the predictive capacity of conventional financial ratios. This result reflects the fact the mounting non-performing loans pressed on the balance sheets of the whole banking system. Banks thus had an incentive to underestimate credit risk and inflate their balance sheets. As we document in the paper, loan-loss provisions are strongly negatively related to credit ratings. A positive bias to credit ratings thus positively reflects in the profit and loss account. This process was to some extent facilitated by regulatory forbearance.

We identify important heterogeneity in these results across groups of banks, which are in line with the differences in the required recapitalisation after the 2013's comprehensive review of Slovenian banking system. While the required recapitalisation of foreign owned banks amounted to 78% of existing capital, it was 244% for domestically owned banks. Also within the group of domestic banks we can find important differences. Decomposing the group of domestic banks according to size and ownership, we can see that the additional required capital for the largest two banks on the market, holding 36% of total assets, that were also majority state owned, amounted to 228% of existing capital, while for the small and predominantly privately owned the figure was 274%.

Consistent with the results of the comprehensive review, the predictive capacity of credit ratings assigned by foreign-owned banks outperforms by a large margin the predictive capacity of credit ratings assigned by domestic banks. Within the group of domestic banks we also observe differences between large and state owned, and small banks. The latter group reveals the worst predictive capacity of credit ratings. As we document in the paper, this group of banks had the largest incentives to underestimate credit risk because their portfolios were more exposed to non-performing loans and had limited possibilities to raise additional capital. In addition to main results, we perform two robustness checks with respect to real-time availability of the information banks have at their disposal when setting credit ratings. Both tests confirm the validity of our results.

The findings of this paper have several important implications for banking regulation. Discretion in credit risk assessment is nothing but an attempt to temporarily avoid the difficulties of deteriorating credit portfolio. The fact is that the true creditworthiness of borrowers is always revealed eventually, credit risk realized and losses incurred. These losses are higher the longer under-estimation of risk postpones solving the problems. For future prevention and better management of such episodes it is important for the regulation to respond to the problem of incentives to under-estimate credit risk in times of financial crises and economic downturns in general.

Netehnični povzetek

V članku je analizirana diskrecija bank pri ocenjevanju kreditnega tveganja. Proučevan je primer slovenskega bančnega sistema v času finančne krize, ki se je začela leta 2008. Diskrecija je v tem članku razumljena kot odločitev bank o standardih za ocenjevanje kreditne sposobnosti komitentov. Poglavitni vir podatkov je kreditni register Banke Slovenije, ki vsebuje podatke na nivoju komitent-banka za obdobje 2006-2012, med katerimi so tudi bonitetne ocene, ki predstavljajo bančne ocene kreditne sposobnosti komitentov. Naš test diskrecije pri ocenjevanju kreditnega tveganja temelji na sposobnosti bonitetnih ocen za napovedovanje neplačila komitentov. Osredotočamo se na dinamiko natančnosti napovedi bonitetnih ocen skozi čas, s poudarkom na obdobju finančne krize. Ločeno opazujemo tudi dinamiko med tremi skupinami bank. Natančnost napovedi bonitetnih ocen je primerjana z natančnostjo napovedi primerjalnega ekonometričnega (logit) modela, ki vsebuje informacije, ki so na voljo bankam v rednih poročanjih, kot so razni finančni kazalci komitentov.

Rezultati kažejo, da se je natančnost bonitetnih ocen za pojasnjevanje neplačila komitentov poslabšala v času krize, tako absolutno, kakor tudi glede na primerjalni model, ki vsebuje samo razne finančne kazalce podjetij. Ta rezultat odraža kopičenje slabih posojil pri bankah, ki so tako imele spodbudo za podcenjevanje kreditnega tveganja in s tem prikazovanje boljših bančnih bilanc kot so dejansko bile. Kot je pojasnjeno v članku so oslabitve močno negativno povezane z bonitetnimi ocenami. To pomeni, da se pristranost, v smislu preoptimističnih bonitetnih ocen, odraža v manjših stroških oslabitev v izkazu uspeha bank. Ta proces je bil do določene mere omogočen z regulatornim popuščanjem.

V rezultatih je zaznati pomembno heterogenost med skupinami bank, ki je v skladu z razlikami v zneskih potrebne dokapitalizacije po skrbnem pregledu slovenskega bančnega sistema, ki je bil izveden v drugi polovici leta 2013. Medtem ko je potrebna dokapitalizacija bank v večinski tuji lasti znašala 78% obstoječega kapitala, je za banke v domači lasti znašala 244%. Tudi znotraj skupine domačih bank obstajajo pomembne razlike. Razdelitev skupine domačih bank glede na velikost in lastništvo kaže, da je bila dodatna potrebna dokapitalizacija dveh največjih bank, ki skupaj predstavljata 36% aktive bank in sta v večinski državni lasti, 228% obstoječega kapitala, medtem ko je za majhne banke, ki so pretežno v zasebnem lastništvu, znašala 274%.

Skladno z rezultati skrbnega pregleda je natančnost napovedi bonitetnih ocen, ki jih dodeljujejo tuje banke precej boljša od natančnosti napovedi domačih bank. Znotraj skupine domačih bank je tudi opaziti razlike med velikimi ter večini državnimi bankami ter majhnimi bankami. Bonitetne ocene majhnih bank imajo najslabšo natančnost napovedi neplačila. Kot je pojasnjeno v članku je imela ta skupina bank tudi največje spodbude za podcenjevanje tveganja saj je bil njihov portfelj bolj izpostavljen slabim posojilom, poleg tega pa so bile te banke tudi bolj omejene pri pridobivanju dodatnega kapitala. Poleg poglavitnih rezultatov, so v članku prikazani tudi rezultati dveh testov robustnosti z vidika časovne razpoložljivosti podatkov s strani bank pri dodeljevanju bonitetnih ocen. Oba testa potrjujeta osnovne rezultate.

Ugotovitve tega članka imajo številne pomembne implikacije za bančno regulativo. Diskrecija pri ocenjevanju kreditnega tveganja ni nič drugega kot poskus začasnega izogibanja težavam, ki nastanejo ob slabšanju kreditnega portfelja. Dejstvo je, da je dejanska kreditna sposobnost komitentov prej ali slej razkrita, tveganje se realizira ter nastanejo izgube. Daljše kot je obdobje podcenjevanja tveganja oz. izogibanja priznavanja izgub, večje so na koncu dejanske izgube. Za potencialno preprečitev oz. boljše obvladovanje takšnih obdobj v prihodnosti, se mora regulativa odzvati na problem spodbud za podcenjevanje kreditnega tveganja v času finančnih oz. gospodarskih kriz.

1. Introduction

Existing accounting standards and banking regulation induce procyclicality in the loan-loss provisions through capital adequacy requirements.² In economic downturns the incidence of corporate default increases and the value of banks' assets decreases. Resulting higher loan-loss provisions negatively reflect in the profit and loss account and, consequently, in bank capital, which creates an incentive for banks to relax the standards of credit risk assessment and valuation of assets in times of economic downturn.³ In a financial crisis raising additional capital to meet with minimum capital requirements is particularly difficult, which only increases the incentives for discretion in credit risk assessment and leads to systematic underestimation of credit risk of loan portfolios.

To overcome the problems with underestimation of credit risk bank regulators could in principle apply discipline on banks to comply with regulatory standards. In a financial crisis, however, financial regulators often apply forbearance in order to partly alleviate the problems with procyclicality of capital requirements and prevent significant disruptions in the banking system (Hoffman and Santomero, 1998).

This paper studies how the current regulatory framework amplifies incentives for discretionary credit risk assessment in times of financial distress by studying the case of Slovenia in the Great recession after 2008. In 2013, ten Slovenian banks, accounting for approximately 70% of total bank assets, went through a comprehensive review, consisting of asset quality review (AQR henceforth) and stress tests, performed by independent external examiners using uniform methodology. The results, announced publicly in December 2013, revealed significant capital shortfalls.⁴ In particular, estimated capital shortfalls of all examined banks amounted to 214% of existing capital, with some pronounced differences across banks.⁵ Namely, there were stark differences in the capital shortfalls between domestic and foreign owned banks. For the former the recapitalisation requirement amounted to 244% of existing capital, while for the latter this figure was "only" 78%. Also within the group of domestic banks we can find important differences. The recapitalisation requirement for the largest two and majority state owned banks on the market, holding 36% of total assets, amounted to 228% of existing capital, while for the small and predominantly privately owned the figure was 274%.

Our working hypothesis is that the incentive to underestimate credit risk is an important factor behind the estimated differences in capital shortfalls. We evaluate this hypothesis in a rather unique historical episode. The Slovenian banking system went through a comprehensive review a year before similar comprehensive reviews became standard practice in the Single Supervisory Mechanism of the Euro area. The comprehensive review revealed large capital shortfalls, which can be almost entirely attributed to underestimation of credit risk in classic loan portfolios of non-financial enterprises. This provides us with a unique environment to study the incentives to underestimate credit risk.

The empirical test of our hypothesis is based on predictive capacity of credit ratings - assigned

²This feature is present both in banks using the internal ratings based or the standardized approach under Basel II.

³Such incentives might be amplified if the regulators make the minimum capital requirements stricter in times of economic downturn. Such was the case of the European Banking Authority, who with the aim of boosting confidence in the European banking system in 2011 set the provision that a minimum of 9% of risk-weighted assets should be held in the form of Core Tier 1 capital.

⁴For details see the Report on the comprehensive review of the banking system, Bank of Slovenia (2013)

⁵Such capital shortages indicate potential problems with insolvency. In fact, for two small private domestically owned banks the central bank initiated insolvency procedures already before the results of the comprehensive review were published. These two banks were subsequently excluded from the stress test part of the comprehensive review.

by banks to their non-financial corporate clients - in predicting financial distress of banks' clients. We estimate how the predictive ability of credit ratings evolves over the period 2007-2012 and across groups of banks. The predictive capacity of credit ratings is compared to that of a conventional econometric (logit) model that uses only publicly available information, such as various financial ratios of banks' clients. Such a model can be used to predict financial distress by an econometrician free of any incentives to underestimate risk and as such serves as our benchmark of comparison.

Our results indicate that the precision of bank ratings in predicting financial distress deteriorated during the crisis, both in absolute terms and, more importantly, against the predictive capacity of the econometric model using publicly available information only. While the loss of predictive capacity of financial ratios in general can be rationalised by a potential structural break induced by the crisis, our finding that predictive capacity of credit ratings on average deteriorated even relative to the econometric model, reflects the fact that, given mounting non-performing loans, banks had an incentive to underestimate credit risk and inflate their balance sheets by keeping lower levels of loan-loss provisions. The classification accuracy of credit ratings assigned by foreign-owned banks outperforms the predictive capacity of credit ratings assigned by domestic banks by a large margin. Within the group of domestic banks we also observe differences between large and state owned, and small banks. The latter group reveals the worst predictive capacity of credit ratings. These conclusions appear to be robust to the effects of the timing of public release of corporate balance-sheet data and prediction horizon.

The results on predictive capacity of credit ratings across groups of banks - domestic/ foreign, private/state owned or large/small - align with the results of estimated capital shortfalls in the 2013 comprehensive review in Slovenia. Banks with the largest capital shortfalls were the ones with the least reliable credit ratings as predictors of default, and vice versa. Predictive capacity of credit ratings can be significantly affected by the incentives to underestimate risk in relation to the ability to raise capital and funding in times of financial distress. Small banks with financially weak owners faced the most pronounced difficulties in raising capital and thus had stronger incentives to apply discretion in risk assessment. Foreign-owned banks, at the other end of the spectrum, had access to the internal capital markets of international banking groups they belong to, and thus had access to more stable sources of funding (Navaretti et al., 2010; de Haas and Lelyveld, 2010). Smaller incentives to underestimate risk by foreign banks can stem also from superior managerial and organizational capacity to absorb losses. Large domestic banks fall in between as they enjoyed the bail-out guarantee by the government.

Our work is related to the paper by Huizinga and Laeven (2012), who for the case of the US mortgage crisis report significant discrepancies between market value and banks' valuation of real-estate related securities. These differences are attributed to the use of discretion over classification of mortgage-backed securities with the aim of inflating banks' books. Moreover, Huizinga and Laeven (2012) notice that the over-valuation of distressed assets is more pronounced if banks are bigger and exhibit higher exposure to these assets.

While addressing a similar topic, our paper is different. Our focus is not on discretion in banks' valuation of assets, but on discretion in credit risk assessment. Our approach is novel in the literature in the sense that we use credit ratings and explore the information content through implied probabilities of default. In addition, our analysis is applied to classic loan portfolios, which constitute the majority of bank assets in continental Europe. Such assets are not traded. For this reason we cannot rely on market information to infer about their implicit riskiness. Instead, we use econometric analysis.

We study the case of a Euro area member country. On one hand, this is instructive as we study the behaviour of banks that operated in the same market and were exposed to same systematic risks and the same regulatory environment. This means that we can abstract from cross-country

differences in factors that are outside of banks' control. On the other hand, results of our analysis are relevant also for the advanced banking systems. A recent paper by Mariathasan and Merrouche (2014) shows that the reported riskiness of banks decreased upon the adoption of the IRB. They find this effect to be especially pronounced among weakly capitalised banks, which have higher incentives to under-report actual riskiness. A similar conclusion is also suggested by Blum (2008), who analyses the effectiveness of regulatory risk-sensitive capital requirements in an adverse selection model. The study by Brown and Dinc (2011) provides empirical evidence that the likelihood of regulatory forbearance is indeed higher when the banking system is weak. These studies suggest that the incentives to underestimate risk exist in banking systems of a wide variety of countries. The methodology we propose to study the incentives to underestimate credit risk is thus applicable quite generally.

Last but not least, the Slovenian case is instructive for the comprehensive review of the Euro-area banking system prior to the launch of the Single Supervisory Mechanism, conducted in 2014, a year later than the comprehensive review in Slovenia. In this review the results also revealed that capital shortages in smaller banks exceeded those in large banking groups by a significant margin. Based on our analysis, it can be argued that the differences in estimated capital shortfalls can be, at least to some extent, attributed to systematic underestimation of credit risk due to incentives to do so in time of financial distress.

The rest of the paper is organised as follows. Section 2 provides stylised facts incentives for discretionary risk assessment in the Slovenian case. Section 3 presents our modelling approach for testing for discretion in credit risk assessment. Section 4 presents the main results. Section 5 contains the robustness checks, while Section 6 concludes and discusses policy implications.

2. Incentives for discretionary risk assessment

To highlight the incentives for discretionary credit risk assessment embedded in the regulatory system, this section provides basic empirical evidence about key developments in the Slovenian banking system in the period 2006-2012. We look at how the credit rating structure of banks' portfolios evolved during the Great recession and what were the corresponding dynamics of loan-loss provisions. In addition to looking at the banking system as a whole, we provide descriptive statistics across groups of banks, divided according to size and ownership.

The source of credit ratings data is the Credit Registry of the Bank of Slovenia, which contains bank-borrower information. These credit ratings represent banks' subjective assessment of firms' creditworthiness. Each bank has its own methodology for estimating borrowers' riskiness, which should at the end be transformed into five-grade rating scale (from A to E) set by the Bank of Slovenia in the Regulation on the assessment of credit risk losses of banks and savings banks (hereinafter Regulation). Banks classify borrowers into credit grades based on the assessment of their financial position, the ability to provide sufficient cash flow to regularly fulfil the obligations to banks, and information on the borrowers' potential arrears on loan repayments. The latter piece of information is regularly available to the banks and in practice carries significant role in determining the credit rating. The credit ratings are independent of the pledged collateral and thus give the assessment of the quality of the borrower and not necessarily of the quality of bank's claims to this borrower. The frequency of Credit Registry data is monthly.

We combine the Credit Registry data with the balance sheet and income statement data for all Slovenian firms, collected by the Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES) at yearly basis.

In the fourth quarter of 2008 Slovenian economy entered a deep recession. From the peak in the third quarter of 2008 to the end of 2012 the cumulative loss of real output exceeded 9%. This protracted economic slump reflected also in the quality of banks assets and corresponding credit

rating structure of banks' borrowers. Table 1 shows how the economic and financial crisis resulted in a deteriorated structure of credit ratings of borrowers. The share of A-rated borrowers had dropped by 14.4 percentage points between 2006 and 2012. On the other hand, the share of the worst performing borrowers rated D or E increased by 6.8 percentage points. The deterioration is even more significant if we look at bottom panel of Table 1 that reports the rating structure weighted by the banks' exposure to borrowers. According to this measure the share of A-rated borrowers decreased by almost 32 percentage points, while it increased by more than 10 points for C-rated, 6.6 points for D-rated and 13.2 percentage points for E-rated clients respectively. The difference between the upper and bottom panel of of Table 1 reveals that credit risk was concentrated in large credit exposures.

Table 1: Credit Rating Structure Over the Business Cycle

Rating	2006	2007	2008	2009	2010	2011	2012
% of borrowers							
A	54.0	53.1	53.5	48.9	46.3	41.7	39.6
B	30.6	32.0	31.0	32.0	32.5	34.0	34.3
C	5.1	5.2	6.1	7.5	7.4	8.0	9.0
D	4.7	4.5	4.6	6.3	5.6	5.5	5.6
E	5.6	5.2	4.8	5.3	8.2	10.8	11.5
% of borrowers weighted by loan size							
A	71.7	70.0	67.8	57.4	52.0	44.8	39.8
B	22.1	24.8	26.5	29.4	25.7	25.4	23.0
C	3.2	3.0	3.6	8.2	11.8	13.5	14.4
D	1.5	1.0	1.1	3.4	7.0	7.8	8.1
E	1.5	1.2	1.0	1.6	3.5	8.5	14.7

Source: Bank of Slovenia, own calculations.

Notes: The table reports the percentage of firms and banks' exposure (in terms of classified claims) to the firms in each grade over time.

Deterioration in the quality of assets as reflected in the credit rating structure led to an increase in the amount of loan-loss provisions banks needed to take onto their balance sheets. In principle, for each individual firm loan-loss provisions need not increase automatically in response to a worse credit rating of the borrower, but the relation is nevertheless positive. Each bank uses its own methodology for determining loan-loss provisions, both for collective as well as individual provisioning. The former is in general based on the credit ratings, although the banks may also use differently formed groups of financial assets. For each of the credit ratings A, B and C the banks calculate the (past) incurred loss for the borrowers that migrated to ratings D or E and thus determine their internally required coverage of loans with loan-loss provisions for each of these three rating classes. The banks are required to regularly update the migration matrices, meaning that their required coverage ratio can change in time.

Collateral plays an important role in provisioning. Banks can apply a lower coverage ratio for the borrowers that pledged the best-quality collateral, but only for the part of the claims that is secured with this collateral. According to the Regulation, individual provisioning is used for the borrowers for which there exists an objective evidence of a possible loss. This could be either significant financial difficulties of the debtor, default on the obligations to the bank, information about potential bankruptcy, financial reorganization, decrease of the estimated future cash flows or other changes that could represent a loss for the bank. When the bank finds that such objective evidence exists, it assesses the value of collateral and expected cash flow and thus determines

the individual provisions for such borrower. In general, all the borrowers that are either more than 90 days overdue or are rated D or E are assessed individually.

Table 2 reports the average coverage of outstanding corporate loans with the loan-loss provisions (end-of-period stocks) banks held across the credit rating classes in the period 2006-2012. It is evident that banks on average needed to provide more for expected loan losses for firms with lower credit ratings. Even though the exact rate of the loan-loss provisions depends also on the potential collateral used to secure a loan, we see that on average loan-loss provisions significantly increase with deteriorating credit-rating structure of banks' portfolios. In the period under investigation this structure exhibited a significant deterioration and an increase in the loan-loss provisions banks took on their books. Consequently increased also the pressure on bank capital, which created amplified incentives for the banks to underestimate credit risk. This corroborates the findings of the comprehensive review of the banking system of 2013 that the loan-loss provision, even though significant, were insufficient to cover the estimated potential future losses.

Table 2: Loan-loss Provisions Across Credit Ratings

Credit rating	Loan-loss provisions in % of outstanding loans
A	0.6
B	3.2
C	13.6
D	41.4
E	80.6

Source: Bank of Slovenia, own calculations.

Notes: The table reports the average coverage of classified claims by the stock of loan-loss provisions, calculated for the 2006-2012 period.

Table 3 provides further evidence on the link between credit ratings and loan-loss provisions by focusing on a subset of observations. Many firms in our dataset are clients of more than one bank and quite a significant number of these are assigned different credit ratings by different banks. The total number of firms in our sample is 41.964, which yields 174.048 firm-year observations. Out of these, 45.161 pertain to clients of more than one bank. And within this sub-sample 24.365 firm-year observations are such that firms are assigned different credit rating by different banks.

Banks are required to assign credit ratings independently of the existing or potential pledged collateral, which implies that the differences in credit ratings we observe are the result of banks' specificities in credit risk assessment and are not conditioned by firm characteristics. Table 3 shows that banks, in accordance with the Regulation, applied on average considerably higher rates of loan-loss provisions for worse credit ratings assigned to the same firms. For instance, the difference in the realized coverage ratio for the firms who have at one bank rating A and at the other bank rating B is on average 3 percentage points. In general, the differences in the ratios of loan-loss provisions increase monotonically with the difference in the assigned credit ratings.

The results in Table 3 might be plagued by the value of collateral held by different banks for the same client. In this respect two comments are in order. First, it is true that banks with better access to the collateral of a given firm have smaller incentives to under-estimate credit risk. What we observe in the data, however, is that on average this is not the case. As Table 3 suggests, a downgrade of a client on average led to an increase in loan-loss provisions even after

a potentially neutralizing effect of collateral.

The second comment is about potential biases in valuation of collateral in addition to underestimation of credit risk. Namely, in addition to having the incentive to overestimate credit ratings banks have an incentive to overvalue the collateral (see Huizinga and Laeven, 2012). In particular, banks with weakly collateralised loans would have an incentive to over value the collateral and decrease the amount of required loan-loss provisions without the need to assign overly optimistic credit ratings. This effect, however, would bias the differences in the ratios of loan-loss provisions downward, which would imply that the true differences in the ratios of loan-loss provisions among credit-rating classes would only be larger than those reported in Tables 2 and 3.

Overall, the information in Table 3 is in line with that in Table 2. It confirms that in times of a financial crisis and deteriorating credit rating structure of bank portfolios, banks can reduce their provisioning costs by underestimating credit risk. Empirical evidence of underestimation of credit risk for the case of Slovenia is found by Volk (2012). He notices that even though the banks downgraded a considerable share of borrowers, the average implied probability of default of rating classes A, B and C increased. This indicates that the risk assessment strategy by the banks changed significantly in the crisis.

Table 3: Average Loan-loss Ratios for the Sub-group of Firms with Different Ratings Across Banks

Pairs of Ratings	Average Coverage Given		Difference
	Higher Rating	Lower Rating	
A-B	0.7	3.7	3.0
A-C	1.1	11.9	10.8
A-D	2.2	35.1	32.9
A-E	12.3	81.8	69.5
B-C	4.0	12.9	8.9
B-D	4.2	32.4	28.2
B-E	4.0	73.4	69.4
C-D	18.8	35.3	16.5
C-E	22.0	64.1	42.1
D-E	48.2	75.2	27.0

Source: Bank of Slovenia, own calculations.

Notes: The table reports the average coverage of classified claims by the stock of loan-loss provisions for the same firms with different ratings assigned by different banks. For all pairs of credit ratings the average coverage ratio is reported separately for the higher and lower assigned rating. The statistics are given in percentages (difference in percentage points) and are calculated for the 2006-2012 period.

The deterioration of banks' portfolios in 2006 - 2012 was very heterogeneous. To demonstrate this we divide 25 banks under analysis into three groups. The first division is according to residence of owners into foreign and domestic. Foreign-owned banks are 11 in number. The second division is that of domestic banks into large and small.⁶ The group of large domestic banks consists of three banks. Two, the NLB bank and the NKBM bank, were the largest on the market, holding more than 35% of total bank assets. From the point of view of the ability

⁶All foreign-owned banks operating in Slovenia in period 2006-2012 can be classified as small.

to raise capital in times of financial distress these two banks can be deemed too big to fail and enjoying an implicit bailout guarantee by the government. The implicit state guarantee assumption rests also on the ownership structure of the largest two banks. They both had the government or government-controlled enterprises as the largest or even majority owners. The classification of these banks as large should thus be understood also in the functional sense due to direct presence of the state ownership. In addition, state ownership could be reflected in business strategy of these banks as it provides a channel for political intervention into bank management and consequently allocation of loans based on other than purely financial criteria. Evidences of political influence on loan allocation and interest rates charged by state-owned banks are provided by Dinc (2005), Khwaja and Mian (2005) and Sapienza (2004). The third bank in the group of large domestic banks, the SID bank, is similarly included not merely because of its size, but because it is a 100% state-owned bank.⁷

The remaining 11 domestic banks were classified as small in terms of size. These banks were also predominantly privately owned.

Table 4 reports the share of non-performing loans (defined as loans with more than 90 days overdue - upper panel) and the coverage of NPLs with loan-loss provisions (lower panel). Non-performing loans increased rapidly after the onset of the crisis and virtually exploded in domestic banks after 2009, exceeding 25% in 2012. These levels of NPL ratios are very high by international standards. The increasing dynamics in foreign-owned banks was significantly less pronounced. Similarly, it can be argued that a better performance of foreign-owned banks was not due to miss-classification of NPLs as performing. The AQR providers reported that the rate of miss-classification of NPLs as performing loans was on average roughly 4% for SMEs (ranging from 0% to 13%), roughly 13% for large corporates (ranging from 0% to 21%) and roughly 10% for real estate developers (ranging from 0% to 19%). Our econometric analysis of classification accuracy of firms in default below suggests that foreign-owned banks were at the lower end of these ranges, which implies that miss-classification was mostly concentrated among domestically-owned banks. These banks had on average considerably higher NPL ratios and thus also higher incentives to miss-classify loans.

The bottom panel of Table 4 reports the corresponding coverage ratios of NPLs with loan-loss provisions. Relative to the levels before the crisis we see that only large domestic banks on average kept the ratio at the same level and, provided unchanged level of collateralization, took on their books the full account of increasing burden of NPLs. Foreign and especially small domestic banks, on the other hand, decreased the coverage ratio quite significantly and thus did not let the required provisions on expected losses from the NPLs to pass in full onto their profit and loss accounts.

Descriptive statistics presented thus far allow to make the following summary observations. The banking regulation in place embeds significant procyclicality in loan-loss provisions. During the Great recession the quality of bank assets in Slovenia deteriorated significantly. This was reflected in the credit rating structure presented in Table 1. The table shows that banks downgraded their borrowers, but the results of the comprehensive review from 2013 suggest that downgrading did not reflect fully the increase in credit risk. Table 4 finally indicates that the incentives to objectively assess the creditworthiness of assets differed significantly across banks.

Foreign-owned banks had the smallest burden of non-performing loans. Foreign-owned banks are also part of international banking groups who have easier access to wholesale finance and can provide funds to daughter affiliates through the internal capital markets. Moreover, it is

⁷SID bank was established with a special purpose of securing international trade deals and enjoys an explicit government guarantee for its liabilities. During the crisis it served as a vehicle to stimulate corporate lending through state guarantee schemes and for disbursement of loans of international financial institutions.

Table 4: Share of NPLs and Coverage Ratio for Three Groups of Banks

	2007	2008	2009	2010	2011	2012
Share of NPLs						
Large Domestic Banks	2.8	3.3	6.6	16.5	26.7	33.2
Small Domestic Banks	2.3	3.5	7.1	11.7	19.2	26.4
Foreign Banks	2.1	3.9	6.6	8.7	9.0	11.9
Coverage Ratio						
Large Domestic Banks	44.5	37.1	40.9	35.6	42.3	46.1
Small Domestic Banks	68.7	49.7	40.1	33.1	36.0	34.9
Foreign Banks	52.2	29.7	26.1	33.7	34.0	36.0

Source: Bank of Slovenia, own calculations.

Notes: The table reports the share of NPLs and coverage of NPLs by the stock of loan loss provisions (in percent). Non-performing loans are defined as classified claims more than 90 days overdue.

possible that these banks employed better risk management techniques and corporate governance mechanisms. A plausible explanation of a smaller NPL burden of foreign banks is the "cherry picking" behavior under which foreign banks choose to serve less risky firms (see Claessens and van Horen (2014) and references therein).⁸ Such a behavior is especially pronounced in emerging markets (Sengupta, 2007).⁹ A smaller NPL burden and easier access to sources of capital offered foreign-owned banks capacity for easier absorption of credit losses. Both factors imply less incentives to apply discretion in credit risk assessment.

Just the opposite was the case of domestic banks, which had a considerably higher NPL burden. Small domestic banks, moreover, had very limited possibilities to raise additional capital.¹⁰ Our prior is that both features translate into significant incentives to underestimate credit risk under stress.

Large domestic banks, even though heavily burdened with non-performing loans, enjoyed an explicit bail-out guarantee by the government. The effect of size and state ownership on the incentives to under-estimate credit risk is not clear a priori. Higher capacity to raise additional capital through the government offers the management to take full account of deteriorating credit portfolio and hence reduces the incentives to underestimate risk. Bail-out guarantee, on the other hand, leads to moral hazard and thus higher incentives to underestimate risk. For a particular Slovenian situation our prior is that the first factor prevails and hence we conclude that large domestic banks had smaller incentives to underestimate credit risk than small banks. Nevertheless, we could think of it as an empirical issue. But given that the two effects work

⁸This appeared to have happened despite the fast expansion of lending activity by foreign-owned banks who actually led the pace of credit expansion in Slovenia prior to the crisis. In the period 2003-2008 the total amount of loans outstanding of foreign-owned banks expanded by 372%, while those of domestically-owned small and large banks grew by 274% and 207% respectively.

⁹While better risk management and corporate governance and "cherry picking" represent plausible explanations for a lower share of the NPL burned reported in Table 4 it is important to note that the comprehensive review revealed a significant 78% capital shortfall for foreign-owned banks also. This demonstrated that, on average, risk management and corporate governance was not at a high level in absolute terms.

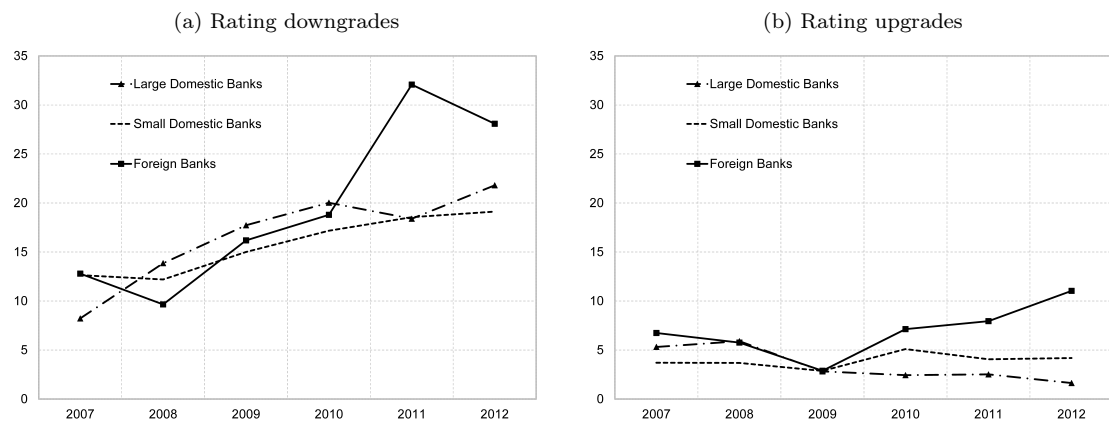
¹⁰The Financial Stability Review of the Bank of Slovenia (Bank of Slovenia, FSR 2013) documented that throughout the crisis smaller domestic banks had on average higher capital requirements for credit risk on overdue and high-risk exposures, with foreign-owned banks on the opposite side of the spectrum. Similar developments were observed regarding capital adequacy. During the crisis it increased the most for the group of foreign-owned banks, while domestic banks, especially small, experienced significant difficulties in raising additional capital.

on the incentives in opposite directions we can say that if our methodology proposed below confirms our prior that bigger size led to smaller incentives to underestimate risk, it will be an overestimation of true incentives to underestimate risk.¹¹

Our ranking of the groups of banks to underestimate risk can be supported with simple descriptive statistics on the evolution of credit rating changes. Figure 1 reports the share of rating changes per year in the period 2007 - 2012 divided into rating downgrades (left panel) and rating upgrades (right panel). It clearly emerges from the figure that as the crisis unfolded the frequency of rating downgrades increased. From roughly 10% ratings revised downwards on average in 2007 the share increased to above 20% on average in 2012. The share of rating upgrades hovered around 5% on average. Across groups of banks we again observe a large degree of heterogeneity. At the onset of the crisis in 2009 and 2010 the pace of rating downgrades was led by large domestic banks, but closely followed by foreign banks. In the last phase of the crisis (2011 - 2012) foreign-owned banks dramatically increased the pace of downgrades to 30%, while in domestic banks it levelled off at 20%. It is true that foreign-owned banks led also the pace of rating upgrades, while domestic banks lowered this rates to levels below 5%, however, the rates of upgrades did not exceed one third of the rates of downgrades. This implies that on net foreign banks led a more restrictive ratings policy and most actively downgraded the quality of their portfolios in face of deteriorating economic conditions. Large domestic banks can be ranked second in this respect, and they even led the pace at the beginning of the crisis.

Small domestic banks introduced the smallest changes to ratings structure of their portfolios. Such a ranking of bank groups is in line with our prior ranking of incentives to underestimate credit risk and consequently inflate bank books.

Figure 1: Share of rating changes (in %): rating downgrades (left panel) and upgrades (right panel)



Source: Bank of Slovenia, authors' calculations.

3. Predictive power of credit ratings and a test of discretion

Our approach to testing the potential bias in credit risk assessment in times of an economic downturn is the following. We focus on loans to non-financial corporations as this segment of

¹¹The incentives to underestimate risk cannot be linked to difference in capital buffers formed before the crisis. In 2008 the average capital adequacy ratio of foreign-owned banks was at 10.6% below average.

bank portfolios held 80% of overall value of loans more than 90 days overdue (our measure of default) in the period 2007 - 2012. For these corporations we have access to data on their credit ratings assigned by corresponding banks. In the process of credit risk assessment banks dispose with publicly available information on firms' balance sheet and income statement and other information collected by the banks such as the information on overdue payments on bank loans. Such information is systematically recorded and can be in principle used also by an econometrician in modelling default. In addition, banks can keep regular contacts with the borrowers to obtain other information that is not systematically recorded and apply expert judgement in assessing creditworthiness and assignment of credit ratings. It is thus sensible to assume that credit ratings are formed using more information about firms' creditworthiness relative to the information used by an econometrician. Indeed, the additional information used in assigning credit ratings could also be a strategic decision to apply discretion in order to inflate the value of the bank's portfolio in a crisis.

The idea of the test for discretion is rather simple. We have two information sets, one in the form of pure financial information and the other in the form of credit ratings. We take both sets and include them separately into two econometric models. The model using pure financial information is denoted below as the *balance-sheet model*. The model that uses the information embedded in credit ratings is denoted as the *credit-ratings model*. Both models are logistic regressions. With both we test for respective classifications accuracy of defaulted firms. For the purpose of our analysis it is important to emphasize that the balance-sheet model is free from incentives to underestimate risk.

Credit ratings should embed superior information and expert knowledge in assessing creditworthiness. In addition, the potential superiority of expert information should become more pronounced in times of financial distress, when rapidly changing economic conditions call for prompt collection of new information from the market. The econometrician using the balance sheet model cannot adapt to the situation as it disposes only with information that is reported by private enterprises for each fiscal year. Under fair assessment of credit risk we should thus observe that in the a financial crisis the information advantage of credit rating results in a relative improvement of default prediction of the credit-ratings model. Conversely, if in such a setting we observe a reduction in explanatory power of credit ratings for the probability of default relative to a model using financial information (ratios) only, this is an indication of the incentives to underestimate risk. In other words, if in times of financial distress banks have incentives to underestimate risk, we should observe a reduction in explanatory power of credit ratings model relative to the balance sheet model. Moreover, we should observe a more pronounced reduction for those banks whose incentives to underestimate risk are larger.

In sum, we test for the presence of discretionary risk assessment with the aim to underestimate risk by comparing the explanatory power of models using (1) credit ratings and (2) pure financial information both along the time dimension and along the cross section of banks. If the hypothesis of increased incentives to underestimate risk is empirically relevant, we expect to observe a deterioration of explanatory power of credit ratings in time as the financial crisis unfolds, and in the cross-section for banks with weaker capital structures and corporate governance, higher exposures to credit risk, and with limited access to the market for funds.

Such a testing approach is in line with Krahnen and Weber (2001) who note that an important requirement for the risk rating system to function properly is that it takes into account possible incentive problems. In relation to this, Kirstein (2002) demonstrated theoretically that even if assumed that banks have better knowledge of the customers than rating agencies, external ratings are better able to implement the goals of the Basel Committee than internal ratings. He argues this is due to lack of the banks' incentive to truthfully assess firms' creditworthiness. Consequently, banks' credit ratings need not be more reliable indicators of financial distress.

Before moving to the presentation of bankruptcy prediction models three remarks are in order. Firstly, it should be noted that a reduction in explanatory power of credit ratings can also be a consequence of standard financial information (like financial ratios) becoming less reliable in a crisis, potentially due structural breaks, and hence be in general less reliable indicators of financial distress. Because this can happen in periods when incentives for discretionary risk assessment increase, the change in explanatory power of credit ratings would not be a reliable gauge of discretionary risk assessment. Our approach, however, does not suffer from this problem because we test our hypothesis through differences between the model with credit ratings and the model with pure financial information. Because the latter in principle enter the information set of both models, they should be similarly affected by a potential structural breaks in explanatory power of financial ratios.

Secondly, with exception of one, all banks in our sample used a standardized approach to determining capital requirements for credit risk. Our testing approach, however, is applicable also to banks using the internal based rating (IRB) system. Under IRB banks use a fully parametric model to determine the probability of default as one of the key ingredients to calculating capital requirements.¹² Based on such a model a rating scale is determined and borrowers sorted accordingly. The information entering the model is of two types: purely financial and information based on bank's expert judgement of various non-measurable determinants of borrower's creditworthiness. The latter set of information is in principle subject to discretionary assessment in times of financial distress (Kirstein, 2002). In such a case, a test of the presence of under-estimation of risk would be based on the test for systematic differences (both across time and banks) between the probabilities of default given by the bank's model and a bankruptcy prediction model free of subjective information. Similarly, the test could be based on the predictive power of credit ratings of the banks operating an IRB system. Both approaches are fully consistent with the approach we use.

Last but not least, our measure of comparison of the models is classification accuracy of firms in default. Classification accuracy of healthy firms is not of primary interest. Our focus is on incentives to under-estimate credit risk through avoiding the regulatory requirement to form more loan-loss provisions for firms with worse credit rating. This means that we primarily study a "one-sided incentive", which corresponds to evaluating the classification accuracy of defaults.

3.1. The Balance Sheet Model

We model corporate default in a fairly standard way in the literature, paved by Altman (1968). The balance sheet model uses financial ratios as predictors of default. Default is defined from the information on number of days overdue on loan payments, which is a common indicator of default in the literature (see Bonfim, 2009, and Carling et al., 2007, among others). Such an indicator is also in line with the Basel recommendations (BCBS, 2006). We define the event of default as:

$$Y_{it} = \begin{cases} 1 & \text{if firm } i \text{ is more than 90 days overdue to at least one bank in time } t \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The probability that the binary dependent variable Y_{it} equals one given the covariates is

¹²The second important quantity is the estimate of the loss given default, which depends on the valuation of underlying collateral. Valuation of collateral is another area where banks can apply discretion to inflate their books. Given that the focus of our analysis is the informativeness of credit rating we focus our discussion on discretion in modeling probability of default.

modelled using the following specification:

$$P(Y_{it} = 1|X_{it-1}) = \Lambda(\alpha + \beta X_{it-1}) = \frac{e^{\alpha + \beta X_{it-1}}}{1 + e^{\alpha + \beta X_{it-1}}} \quad (2)$$

where α and β are parameters to be estimated and X_{it-1} is a vector of firm specific variables measuring size (log of sales), firm life-cycle (age), liquidity (quick ratio, cash-flow ratio), number of days with blocked account, asset turnover, financial structure (debt-to-assets ratio) and position on the financial market (number of relations with banks). The information in the balance-sheet model is also available to banks in the process of assessing firms' creditworthiness. All explanatory variables enter the model lagged one year.

The model is estimated for the period 2007-2012. Given that our aim is to compare the classification accuracy between the balance-sheet model and the credit-ratings model during the crisis, the models are estimated for each year separately.

3.2. The Credit Ratings Model

To be able to compare the prediction accuracy of the balance sheet model with the banks' accuracy in firms' credit risk assessment we propose the following credit-ratings model. Since each bank assesses firms' riskiness with its own methodology and same firms can thus have different credit ratings across banks, we define the default event at bank-borrower level as

$$Y_{ijt} = \begin{cases} 1 & \text{if firm } i \text{ is more than 90 days overdue to bank } j \text{ in time } t \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

and estimate the logit model:

$$P(Y_{ijt} = 1|R_{ijt-1}) = \Lambda(\gamma + \delta R_{ijt-1}) = \frac{e^{\gamma + \delta R_{ijt-1}}}{1 + e^{\gamma + \delta R_{ijt-1}}} \quad (4)$$

where γ and δ are parameters to be estimated and R_{ijt-1} is a set of four dummy variables for each of the credit ratings from A to D, indicating firm i 's credit rating, given by bank j in time $t - 1$. The credit rating E is accounted for by the constant. Similarly to the balance sheet model we estimate the model for the 2007-2012 period year by year.

4. Results

Tables 5 and 6 present the estimated coefficients of the balance sheet and credit ratings model respectively. In the period under analysis, the variables included in the balance-sheet model are consistently statistically significant. The estimates of the credit rating model in Table 6 show that all credit rating dummies enter statistically different from zero. The base rating is E - the worst rating - and in line with our expectations we can observe the coefficients of other dummy variables monotonically decrease with increasing rating. Through time the constant increases quite significantly, corresponding to an increase in probability of default in line with an increase in the share of non-performing loans in the banking system. Note that other coefficients that measure differential effects relative to the credit rating E do not exhibit similar changes, which reflects the fact that the probability of default increased consistently across all credit ratings.

Table 7 contains a comparison of the classification accuracy of the two models. While overall classification accuracy decreases slightly from 2007 to 2012 (and less so for the balance sheet model), the classification accuracy of defaulted firms exhibits more pronounced dynamics that is depicted in Figure 2. What we observe is that before the crisis (default in 2007 based on 2006

Table 5: The Balance Sheet Model - Estimates for Each Year Separately

	2007	2008	2009	2010	2011	2012
$\log(\text{Total sales})_{it-1}$	-0.292***	-0.170***	-0.143***	-0.105***	-0.122***	-0.107***
Age_{it-1}	-0.024***	-0.040***	-0.051***	-0.046***	-0.041***	-0.043***
$\text{Quick ratio}_{it-1}$	-0.131***	-0.090***	-0.158***	-0.215***	-0.221***	-0.156***
$\text{Debt-to-assets}_{it-1}$	0.016**	0.006	0.069*	0.378***	-0.018	0.037
$\text{Cash flow ratio}_{it-1}$	-0.300***	-0.224***	-0.133**	-0.272***	-0.433***	-0.317***
$\text{Asset turnover ratio}_{it-1}$	-0.459***	-0.643***	-0.450***	-0.723***	-0.598***	-0.470***
$\text{No. of days with bl. ac.}_{it-1}$	0.011***	0.011***	0.012***	0.012***	0.014***	0.014***
$\text{No. of bank-bor. rel.}_{it-1}$	0.484***	0.429***	0.420***	0.418***	0.468***	0.540***
Constant	-0.911**	-2.247***	-1.862***	-1.399**	-0.486	-0.744
No. of observations	15638	15970	17546	17985	18164	18218

Source: Bank of Slovenia, AJPES, own calculations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the logit estimates for each year from 2007 to 2012, where the dependent variable is equal 1 if firm i is more than 90 days overdue to at least one bank in year t and zero otherwise. Sectoral dummies are included to control for the specificity of each sector.

Table 6: The Credit Ratings Model - Estimates for Each Year Separately

	2007	2008	2009	2010	2011	2012
Credit rating A_{ijt-1}	-6.184***	-5.556***	-5.173***	-5.795***	-6.102***	-5.833***
Credit rating B_{ijt-1}	-4.776***	-4.218***	-4.204***	-4.668***	-4.944***	-4.673***
Credit rating C_{ijt-1}	-3.423***	-2.954***	-3.043***	-3.340***	-3.233***	-3.058***
Credit rating D_{ijt-1}	-1.900***	-1.898***	-1.918***	-2.240***	-2.411***	-2.112***
Constant	1.290***	1.177***	1.480***	1.946***	2.168***	1.946***
No. of observations	21200	21480	23906	24926	25203	25595

Source: Bank of Slovenia, own calculations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports the logit estimates for each year from 2007 to 2012, where the dependent variable is equal 1 if firm i is more than 90 days overdue to bank j in year t and zero otherwise. Credit rating A to D are dummy variables for each of the credit ratings, which are assigned to the firms by the corresponding banks.

data) both models had a very similar classification precision. The balance sheet model outscored the credit ratings model only by 2 percentage points. In the initial years of the crisis, 2008 and 2009, the classification accuracy of both models drops.¹³ Such a result is expected. The beginning of the crisis represents also a turnaround in defaults. Bankruptcy prediction models use $t - 1$ -dated information. This means that predicting default in the first year of the crisis involves using only information from before the crisis, when balance sheets of firms appeared healthy. It is important to note, however, that the deterioration in classification precision is higher for the credit ratings model. Credit ratings should in principle reflect information superior to pure $t - 1$ -dated information of the balance-sheet model and thus suffer less from the problem of time delays in availability of information. Banks can learn about the crisis before its effects are recorded in end-of-the year balance sheet and income statement data that the balance-sheet model uses. This information advantage could serve to adjust the ratings in a timely manner so as to reflect the increase in the incidence of firm default. It would be thus sensible to expect that the credit ratings would suffer less in terms of loss of defaults classification precision. This is not what we observe in our estimation results, which leads us to conclude that the lack of adjustment of credit ratings in face of financial crisis was used to inflate banks' balance sheets.

Table 7: Classification Accuracy Through the Business Cycle

	The Balance Sheet Model		The Credit Ratings Model		Difference	
	Overall	Defaulters	Overall	Defaulters	Overall	Defaulters
2007	96.2	21.3	96.9	19.3	-0.7	2.0
2008	95.2	17.2	96.0	13.9	-0.8	3.3
2009	93.8	17.0	94.5	10.2	-0.7	6.8
2010	93.8	28.0	93.8	9.2	0.0	18.8
2011	93.8	33.2	93.5	16.0	0.3	17.2
2012	93.3	35.1	92.9	19.9	0.4	15.2

Source: Bank of Slovenia, AJPES, own calculations.

Notes: The table reports the overall classification accuracy and correctly classified defaulters in percentages as predicted with the balance sheet model and the credit ratings model estimated for each year in the sample. The difference between both models is given in percentage points.

A diverging performance of the models continues to the end of the period under investigation. We can note first that the turnaround in classification precision of the balance sheet model occurs one year before the turnaround of the credit ratings models. This represents another piece of evidence that the banks were slower to incorporate new overwhelming evidence of deteriorating financial health of enterprises than a pure mechanical econometric procedure would do. The last column of Table 7 shows that because of this in 2010 the difference in classification accuracy of defaulted firms grows to 19 percentage points, almost tenfold of the pre-crisis difference.

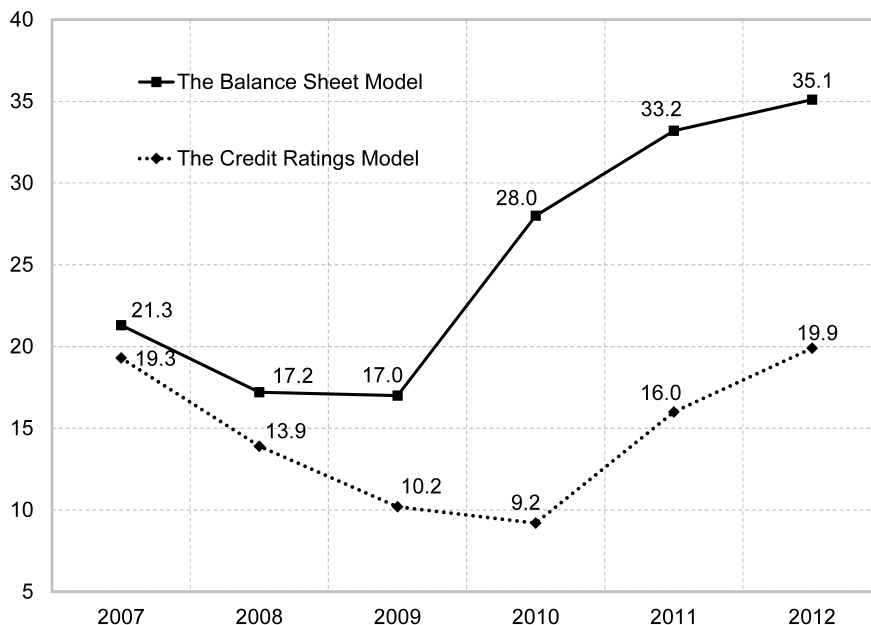
In 2011 and 2012 the classification accuracy of the credit rating model picks up and closes some of the gap to the balance sheet model, but remains at more than 15 percentage points, which is seven times higher than before the crisis. Moreover, for the credit rating model the classification accuracy in 2012 returns to the pre-crisis level. For the balance sheet model, however, we can see that it is considerably higher than before the crisis, 35.1% relative to 21.3%.¹⁴ Overall, this comparison provides time-series evidence of a potential problem with

¹³Slovenia slid into a recession in the fourth quarter of 2008.

¹⁴To some extent, this can be explained by the fact that with the crisis the number of firms in default increased considerably. In estimation of a bankruptcy prediction model this implies that a higher probability mass is

discretion in credit risk assessment. Banks could in principle incorporate information about mounting financial difficulties of their clients much faster and in a forward-looking manner than a purely econometric backward-looking procedure that uses only published information from the previous period. In the data we observe just the opposite.

Figure 2: Correctly Classified Defaulters (in %)



Source: Bank of Slovenia, AJPES, author's calculations.

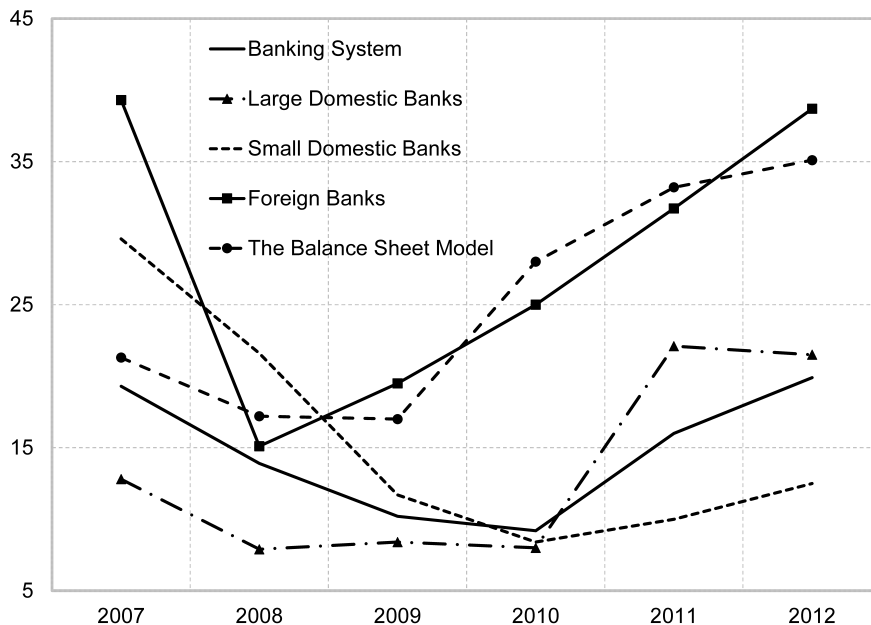
We now turn our attention to classification accuracy of defaulters across groups of banks. The corresponding results are presented in Figure 3. The results for the credit rating model estimated on the data for banking system as a whole (solid line) and the balance-sheet model (dashed line with circle markers) are the same as in Figure 2. The remaining results are for the credit ratings model estimated on observations corresponding to each of the banking groups: foreign-owned banks, large domestic banks and small domestic banks.

What we can observe are large differences across groups of banks. Classification accuracy of foreign-owned banks stands out as the most precise. With 40% accuracy before the crisis (2007) it outperforms all other models, declines significantly in the first three years of the crisis, but remains quite comparable to the balance-sheet model, and results again to be the best performing model in the final year under analysis. Moreover, evolution of the classification accuracy of foreign-owned banks is very similar to the evolution of the balance-sheet model. The latter is a purely econometric procedure free of incentives to underestimate credit risk. The experience of the classification accuracy of credit ratings of small banks is at the opposite end of the spectrum. While they performed quite well before the crisis, their classification precision of defaulters steadily decreases through to 2010 to less than 10% accuracy and remains at these low levels thereafter. The classification accuracy of the credit-rating model of large domestic banks

accounted for by the default cases, which facilitates a more precise discrimination between healthy firms and firms in default. See Brezigar-Masten and Masten (2012) for a discussion.

stands in between. It is the least precise before the crisis and the initial two years, but it picks up quite significantly at the end of the period, reaching levels of precision above 20%, which is double the pre-crisis rate.¹⁵

Figure 3: Correctly Classified Defaulters Across Groups of Banks (in %)



Source: Bank of Slovenia, AJPEs, authors' calculations.

These results go hand in hand with the evidence on the incentives for discretionary risk assessment presented in Section 2. Mounting burden of non-performing loans in the banking system as a whole led to an average increase in incentives to under-estimate risk, assign higher credit ratings on average and consequently make smaller loan-loss provisions. In such a case, we would expect to find that with the financial crisis unfolding credit ratings on average lose the explanatory power for default. The empirical evidence in Figure 2 is consistent with this view.

Section 2 presents also evidence that the incentives for under-estimation of risk differed significantly across banks. Foreign-owned banks experienced smaller problems with the NPLs and had smaller difficulties with maintaining capital adequacy and funding because of a more stable access to finance through internal capital market of the banking groups they belong to (Navaretti et al., 2010). Domestically-owned banks were more heavily exposed to NPLs and had weaker capital adequacy ratios. Among them, large banks enjoyed a strong implicit state bail-out guarantee, which also materialized in capital injections into two largest banks in 2011 and 2012. Small domestic banks, on the other hand, experienced significant problems with raising additional capital and with access to wholesale funding. As we noticed above, this group of banks did not make a similar adjustment of credit risk assessment standard towards more stringent policy we observe

¹⁵While the worst classification accuracy of large domestic banks before the crisis is consistent with the moral hazard explanations of incentives to underestimate risk, this no longer prevails in the crisis. The fact that the classification accuracy of large banks outperforms those of the small banks indicates a stronger effect of smaller incentives to underestimate risk due easier access to capital and funding.

for foreign-owned banks and large domestic banks. In sum, these observations suggest that it was the group of foreign-owned banks with smallest incentives to under-estimate risk in order to artificially protect their balance sheets. Small domestic banks were on the other end of the spectrum. The results on classification accuracy in Figure 3 are in line with these observations. Credit-ratings of foreign-owned banks appear considerably more reliable determinants of default than those of domestic banks. In the latter group it is the group of small banks whose credit ratings' classification accuracy deteriorated most significantly during the financial crisis and even remained well below the classification accuracy of large domestic banks.

The best classification accuracy of credit rating of foreign-owned banks could be in principle attributed also to better corporate governance and better risk management practices. Note, however, that the pre-crisis levels of classification accuracy of small domestic and privately owned banks, that did not have any direct access to technology of large multinational banking groups, was quite comparable. About 5 percentage points lower than foreign banks, but at the same time roughly 15 percentage points higher than the classification accuracy of large domestic banks. Because of state ownership the weak initial performance of the latter group could be attributed also to political interference and moral hazard. Relative positions in classifications accuracy before the crisis can thus be rationalized with factors related to corporate governance. In addition, corporate governance and risk management technology can play an important role in in shaping the incentives to underestimate risk in times of financial distress. However, in the period under analysis no major ownership changes occurred in the Slovenian banking system. For this reason we consider the potential effect of corporate governance heterogeneity as fixed in time. Consequently, the dynamics in classification accuracy in the crisis can be explained with the differences in the incentives to underestimate credit risk described above.

5. Robustness checks

The analysis so far has been conducted on yearly frequency in which we use only end of year data to predict default one year ahead. Our data on credit ratings are on quarterly, which enables us to conduct two robustness checks. Both check robustness of our results with respect to real-time availability of the information banks have at their disposal when setting credit ratings.¹⁶

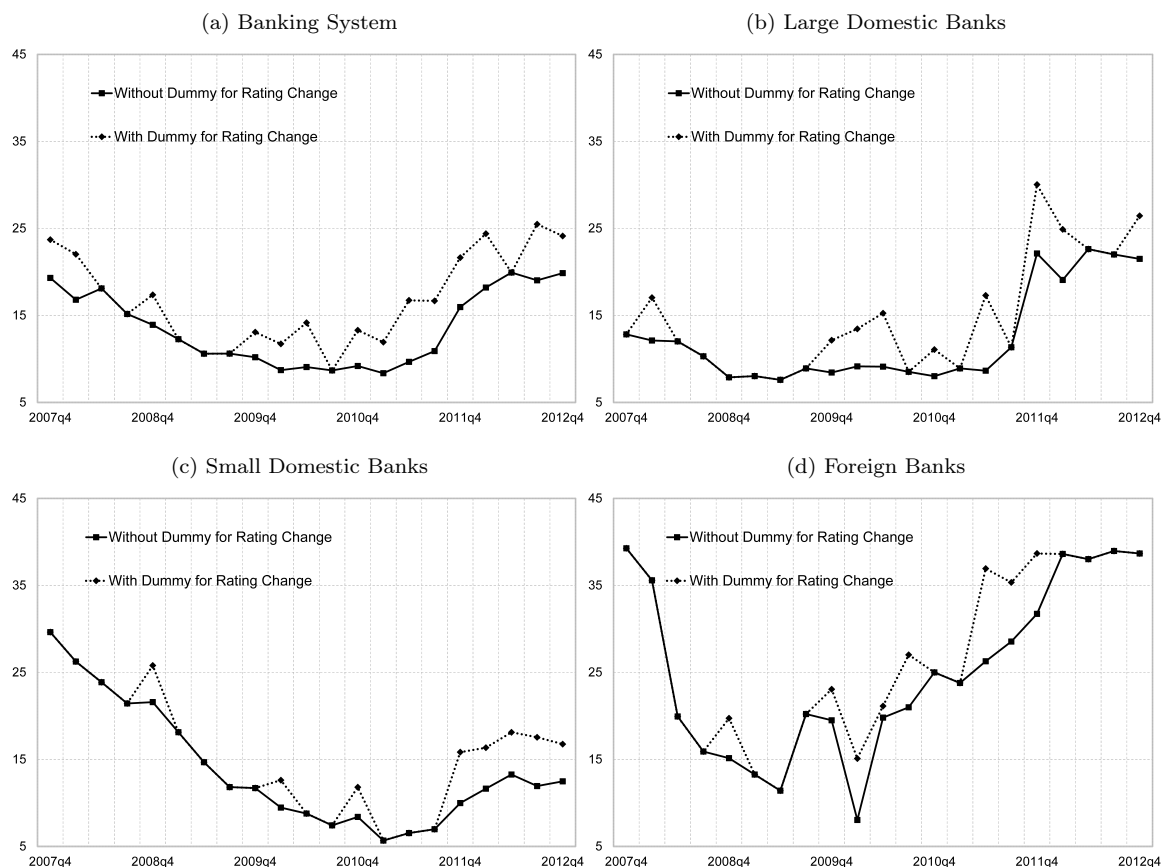
5.1. Controlling for rating changes

It is sensible to expect that ratings that change as banks acquire new information about specific clients will have a better explanatory power of firms' default. Namely, banks' cannot instantaneously and simultaneously review all the clients in the portfolio, because of insufficient capacity to do so. Instead, priority is given to subsets of firms. In a crisis these are foremost firms in distress. Not controlling for rating changes thus potentially biases our previous analysis at the expense of the credit rating model, thereby showing it less reliable in predicting default.

Data on credit ratings are on quarterly, which enables us to trace the timing of rating changes and hence the time when a bank updated the information set. Accounting for updating of the information sets is imperfect since we cannot identify cases where information set was updated, but rating did not change. Nevertheless, given that empirical analysis uses data mostly from the Great recession in which rating downgrades heavily dominated the process (see Figure 1), controlling for rating changes could improve the performance of the credit ratings model.

¹⁶We checked also robustness of our results with respect to the forecast horizon. In particular, horizons between 1 and 8 quarters were considered. Our conclusions obtained in the previous section are robust to different forecast horizons. Results available upon request.

Figure 4: Effect of Rating Changes - Correctly Classified Defaulters 1-year Ahead Across Groups of Banks (in %)



Source: Bank of Slovenia, authors' calculations.

Classification accuracy of credit rating models, estimated for each quarter, with and without a dummy variable for rating change is shown in Figure 4. For the whole banking system, controlling for rating changes improves the share of correctly classified defaulters in 14 out of 21 quarters. In the cases where its impact is positive, it contributes on average 4.8 percentage points to the classification accuracy. Rating change thus improves the performance of the credit rating model. However, the credit rating model still hits considerably lower share of defaulters than the balance sheet model, especially in the crisis period.

Controlling for rating changes also does not change our conclusions about the different behaviour of the three groups of banks. From Figure 4 we can still conclude that it is the ratings of foreign banks that are throughout the crisis the most precise in classifying firms in default. Conclusions about large domestic and small domestic banks are also fully consistent with the evidence presented in Figure 3. This leads us to conclude that our basic conclusions are robust to the timing of rating changes.

5.2. Controlling for public release of corporate balance sheet data

In this section we investigate whether the timing of public release of balance sheet and income statement data has an effect on the dynamics of rating changes. Namely, firms are required to

report their balance sheet data for the past fiscal year to the Agency of public and other legal records until the end of March of the current year. The data become publicly available during the second quarter of current year. We could thus assume that banks are informed about the financial state of each firm in year t in the second quarter of year $t + 1$. The balance sheet model in the previous sections, however, assumes that this information is available already at the end of each year t . In this sense the balance sheet model has a potential information advantage over the credit-rating model, which uses the information on credit ratings in real time.

Table 8 reports the percentage of credit rating changes over individual quarters (averaged across years). If the newly available balance sheet data would be the main driver of rating changes, we expect that the large majority of changes would happen in the second and/or third quarter. Results in the table indicate that this might be the case on average, but not systematically so. On average, the frequency of rating changes is the lowest in the first quarter, but this observation does not hold uniformly across bank groups as the minimum for large domestic banks is in the third quarter. The frequency of rating changes is on average the largest in the second quarter, but again not uniformly across bank groups. Finally, one can note that the differences in rating changes across quarters are not stark. The largest is the difference between the third and the first quarter for small domestic banks of about 15 percentage points. The remaining differences are considerably smaller.

Table 8: Credit Rating Changes Over Quarters (in %)

	Q1	Q2	Q3	Q4
Large Domestic Banks	25.0	28.7	22.5	23.8
Small Domestic Banks	18.5	25.5	34.2	21.8
Foreign Banks	18.0	28.4	25.8	27.8
Overall	21.6	27.7	26.8	23.9

Source: Bank of Slovenia, own calculations.

Notes: The table reports the percentage of credit rating changes in each quarter. The statistics are calculated for the period 2007q1-2012q4.

Thus, the timing of the release of the balance sheet and the income statement data might not be a decisive element in determining the relative performance of the credit ratings model. There are two reasons for such a finding. The information on delays in loan repayment and information on blocked accounts are an important determinant of the credit rating and available in real time. Moreover, banks' reliance on the release of official balance sheet and income statement data is crucial for smaller firms. Larger firms, to which banks have larger exposures, are monitored on a more regular basis.

To investigate the effects of the potential information advantage of the balance sheet model formally, we compare the classification accuracy of competing models by suitably adjusting the prediction horizons. Namely, we position the models in a pseudo-real time context into the second quarter of each year, when corporate balance sheet data become publicly available. Exploiting the availability of credit ratings at quarterly frequency we can estimate the credit ratings model for the second quarter of each year and consider predicting default one year ahead.¹⁷ From the point of view of the balance-sheet model the corresponding prediction horizon is 6 quarters because this model uses the data for the end of the previous year, which become available with a 2-quarter delay, i.e. in the second quarter of the current year. Different forecast horizons between

¹⁷Results for different prediction horizons are similar and available upon request.

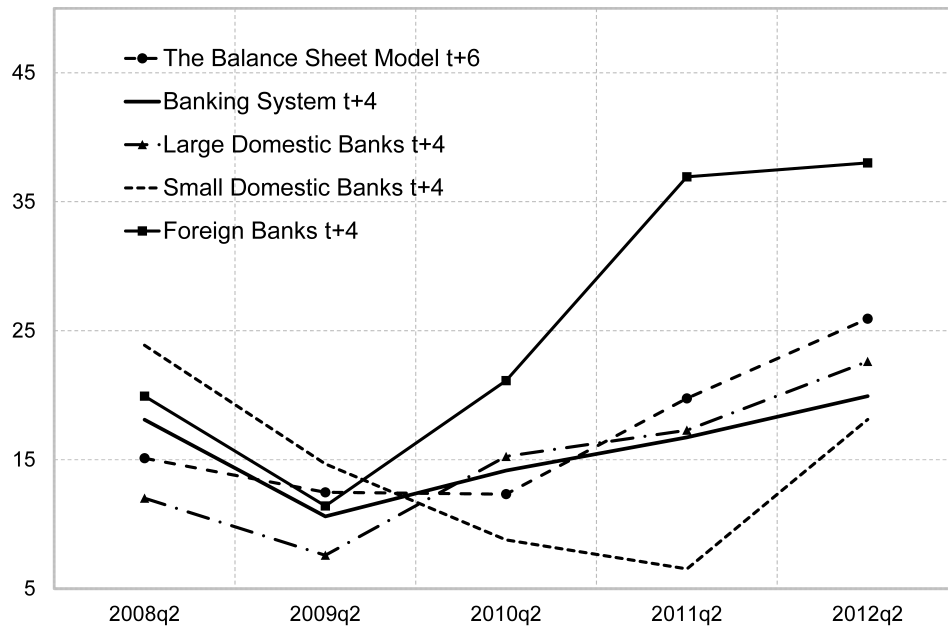
models are in terms of notation. From the point of view of balance sheet data availability in real time, the forecast horizons are aligned.

Constructing the comparison this way puts the models at par as regards the availability of balance sheet and income statement data. It favours, however, the credit ratings model from two other important points of view. First, the balance sheet model uses the information on incidence and the duration of blocked transactions accounts of firms. This information is available in virtually real time to banks and, as explained above, it is an important determinant of credit rating. So it is in principle contemporaneously embedded in the credit rating model. However, because we compare the 4-quarter ahead prediction of the credit ratings model with the 6-quarter ahead prediction of the balance-sheet model, the latter essentially uses the information on blocked accounts that is 2 quarters old.

The second aspect is the information on overdue loan repayments. This information is not used in the balance sheet model, but is readily available to banks in real time when they monitor their clients. Consider, for instance, a firm that in the second quarter accumulates significant days overdue, but not more than 90, which is our measure of default. This is a clear indication of a high probability that the firm will be in default in the near future. Clearly, the information on cumulating overdues is a signal to the bank to downgrade the firm, which should thus be a good predictor of default. This is another feature that puts the credit ratings model in a more favourable position from the point of view of available information.

In sum, by adjusting the forecast horizons as explained above we neutralize the information advantage of the balance-sheet model due to availability of balance sheet data in real time. At the same time, however, we additionally penalize the balance-sheet model from the point of availability of data on blocked transaction accounts and payments overdue. The robustness check we consider is thus rather extreme.

Figure 5: Effect of public release of data - Correctly Classified Defaulters One Year Ahead (Balance Sheet Model $t+6$, Credit Rating Models $t+4$) (in %)



Source: Bank of Slovenia, AJPEs, authors' calculations.

Figure 5 presents the results of the robustness check. As in the previous subsection, the credit rating model is augmented with the dummy variable for the rating change. Our conclusions from the previous section appear to be robust. The balance-sheet model exhibited a less precise classification accuracy than the credit ratings model before the crisis. Even if put into an informational disadvantage, however, results to end up as more precise than the average and domestic banks in particular. As before, the credit ratings model estimated for the group of foreign banks outperforms all other models, especially in the crisis period. On the other hand, the classification accuracy of small domestic banks dropped considerably during the crisis, becoming the least precise. From the best position before the crisis, it declined both relative to other two banking groups and, more importantly, to the balance sheet model. The pattern for large domestic banks is also fully consistent with our basic analysis. From the worst position before the crisis, classification accuracy improves in the crisis significantly more than it does for small banks. This is another indication that our basic conclusions that the largest incentives to underestimate risk could be found with the small domestic banks are robust.

6. Conclusion

In this paper we study the discretion in credit risk assessment for the case of Slovenian banking system during the Great recession. The Slovenian case is instructive as 10 major banks of the system in the second half of 2013 went through a comprehensive review similar to comprehensive reviews major banks in the Euro area went through before the establishment of the Single Supervisory Mechanism in November 2014. The comprehensive review applied common methodology to all banks involved and estimated significant shortages of capital in banks that reported sufficient capital adequacy ratios just a quarter before. Moreover, the review revealed stark differences across groups of banks that differ primarily with respect to ownership (domestic - foreign, state - private) and size. Our analysis addressed the question whether these differences can be explained with the incentives of banks to apply discretion in credit risk assessment, whereby over-estimation of credit ratings helped the banks to conceal some of the problems with deteriorating quality of their portfolios. This allowed them to temporarily avoid taking additional loan-loss provisions and hence inflate their balance sheets.

Our empirical analysis, by using data on firms' credit ratings, shows that discretion in credit risk assessment is a plausible explanation of differences in the required recapitalisation revealed by the comprehensive review. Banks that needed higher relative recapitalizations resulted to be the ones with the highest incentives to over-estimate ratings and whose ratings, as a result, proved to be the least reliable indicators of the incidence of financial distress of borrowers. These conclusions remain valid also after considering two robustness checks about the information structure in the credit rating process.

Moreover, the analysis provides a plausible explanation for the results of the comprehensive review of banks that entered the Single Supervisory Mechanism in November 2014. The results released by the European Central Bank in October 2014 indicate a clear divide between the estimated shortages of bank capital across the size distribution of banks. Capital shortfall for banks with total assets above the average on average amounts to 0.66% of their capital. For banks below average size the number is almost ten times bigger, 6.46%. By taking the median as the divisor between small and large banks, the respective numbers are 1.70% and 8.18%. Across the quartiles of the bank size distribution the estimated capital shortfalls are 5.96%, 9.05% and 6.30% for lower three quartiles respectively, and only 0.64% for the top quartile. These results are clearly in line with the conclusions of our analysis. Smaller banks likely have more limited options to raise additional capital either from the market or through government intervention and thus have bigger incentive to underestimate credit risk and inflate their books.

Our empirical findings have a number of important implications for banking regulation. Discretion in credit risk assessment is nothing but an attempt to temporarily sweep the problems under the rug. The fact is that the true creditworthiness of borrowers is always eventually revealed, credit risk realized and losses incurred. These losses are higher the longer the under-estimation of risk postpones solving the problems. As it turned out for the case of Slovenia, the estimated direct fiscal costs of bailing out these banks exceeded 10% of GDP.

In this respect, for future prevention and better management of such episodes it is important for the regulation to respond to the problem of incentives to under-estimate credit risk in times of financial crises and economic downturns in general. Clearly, discretion can be in principle mitigated by stricter control over credit risk assessment. Stricter control is possible already in the current system, but regulatory forbearance is often applied in similar crisis situations. Stricter regulatory control should thus take the form of standardized and externally controlled credit rating procedures. Currently, banks using both the basic and advanced rating approaches under Basel Accord regulation develop internal methodologies that need to be approved by the regulators. The application of these methodologies is, however, still subject to discretion. Discretion can only be avoided if risk assessment is subject to simultaneous external evaluation or even externally determined.

A more important result of our analysis is the importance of monitoring the incentives for discretion in credit risk assessment. As we show, the firms' ratings that are regularly reported to the central bank can be tested for their precision in predicting distress. In times of financial crisis significant differences across time and banks emerge that, if persistent, may lead to a significant destabilization of the banking system. Indeed, smaller banks and banks with weaker position on the market for funds may represent a disproportional risk to the system as a whole. The current IFRS provisioning model, based on incurred losses, led to delays in loss recognition and to significant pro-cyclicality in loan-loss provisions during the financial crisis. The International Accounting Standards Board (IASB) intends to introduce a new impairment model where losses will be recognised in more forward-looking manner. According to their proposal from March 2013 there would no longer be a threshold before credit losses would start to be recognized. Instead, expected credit losses would be recognized from the point at which financial instruments are originated or purchased. The amount of expected credit losses would be regularly updated to reflect changes in the credit quality. In this way, the credit losses would in principle not be delayed until the default event, but would at least partly be recognized in earlier stages. These provisions, however, assume away the problems with discretion in valuation of assets and credit risk assessment. Despite being forward-looking in nature, such a provision could be distorted by the banks incentives to over-value assets and under-value risk. Indeed, if such new regulation would result to be the most binding at times of extreme financial distress, its major expected effect could be undone by amplified incentives to conceal the true state of banks' portfolios.

In addition, policy measures increasing capital requirements in times of financial distress, increase the incentives to under-estimate risk and thus may undo the expected effect of strengthening confidence in the banking system. An example of such a measure in the Great recession is the measure by the European Banking Authority that required banks to hold at least 9% Core Tier 1 capital adequacy ratio by mid 2011, which was in the middle of still intense financial turmoil in the Euro area. From the point of view of our analysis, the timing of this policy measure could have amplified the incentives to under-estimate credit risk. The new Basel III and CRD IV capital regulation introduce a countercyclical capital buffer that could somewhat alleviate this problem. In the periods of excessive credit growth and possible build-up of system-wide risk, banks will be required to build a capital buffer (of up to 2.5% of RWA) in the form of Common Equity Tier 1 capital. When the crisis hits the buffer could be released and banks would thus have additional capital at hand, increasing their loss absorption capacity and possibly decreasing

the incentives to underestimate credit risk.

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